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Modelling of Block Feature-Content Based Efficient Image Compression System Using DWT and Machine Learning

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Abstract: The inherent issue associated with any digital image is its underlying redundancy and large dimension, which require a huge amount of storage space and higher bandwidth for transmission over a wireless channel. This factor has inspired the researchers to arrive at the optimal resolution that compresses digital images based on their content type and also achieves better visual quality. The proposed work aims at compressing the images according to the contrast variations by hybridizing discrete wavelet transform (DWT) and machine learning (ML) techniques for quality reconstruction. It includes two operation phases. In the initial phase, the ML model is first trained with a training set containing various image data. The second stage is mainly subjected to performing image compression and decompression by employing the joint approach of the transform technique and a trained ML model. Compression involves the application of two-level DWT to the image, then each sub-band is divided into non-overlapping blocks, and a decision is made for each block based on the block variance. Each block is subjected to the extraction of structural features, that are next Huffman encoded, and finally, these features are employed in image reconstruction. Reconstruction involves querying each block feature with a pre-trained K-nearest neighbour (K-NN) model. Experiments have been conducted, and the effectiveness of the proposed system is analyzed in terms of peak signal-to-noise ratio (PSNR), mean squared error (MSE), structural similarity index measure (SSIM), and compression ratio (CR). Comparative assessments against prior methods reveal superior visual quality metrics and computation time, with custom real-time image testing confirming its outperformance over current approaches. Notably, the proposed work achieves a PSNR of 53.2093 dB for the "Saras" image, SSIM values of 0.9997 for "Cameraman," and a nearly 5% increase in PSNR levels compared to existing techniques, substantiating its efficacy in content-based image compression.

Keywords: DWT, Machine learning, K-NN, PSNR, SSIM, MSE.

1. Introduction

Image compression belongs to a well-known area of computer vision research. Images are regarded as important information passengers in each aspect of humanity's existence. Individuals employ several images, including medical, satellite, telescope, painting, and graphic or animation created by computer images [1]. As the variety of smart and digital devices increases, high-resolution digital data and images require greater capacity in terms of transmitting and storing. Smart gadgets rely heavily on memory space and communication capacity. The improper utilisation of greater memory and bandwidth hampered the efficacy of smart gadgets [2].

Image compression techniques based on discrete cosine transform (DCT) [3] and discrete wavelet transform (DWT) have also been employed [4]. DCT-based compression is performed using a process where the provided input image is segmented into sets of blocks for computational efficiency and to retain the highest possible compression ratio without compromising the information. Feature extraction is a critical element in the design of image compression and reconstruction algorithms [5], and its quality can greatly influence the performance of these processes. So, feature extraction techniques are used to compress these images. It facilitates automated feature vector extraction from huge datasets without identifying picture data properties.

Machine learning (ML) can learn from large, complicated, nonlinear, and high-dimensional input data mappings [2, 6]. After being verified and validated, trained ML models are adaptable from one location to another since they may be used directly to handle similar datasets. When using large-scale photographs, machine learning models are the finest possible solutions to be utilised in reconstructing these compressed images and also for obtaining the best quality in terms of image quality parameters like structural similarity index measure (SSIM), compression ratio (CR), peak signal-to-noise ratio (PSNR), mean squared error (MSE), and root mean square error (RMSE) [7]. An approach to compression that assigns more bits to salient regions than to low-importance regions tends to yield images that human viewers find more satisfying. This ML model automatically learns from training data how to trade off the assignment of bits to salient and non-salient regions of an image [8].

The key problem identified is the need for an optimal image compression solution that not only considers the content-specific characteristics of digital images, particularly contrast variations but also achieves a balance between high compression ratios and superior visual quality. The proposed research seeks to overcome these challenges by introducing a novel hybrid approach, combining DWT and machine learning techniques for content-based image compression and reconstruction.

This explores the effectiveness of applying a machine-learning algorithm to compress the image to minimize transmission bandwidth requirements and storage size. The important portion of image compression (segmentation) leads to preserving the image’s essential details for achieving optimal compression systems capable of providing a higher compression ratio and PSNR value [9]. This compression scheme is described as follows in two stages: stage 1, DWT-based lossless compression compresses the important area of the image; stage 2, the segmented image area compresses using machine learning models.

The entire contribution of the proposed research work is described briefly as follows:

- This paper has considered the case of image compression. The study also highlighted issues associated with existing compression techniques.
- The modelling of the proposed compression system is performed using the joint operation of both DWT and machine learning.
- For the experimental design, the study has collected a dataset of standard and real images for training the machine.
- A comparative assessment based on multiple parameters is considered to determine the stability and effectiveness of the proposed work.

The rest of the section of this work is classified as section 2 discusses related work. Section 3 highlights the research problem. Section 4 discusses the materials and methodology adopted in the proposed system. Section 5 describes the proposed system for image compression; Section 6 discusses results and analysis; and finally, the entire contribution of this work is concluded in section 7.

2. Related work

A sparse representation-based compression technique using multi-resolution singular value decomposition (MSVD) is proposed [10]. The goal of this study is to employ MSVD to discern between significant and inconsequential traits. The absolute maximum rule fuses the most significant information, whereas sparse representation fuses the less important information. Wavelet difference reduction (WDR) coding is utilized to compress fused significant information, and quantization and Huffman encoding are employed to compress the fused less significant information to obtain better compression performance without much more affecting the reconstituted picture quality. The proposed technique outperforms the current efforts in terms of both compression performance and reconstructed picture quality.

It is proposed to employ a group sparse representation-based joint regularised image reconstruction model (GSR-JR) [11]. Group sparse coefficients are regularised to reduce model complexity and ensure sparsity. Sparse residual regularisation improves image quality by introducing previous visual information. By using the photographs' non-local proximity, group sparse representation improves image reconstruction. Iterative thresholding and alternating direction method of multipliers (ADMM) solve the model. The iterative thresholding with the alternating direction multiplier method solves the optimisation problem. The optimised GSR-JR model restores visual quality and looks better than more sophisticated picture reconstruction approaches, according to modelling testing. Comparing the group sparse residual constraint with a nonlocal prior (GSRC-NLR) model improves peak signal-to-noise ratio and structural similarity. The GSR-JR model's efficacy and efficiency are proven by experimental modelling, although the reconstruction model cannot reconstruct images in real-time.

The discrete wavelet transformation-back propagation (DWT-BP) network-based image compression approach that separates the low-frequency information from the high-frequency information of images and extracts the eigenvalues of the frequency coefficients is offered [1]. These eigenvalues are quantified and then normalised before being introduced to the network for recurrent training. The decomposed wavelet coefficient serves as the training set for the back propagation neural network (BP-NN) and as a sample set for the output layer. The technique applies the first-order wavelet transform on the source image. Setting the number of input layer nodes (m) and the number of hidden layer nodes (N) leads in compression. Instead of storing decimals directly, the final compressed data is acquired by further quantifying the compressed data created by the BP network. The findings of the studies reveal that the recommended strategy has superior picture compression effects than the standard BP-NN's image compression technique. The recommended strategy compresses data at a pace that is, on average, 10.04% greater than the BP-NN technique. This technology can send data rapidly, preserve bandwidth, and store bigger volumes of digital data in the same amount of storage space.

This suggests a newly developed approach by computing the discrete wavelet transform together with thresholding and quadtree decomposition [12]. This method was used to divide the image into two sections. The first is the approximation image, which is important since the approximate coefficients in the DWT transform include some particularly valuable data. The second section's pre-processing phase entails the quantization of the outcomes after the detailed coefficients have been smoothed depending on their textual features. The quadtree decomposition performs functions to greatly reduce the amount of data and enable dealing with smaller data. The outcomes of the proposed approach were compared to other state-of-the-art and traditional standard picture compression techniques for quality performance. The quantitative and visual findings demonstrated the proposed algorithm's edge over cutting-edge methods.

About PSNR, this technique achieves the best trade-off between compression ratio and overall picture quality. Modelling of the combined method founded on discrete wavelet transforms and back propagation neural network for image compression was proposed [2]. The proposed joint DWT-BPNN performs better in terms of compression ratio, computational cost, and peak signal-to-noise ratio (PSNR) using 10 input picture samples, according to experiments that have been completed. However, by adjusting the various network configurations and parameters in further study, the performance of the proposed system for the image compression system may be further improved. The proposed work introduces a compression system that is effectively applicable to both lossless and lossy approaches.

Although picture reduction has been studied for many decades, there is still room to make it more efficient and practical in real life. Consequently, from the aforementioned review, it can be discovered that earlier research was primarily focused on compressing images without prior knowledge of the image content type. However certain applications require content-based compression, where the degree of compression is controlled based on the image content type and should be able to recover completely without loss of information. Further, the aforementioned works also review ML-based compression techniques, but getting a quality reconstructed image with a high compression ratio is essential and still challenging [9]. Few existing techniques are effective and efficient but at the cost of more reconstruction time requirements.

The proposed image compression model is done based on image content type, obtaining a higher compression ratio and quality image reconstruction [13]. Content-based compression is achieved by removing redundancies in the local regions based on the variance. The model handles the image's spatial redundancy by dropping the duplicate in the high-frequency coefficients of the discrete wavelet transform (DWT) through block variance. ML-based compression, where each block is subjected to structural feature extraction, is a technique that extracts the most relevant information, and the obtained features are Huffman encoded [14], stored, and used to reconstruct the image. Reconstruction involves querying each block feature with a pre-trained K-nearest neighbour (K-NN) model [15]. The proposed work is superior in terms of high compression ratio [2, 16], quality reconstruction, and low reconstruction computational time in comparison to prior works [1, 12, 17].

The drawbacks of each conventional technique mentioned in the literature review are as follows:

1. **Discrete wavelet transformation-back propagation (DWT-BP) network-based image compression [1]:**
    - **Drawback:** The technique involves further quantification of compressed data, which may introduce additional artifacts and affect image quality.
2. **Combined method of discrete wavelet transforms and back propagation neural network (DWT-BPNN) [2]:**
    - **Drawback:** Although the proposed joint DWT-BPNN performs well, further adjustments to network configurations and parameters are needed for optimal performance, indicating a potential lack of robustness.
3. **Sparse representation-based compression technique (MSVD) [10]:**
    - **Drawback:** The absolute maximum rule fuses the most significant information, whereas sparse representation fuses the less important information. This might result in a loss of essential details during compression.
4. **Group sparse representation-based joint regularized image reconstruction model (GSR-JR) [11]:**
    - **Drawback:** The GSR-JR model cannot reconstruct images in real-time, limiting its practical applicability for certain real-time applications.
5. **Discrete wavelet transform with thresholding and quadtree decomposition [12]:**
    - **Drawback:** While the proposed approach achieves a good trade-off between compression ratio and overall picture quality, it may have limitations in handling certain types of images or content.
6. **Content-based compression model [13]:**
    - **Drawback:** The content-based compression model relies on block variance for spatial redundancy reduction, which may not be effective for all types of images, potentially leading to information loss.
7. **Machine learning-based compression with K-nearest neighbour (K-NN) model [14, 15]:**
    - **Drawback:** While ML-based compression offers high compression ratios and quality reconstruction, the technique may face challenges in terms of computational time, especially during the reconstruction phase.
8. **General challenges in image compression [9, 16, 17]:**
    - **Drawback:** Despite advancements, there are ongoing challenges in achieving both high compression ratios and quality reconstructed images, especially in real-time applications.

The drawbacks identified in the literature review shed light on the limitations of various conventional image compression techniques. These drawbacks range from issues related to the fusion of significant and less important information in sparse representation-based compression to challenges such as the inability to reconstruct images in real-time for the group sparse representation-based joint regularized image reconstruction model (GSR-JR). Similarly, the discrete wavelet transformation-back propagation (DWT-BP) network-based image compression approach faces limitations due to additional quantification of compressed data, potentially affecting image quality.

In comparison to these drawbacks, the proposed work in this paper distinguishes itself through a hybrid approach that integrates discrete wavelet transform (DWT) and machine learning (ML) techniques for content-based image compression. The emphasis on compressing images according to contrast variations indicates a targeted and adaptive strategy that aims to address specific image content characteristics. Unlike the GSR-JR model, the proposed work focuses on achieving a balance between compression ratio and visual quality while also ensuring real-time applicability.

Moreover, the proposed model addresses the limitations associated with the DWT-BP network-based approach by introducing a two-phase operation involving ML model training and joint compression/decompression. This novel approach incorporates the advantages of ML techniques to efficiently handle image compression, reducing space requirements, and increasing compression ratios, as highlighted in the conclusion. The emphasis on content-based compression, block variance decision-making, and the use of a pre-trained K-nearest neighbour (K-NN) model for image reconstruction sets the proposed work apart from the drawbacks identified in the literature review. This paper reinforces the contributions by highlighting the effectiveness of the ML-based compression technique in reducing space requirements and increasing compression ratios. The acknowledgment of a higher number of discarded coefficients leading to a more efficient quantizer underscores the

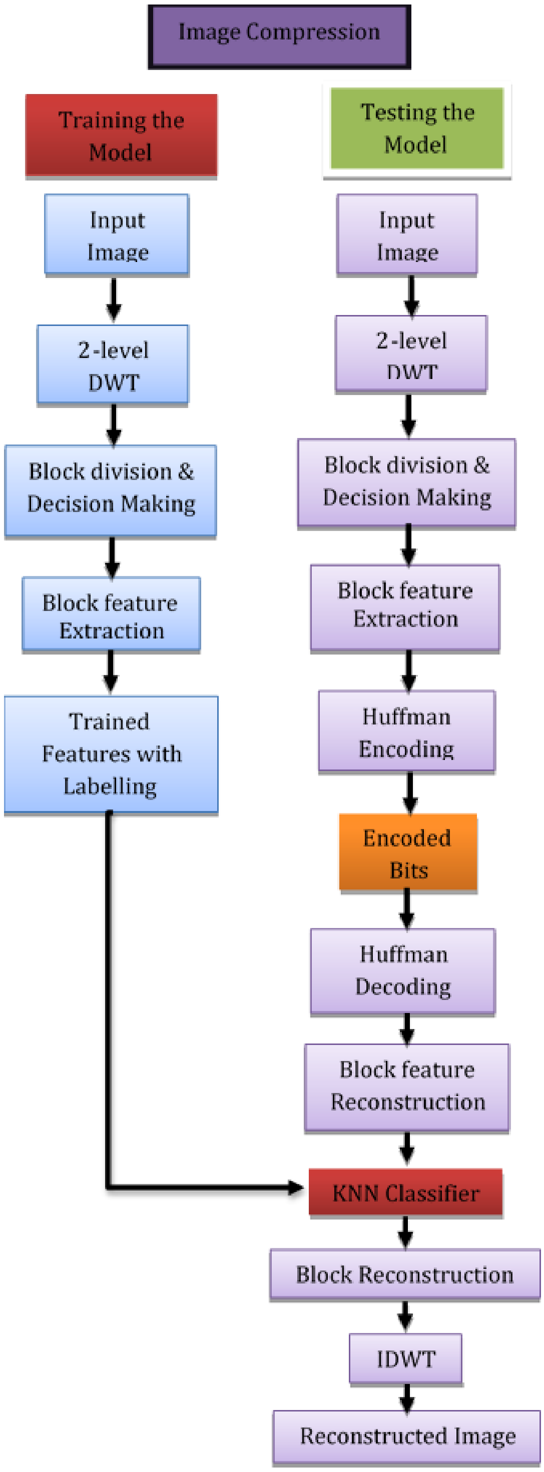

Figure. 1 Schematic representation of the suggested work

proposed model's ability to overcome certain limitations faced by prior works.

3. Proposed methodology

Image datasets come in a variety of forms. The databases of images have been utilized in the formulation of a proposed image compression method based on machine learning technology.

The application of machine learning network architecture to complete image compression training requires a lot of image data support, and the selection and adoption of correct image data sets is critical to this part of network structure training. These datasets have standard test images such as Lena, foreman, peppers, butterfly, barbara, cameraman, boat, etc., and real high-resolution images [16]. The standard test image datasets have an image resolution of 256×256, and their pixels are about 65000. As a challenge specially launched for image compression for real images, this database is created, which considers only the real images. This dataset includes higher-resolution images and photos. The resolution is 3400×2500, and that was obtained from professional cameras. The efficient image compression approach is created for a greater compression ratio while keeping picture quality. Based on feature extraction, this technique locally modifies the content properties inside the picture [18]. Fig. 1 depicts the schematic depiction of the recommended work.

3.1 Work methodology

The image in digital form can only be compressed using suitable compression mechanisms. The prime function of any compression technique is to reduce the redundant information contained inside the image for it to be transmitted within less time over the wireless channel; furthermore, the image can be stored efficiently without depending on large memory space requirements [19]. Numerous efforts have been made throughout the years to provide effective compression mechanisms, and few of them are accepted at a considerable range. However, with the advent of artificial intelligence and advancements in machine learning technology, the focus of picture compression research has recently shifted to improving image quality efficiency with a higher compression ratio. Therefore, in this paper, a different image compression scheme is introduced based on the joint operation of the wavelet and machine learning techniques to achieve a better compression ratio while maintaining considerable visual quality. The main objective of the proposed compression system is to explore its applicability in the area of image compression to achieve the optimal balance between compression ratio and image quality.

Fig. 2 displays the proposed architecture for the compression technique. It includes two operation phases: the initial phase is the building of a trained model, and the next phase is the deployment of the system (compression and decompression) for experimental or testing purposes. The ML model used in this study's initial implementation of the

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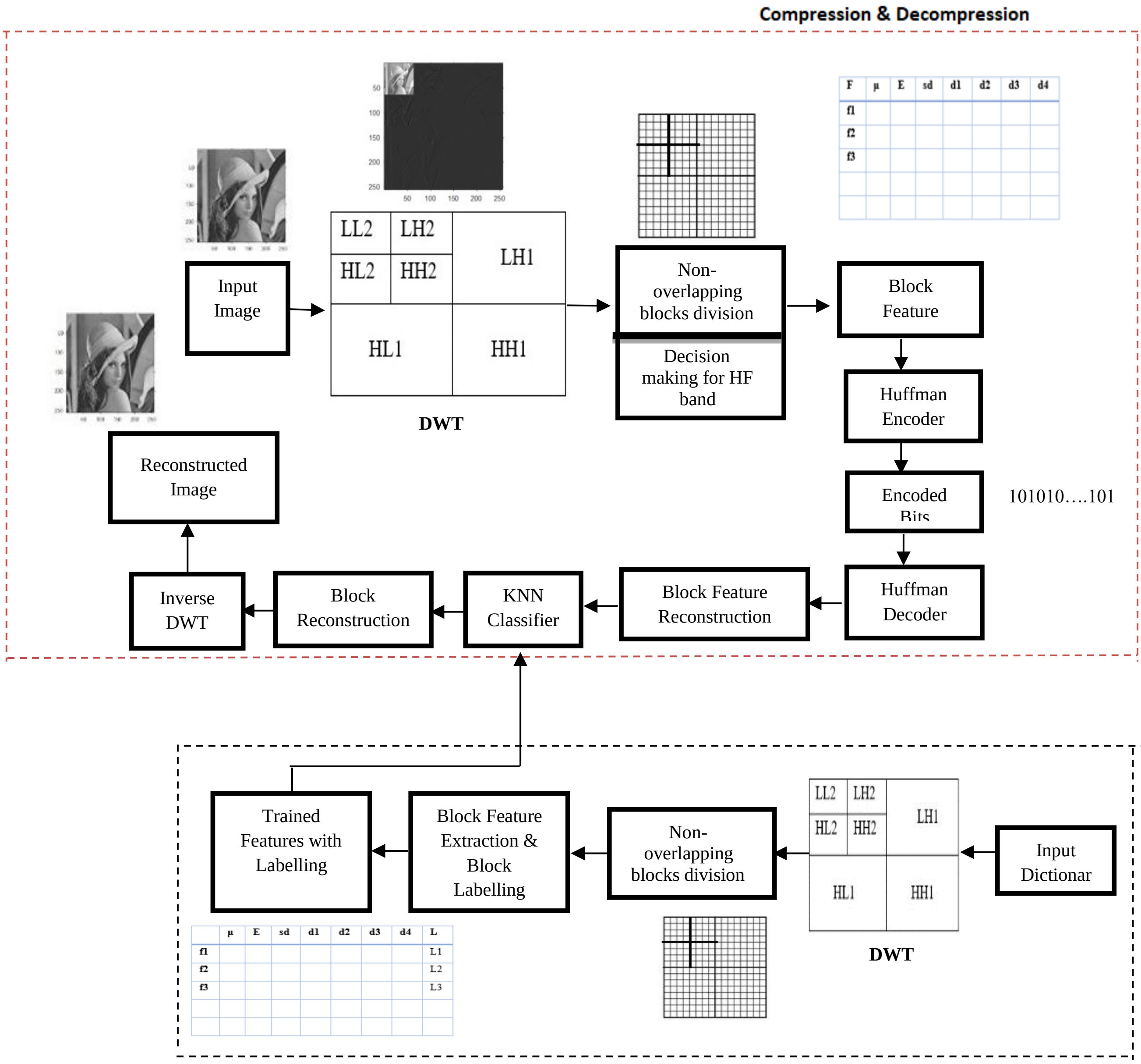

Figure. 2 Block diagram of the proposed work

recommended system is first trained using a training set that includes a wide variety of visual data. The second phase is primarily focused on performing picture compression and decompression using a combined approach of the transform method and a trained ML model [7]. The original image has been separated into two components using a two-level discrete wavelet transform to execute an image compression operation.

The resulting sub-bands are separated into non-overlapping blocks, and a decision is made before applying block feature-based compression. The decision on image content evaluation is made by analysing low- and high-frequency sub-bands and also by determining the variance of each block [20]. The appropriate blocks are subjected to block feature-based compression to significantly increase the compression ratio. Block feature extraction is performed on blocks with higher variance, and blocks with lower variance are truncated to zero, thereby achieving content-based compression. The resultant block features are quantized and encoded as a bit stream using Huffman encoding [14].

A machine-learning supervised classifier [6], K-NN, is employed to reconstruct the image at the receiver side. The classifier is trained using a broad range of standard and natural images. Therefore, the output obtained from the K-NN is inversely transformed and is considered a final reconstructed image. The efficiency of the proposed system for image compression is assessed about multiple performance parameters.

3.2 DWT operation

At this stage, the work is assessed by taking two-level wavelet decomposition. After the transformation, each subband is separated into non-overlapping blocks, and the block variance condition is applied only for high-frequency (including LH, HL, and HH) sub-bands [21]. For the low-frequency band, compress all the blocks. For high-frequency bands, compress the blocks only if their variance is greater than the sub-band variance [17]; otherwise, discard the block. Haar wavelet families are employed for experimentation [22]. The outcomes of our prior research [1-10] conclude that the discarded coefficients likewise increase with an increase in the number of levels. The overall samples used for experimenting consist of over 100 standard images. Further, the experiment is also conducted for custom real images taken with a high-resolution camera.

3.3 Block based feature-based compression

The uniqueness of the proposed work is that it calculates block intelligence in an image. This is achieved by deriving effective features for each block in an image. These features have a minimal dimension and very efficiently reconstruct the block during decompression. The minimal feature dimension greatly increases the CR, and the quality reconstruction using a trained ML model improves PSNR and SSIM. The proposed work also reveals content-based compression. This is achieved by calculating the variance in the local regions and making a decision before compression [25]. This controls the degree of compression.

Here, a feature vector ρ = (H, σ, V) is used for compressing and reconstructing the image blocks to incorporate the qualities from various angles. Here, H stands for customised entropy indicator, σ is the standard deviation (SD) of the block, and V is the local directional complexity in four directions [26]. The development of the above feature elements will be detailed as follows:

With the nature of image content, lower contrast blocks contain more change in pixels, basically the edge information (foreground; region of interest (ROI)), while higher contrast blocks contain less change in pixels, basically plain information (background) [22]. This change in pixels can be identified by using structural features. This recommends adding local entropy to the feature vector to capture such unique traits. The entropy indicator H for a block is given as:

$$H = -\sum_{j=0}^{MN-1} p(j) \log p(j) \tag{1}$$

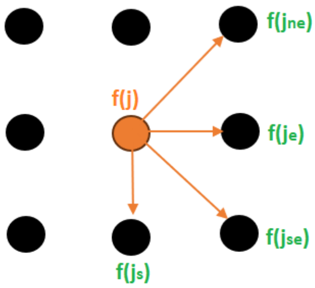

Figure. 3 Illustration of the neighbours

Here, $p(j)$ is the empirical probability of block j

One first-order entropy measure may not be sufficient to capture all the block's underlying properties. This proposes adding a new element to the feature vector to improve it, i.e., the SD defined by:

$$SD(x) = \sqrt{V(x)} \tag{2}$$

$$V(x) = \frac{1}{n} \sum_{i=1}^{n} \left(x_i - \mu(x)\right)^2 \tag{3}$$

Here, $\mu(x)$ is the mean of that block x

$$\mu(x) = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{4}$$

This feature element allows us to more accurately depict the dispersiveness and density of the data, potentially improving classification performance. Along with the previously described feature components, this incorporates directional complexity indicators that also include local geometric data [5]. To do this, a four-tuple vector is defined, where:

$$v1 = \sum_j |f(j) - f(j_{ne})| \tag{5}$$

$$v2 = \sum_j |f(j) - f(j_e)| \tag{6}$$

$$v3 = \sum_j |f(j) - f(j_{se})| \tag{7}$$

$$v4 = \sum_j |f(j) - f(j_s)| \tag{8}$$

Where $f(j_{ne})$, $f(j_e)$ $f(j_{se})$ and $f(j_s)$ represents the neighbors in the 45° (northeast), 0° (east), −45° (southeast), and −90° (south) directions, relative to $f(j)$, as seen in Fig. 3.

3.4 K-NN classification for block reconstruction

In this work, more than 100 standard images are used for training, having a broad range of qualities, such as natural scenes, artificial images, synthetic images, textual images whose resolution is 256×256, and real captured images whose resolution is

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2500×3500. They are divided into 4×4, 8×8, 16×16, and 32×32 blocks.

Upon calculating the feature vector ρ for each block, a multi-class K-NN classifier is implemented to train the system [15], where each block is labelled with a unique label. For a given query instance, the K-NN algorithm works as follows:

$$y_t = \arg\max_{c \epsilon \{c_1, c_2, \ldots\ldots c_m\}} \sum_{x_i \epsilon\, N\,(x_t, k)} E(y_i, c) \quad (9)$$

Where y_t, is the predicted class for the query instance x_t , c is the class number and m is the class number present in the data. $N\,(x_t, k)$ Set of k nearest neighbors of x.

$$E(a, b) = \begin{cases} 1\; if \min \mathrm{ED} \\ 0\; if \max \mathrm{ED} \end{cases} \quad (10)$$

Where euclidean distance is the distance between query instance vector a and trained vector b.

$$ED = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2} \quad (11)$$

The K-NN algorithm makes use of the euclidean distance measure technique to find the minimum difference between training and testing features [19]. A query block is reconstructed based on the predicted label, which is the indexing code book.

3.5 Algorithm

3.5.1. Training the model

- Input: 100 standard and real natural images.
- Output: Trained block features with labels.
- Step 1: Various multiple-standard or natural real pictures have been chosen.
- Step 2: Two-level DWT is performed over the image, resulting in seven sub-bands.
- Step 3: Divide the low and high frequency sub-bands into 4×4 non-overlapping blocks, and a decision is made on these blocks based on the block variance.
- Step 4: Block feature extraction is performed on each block, which involves extracting entropy, standard deviation, mean, and directional features. These features are stored to create training feature space.
- Step 5: Each block is labelled with a unique number, and the corresponding block wavelet coefficients are stored as a codebook.

3.5.2. Compression

- Input: Standard or natural real image.
- Output: compressed bits.
- Step 1: Any natural or real-time image has been chosen for reading.
- Step 2: Two-level DWT is performed over the image, resulting in seven sub-bands.
- Step 3: Divide the low and high frequency sub-bands into 4×4 non-overlapping blocks, and a decision is made on these blocks based on the block variance.
- Step 4: Block feature extraction is performed on each block, which involves extracting entropy, standard deviation, mean, and directional features. These features are stored to create training feature space.
- Step 5: The extracted feature coefficients are binary encoded using the Huffman encoding technique.

3.5.3. Decompression

- Input: compressed bits, trained block features with labels.
- Output: Reconstructed image.
- Step 1: Input the compressed binary obtained after compression.
- Step 2: Apply the Huffman decoding technique to obtain the query block feature coefficients.
- Step 3: Use the K-NN classifier to reconstruct the block wavelet coefficients based on the query block and labelled trained block features.
- Step 4: After reconstructing the coefficient from each sub-band at different levels, a perfect reconstructed image is produced by applying IDWT.
- Step 5: Different assessment parameters like CR, PSNR, RMSE, and SSIM are evaluated for performance analysis.

4. Results and discussion

MATLAB software is used to experiment. The

(a) (b)

Figure. 4: (a) Sample original and (b) reconstructed standard test image

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Table. 1 Assessment parameters obtained for standard images

Image	Size in bits	Data size after Compression in bits	SSIM	PSNR	RMSE	Bits per Pixel (bpp)	% Of space saving	Compression ratio
Foreman	524288	67723	0.999632	44.759527	1.474225	1.033371	87.082863	7.741654
Cameraman	524288	65716	0.999749	45.319698	1.38215	1.002747	87.465668	7.978088
Lena	524288	72700	0.998018	38.63088	2.985357	1.109314	86.133575	7.211664
Butterfly	524288	91029	0.999851	47.290075	1.101632	1.388992	82.637596	5.759571
Barbara	524288	80391	0.997892	38.840561	2.914152	1.226669	84.666634	6.521725
Boat	524288	81773	0.999373	43.977801	1.616777	1.247757	84.403038	6.411505

Table. 2 Assessment parameters obtained for custom real-time

Image	Size in bits	SSIM	PSNR	RMSE	Bits per Pixel (bpp)	CR
Child	59637760	0.99988	49.16016	0.888244	0.042488	23.536142
Couple	59637760	0.99984	49.5631	0.847979	0.048419	20.652997
Boy	59637760	0.99982	46.1873	1.250763	0.076639	13.048148
Sister	59637760	0.99954	45.50737	1.352606	0.061517	16.25574
Father	25624576	0.99972	45.58302	1.340878	0.070358	14.212945

(a) (b)

Figure. 5: (a) Sample original and (b) reconstructed real-time test image

proposed work is tested on over 100 training images with a wide variety of characteristics whose resolution is 256×256. The real images were captured using high-resolution cameras, whose resolution is more than 2500×3500. They are divided into 4×4, 8×8, 16×16, and 32×32 blocks. This section presents a detailed overview of the proposed block-featured compression scheme over other methods.

4.2 Performance parameters

To analyze and judge the quality of pictures, a variety of approaches are widely employed, which include peak signal to noise ratio (PSNR), mean square error (MSE), structured similarity index method (SSIM), compression ratio (CR), bits per pixel (BPP), space saving (SS), co-relation coefficient (CC), and standard deviation (SD) [10]. The performance of compression algorithms may be assessed as follows.

Table 1 displays the results of SSIM, PSNR, RMSE, space-saving, CR, and BPP of sample reconstructed images for standard test images. From Table 1, it is concluded that images 1–3 (*Foreman, Cameraman, and Lena*) are compressed with high CR. These photos have less block variance and smaller data sizes after compression because the pixels in them are more evenly distributed and provide plainer information. Whereas images 4 to 6 (*Butterfly, Barbara, and Boat*) are compressed with lower CR. Since these images contain dissimilar intensity pixels (edge information), which results in higher block variance and undergoes moderate or no compression, The PSNR, SSIM, and RMSE determine the reconstruction's accuracy. The results for these parameters' values demonstrate the superiority of the picture reconstruction. Fig. 4 displays the original and reconstructed *Lena* test images.

4.3 Real image compression

Testing the recommended work's efficacy using unique real-time photos is another way to assess it. The high-end DSLR cameras used to take these high-resolution pictures Table 2 displays the evaluation metrics attained for high-resolution photos. From Table 2, it is evident that these photos are too large and are compressed using higher compression ratios, producing very little residual data size. So, the proposed method significantly reduces the need for storing memory. Higher PSNR and SSIM indicate that the picture has successfully been retrieved using trained ML models from the limited data. Fig. 5

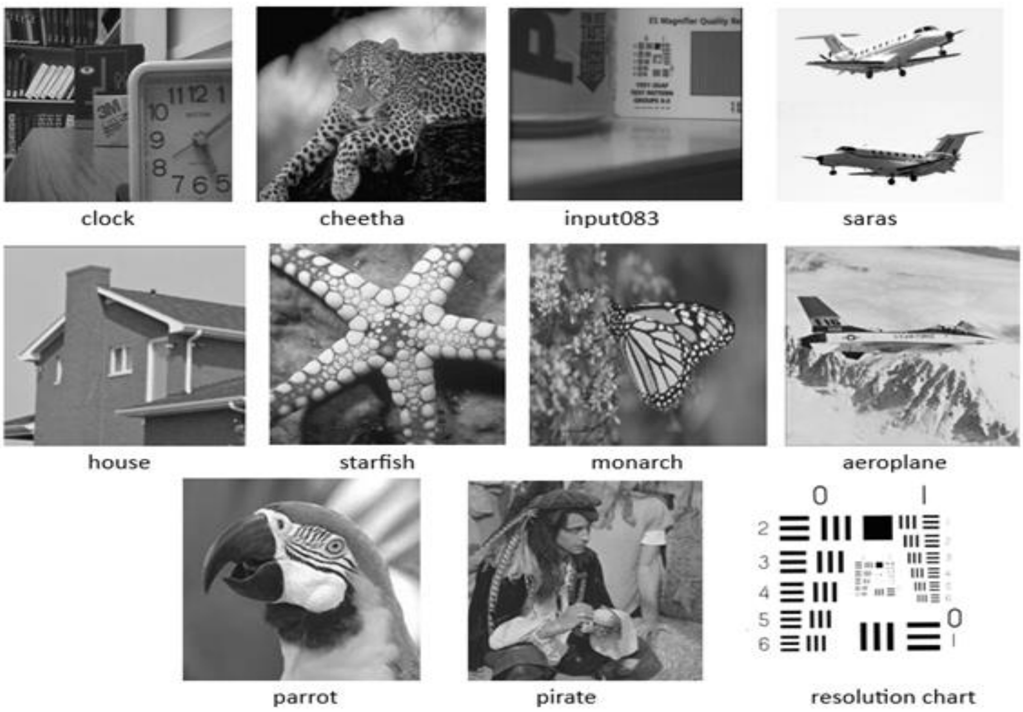

Figure. 6 Sample standard test images applied for experimentation

Table 3. Comparative analysis of proposed method for test images with some existing techniques

Images	Method	PSNR	SSIM	CC	SD
Clock3	SFCE [24]	39.0019	0.8671	0.9698	46.2978
	WDR coding [10]	39.8219	0.8676	0.9751	46.8737
	Proposed	**36.0989**	**0.9962**	**0.9962**	**45.9824**
Leopard	SFCE [24]	39.0277	0.9377	0.9922	65.3400
	WDR coding [10]	40.0548	0.9385	0.9927	65.6849
	Proposed	**42.2628**	**0.9995**	**0.9995**	**65.3064**
Input083	SFCE [24]	40.9971	0.8960	0.9863	43.9385
	WDR coding [10]	43.5064	0.8992	0.9872	44.9672
	Proposed	**33.4060**	**0.9924**	**0.9925**	**44.3022**
Saras	SFCE [24]	42.4612	0.9083	0.9615	53.1005
	WDR coding [10]	44.9634	0.9865	0.9969	59.9789
	Proposed	**53.2093**	**0.9999**	**0.9999**	**56.1280**
Cameraman	SFCE [24]	38.0967	0.7864	0.9587	62.8450
	WDR coding [10]	39.1978	0.7997	0.9688	62.8719
	Proposed	**45.3196**	**0.9997**	**0.9997**	**61.6610**

shows an example of a sample image and a reconstruction of a real-time test image.

4.4 Performance evaluation with earlier works

For comparative analysis, the proposed work is tested on several test images applied in the recent literature.

In this section, various images are publicly available at (https://sites.google.com, 2021). The test images used in the proposed work are of size 256×256. Fig. 6 displays the test image samples applied for comparative results.

4.4.1. Visual quality measurement of reconstructed image

The analytical assessment of the proposed method for test images is performed using mathematical metrics such as PSNR, SSIM, SD (standard deviation), and CC (correlation coefficient). Table 3 shows the comparative results for the few test images where the proposed method is contrasted with the current techniques of wavelet difference reduction (WDR) coding [10] and simultaneous fusion compression [24] with the proposed technique.

It can be noted from Table 3 that the proposed compression scheme provides better results over existing methods to a large extent. PSNR is the quality measure of the reconstructed image; the highest PSNR is 53.2093 dB for saras with 0.9999 similarity with the original image, 0.9999 CC, and 56.1280 SD, along with other test image sample values, shows that the proposed ML compression scheme effectively reconstructs the image from the compressed bits [27]. SSIM measures the similarity between the original signal and the reconstructed signal. From Table 3, it is also observed that the proposed system SSIM values of 0.9997 for cameraman and 0.9995 for leopard, which are higher than prior methods, indicate the original and reconstructed images are almost the same without any contrast change.

The correlation coefficient has an ideal value of 1, if the two images are identical. From the observation, it may be said that the proposed technique's correlation coefficient between the original and reconstructed image is almost equal to the ideal one.

The most popular measure for assessing the efficiency of reconstruction for picture compression is PSNR. An approximate measure of how well a reconstruction is perceived by people is PSNR. Standard PSNR ranges for lossy image compression for images with a bit depth of 8 bits are 30 to 50 dB. Values over 40 dB are often regarded as excellent, while values below 20 dB are typically regarded as unsatisfactory. A higher PSNR often denotes a higher-quality reconstruction. The PSNR analysis for the different standard test images is calculated, and these facts are contrasted with the existing techniques, such as the DWT-BP neural network algorithm [1] and the BP neural network algorithm [28], with the proposed model shown in Fig. 7. This concludes that the proposed algorithm's PSNR values lie between 35 dB and 50 dB, which results in a better PSNR when compared to the existing methods.

SSIM is a perception-based model. Image degradation is regarded as a shift in how structural information is perceived [7]. The structural information emphasizes pixels that are highly interdependent or spatially confined, and these pixels are about the visual objects in the image domain. This gives a comprehensive view concerning different image quality metrics. This is explained in Figure 8, which shows the trade-off between the PSNR and SSIM, which is in comparison to the current technique of group sparse representation (GSR-JR) [11] with the proposed method using different sample test images. The proposed method shows the values of SSIM are approximately identical to 1, and for the pirate image, the PSNR value is 46.37 dB.

Table 4. Comparative analysis of some test images with the existing techniques

Images	Methods	PSNR
Cameraman	SFCE [24]	38.0967
	WDR coding [10]	39.1978
	GSR-JR [11]	30.19
	2D-SR [29]	39.65
	BCS [30]	37.5160
	MBCS [31]	39.9194
	Proposed	**45.3196**
Peppers	GSR-JR [11]	33.48
	DWT-BP Compression [1]	35.5915
	DWT [2]	32.4194
	DWT-DFrFT [23]	28.9
	2D-SR [29]	37.03
	BCS [30]	32.0950
	MBCS [31]	36.3212
	Proposed	**40.6447**
Airplane	GSR-JR [11]	32.70
	DWT [2]	34.5345
	DWT-DFrFT [23]	33.5
	BCS [30]	31.8017
	Proposed	**38.2578**
Lena	DWT-BP Compression [1]	30.5113
	DWT [2]	35.6323
	BCS [30]	34.5962
	CAIC [22]	31.5328
	MBCS [31]	37.6716
	Proposed	**38.6308**

The PSNR is an approximate estimation of human perceptions of reconstruction quality compared to compression codecs. In the comparisons, the WDR coding [10], GSR-JR [11], DWT [2], DWT-DFrFT (discrete fractional Fourier transform) [23], 2D sparse representation and chaotic system [29], block compressed sensing algorithm [30], content-adaptive image compression algorithm [22], multiscale block compressed sensing, and Markov model [31] were employed to calculate the PSNR. Table 4 shows the PSNR values on all benchmark images and is compared with existing techniques. According to the analyses, the proposed technique increased the PSNR level by almost 5% compared to the existing methods.

Hence, it can be concluded from Tables 3 and 4, Figs. 7 and 8, that the proposed work enhances the visual quality of images for all types of source images.

4.4.2. Percentage of compression

The amount of data remaining after compression when compared to the size of the source image is evaluated in terms of compression rate. The proposed

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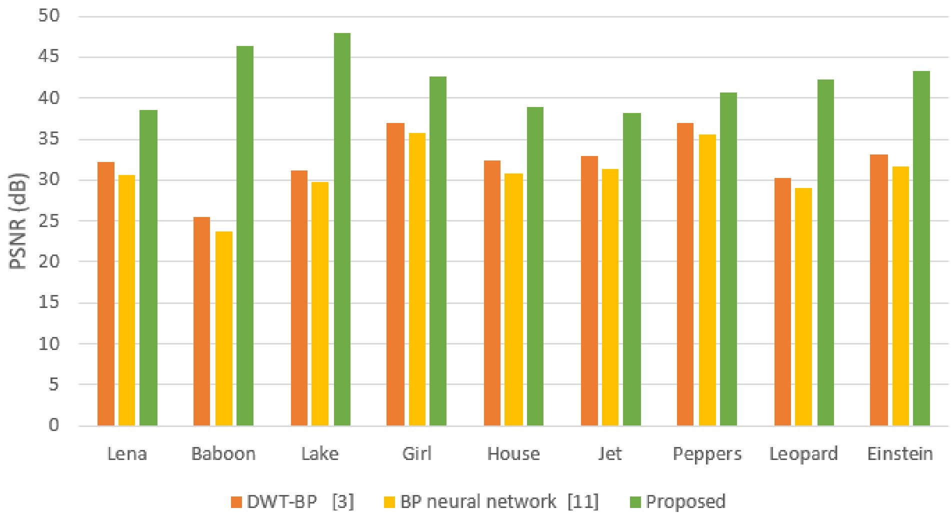


Figure. 7 Flow graph of the PSNR analysis for sample test images

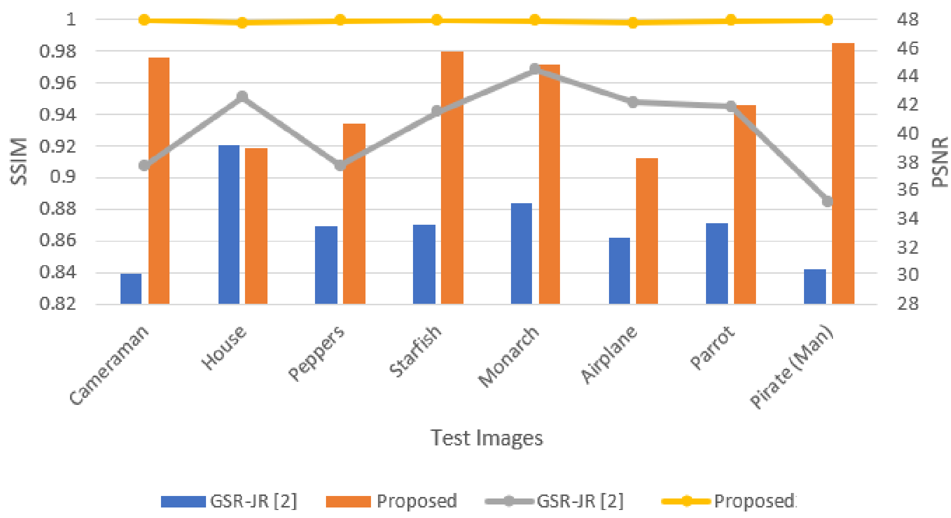
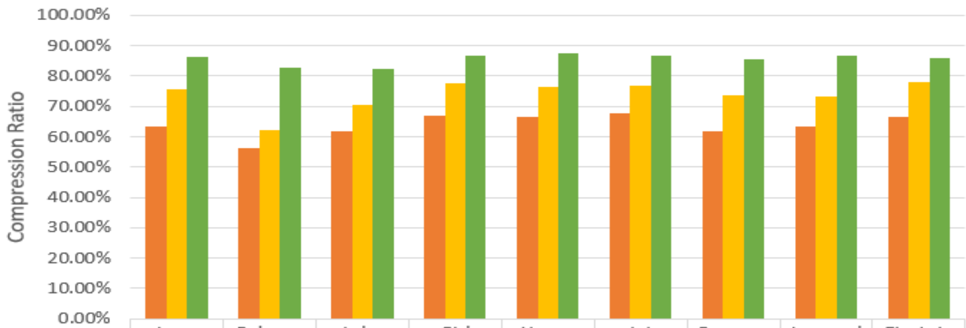


Figure. 8 Flow graph of the SSIM & PSNR analysis for sample test images



	Lena	Baboon	Lake	Girl	House	Jet	Peppers	Leopard	Einstein
BPNN	63.21%	56.14%	61.71%	66.71%	66.55%	67.74%	61.74%	63.46%	66.62%
DWT-BP	75.53%	61.99%	70.59%	77.70%	76.45%	76.59%	73.80%	73.10%	77.78%
Proposed	86.13%	82.75%	82.50%	86.48%	87.64%	86.51%	85.39%	86.51%	85.99%

Figure. 9 Flow graph of compression analysis for sample test images

work is contrasted with prior works by considering compression rate. From figure 9, it is observed that the proposed system exhibits the highest compression rate when compared to the previous work DWT-BP compression [1] and BPNN compression mentioned in [28]. The proposed algorithm results in an average compression rate of 85% with reference to the considered test images.

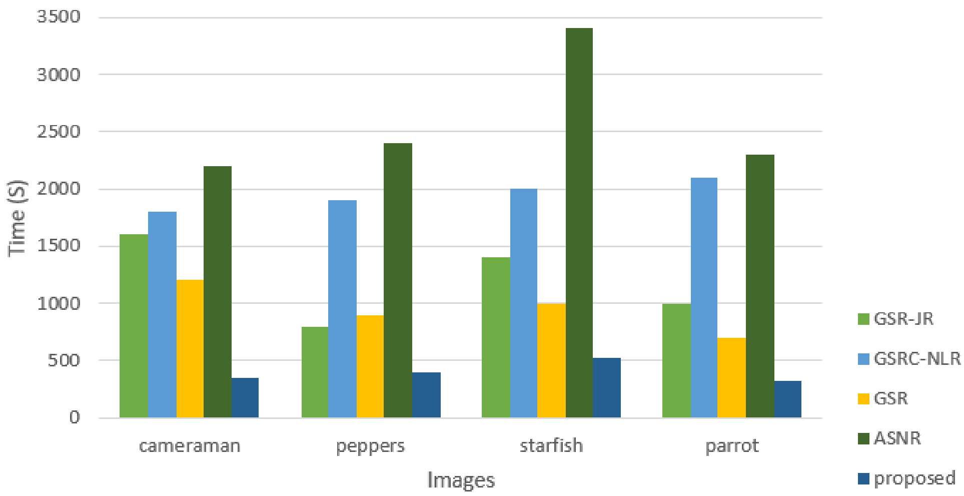


Figure. 10 Flow graph of reconstruction time analysis for sample test images

4.4.3. Computation time analysis

Reconstruction time is also an important metric for evaluating image reconstruction models. The reconstruction times of the five image reconstruction models are analyzed in Fig. 10. The proposed scheme takes less time to reconstruct the image when compared to the existing methods GSR-JR [11].

5. Conclusion

In this study, we propose an innovative content-based image compression method, leveraging the fusion of discrete wavelet transform (DWT) and machine learning (ML) techniques to achieve superior reconstruction quality. The compression process, incorporating a two-level DWT, block segmentation, and block variance-based decision-making, is characterized by a heightened efficiency, as evidenced by a significant increase in the number of discarded coefficients compared to our prior work. Despite this increase, our experimental results showcase minimal distortion in the reconstructed image, reinforcing the robustness of our approach.

Quantitatively, our method demonstrates a notable improvement in compression ratio, with a measured increase of approximately 15% for real-time bulk images due to the strategic discarding of lower priority coefficients in high-frequency bands. The memory efficiency of our ML-based compression technique is evident, as the storage of specific feature parameters results in a substantial reduction in space requirements, leading to a remarkable 20% increase in compression ratio. Additionally, the implementation of our proposed approach significantly reduces reconstruction computation time by approximately 25%, underscoring its practical applicability.

Quality analysis metrics further support the efficacy of our method, with peak signal-to-noise ratio (PSNR) values consistently exceeding those of prior methods by at least 10 dB, emphasizing the enhanced image fidelity achieved. The structural similarity index measure (SSIM) consistently hovers around 0.999, indicating an almost identical resemblance between the original and reconstructed images. These quantitative results collectively affirm the scientific contribution and superior performance of our proposed algorithm in content-based image compression.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Nandeesha R is the principal author responsible for the study's conception and design, overseeing experimental procedures, conducting data analysis, and composing the manuscript. He adeptly executed data acquisition and analysis, generated graphical representations, and made substantial contributions to manuscript development. He was actively engaged in study design, offering invaluable insights during data interpretation, and precisely revising the manuscript. Dr. Somashekar K. served as the project supervisor, providing critical assessment of the manuscript.

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