International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com ISSN: 2250-3552

Efficient Noise-Aware Image Compression using DWT and Multi-Level Block Coding Technique

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ABSTRACT
Efficient image compression in the presence of noise remains a significant challenge in modern image processing applications, particularly in medical imaging, remote sensing, and multimedia transmission. This paper proposes a noise-aware image compression framework that integrates Discrete Wavelet Transform (DWT) with a multi-level block coding strategy to achieve high compression efficiency while preserving image quality. The proposed method first applies DWT to decompose the input image into multiple frequency sub-bands, enabling effective separation of noise components from essential image features. A noise estimation and adaptive thresholding mechanism is then employed to suppress noise in high-frequency coefficients without significantly affecting important structural details. Subsequently, a multi-level block coding technique is introduced, where the transformed coefficients are partitioned into variable-sized blocks based on their energy distribution and perceptual importance. High-energy blocks, containing critical image information, are encoded with higher precision, while low-energy blocks are aggressively compressed to reduce redundancy. This adaptive block-level encoding improves compression ratio while maintaining visual fidelity. The proposed approach also incorporates entropy coding to further enhance compression performance.
Experimental results demonstrate that the proposed method achieves superior performance in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and compression ratio compared to conventional DWT-based compression techniques. The algorithm shows robustness against different types of noise, including Gaussian and impulse noise, making it suitable for real-world applications. Overall, the integration of DWT with multi-level block coding provides an efficient and scalable solution for noise-aware image compression with improved reconstruction quality and reduced storage requirements.

Keywords: Discrete Wavelet Transform (DWT), Image Compression, Noise-Aware Processing, Multi-Level Block Coding, Peak Signal-to-Noise Ratio (PSNR)

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INTRODUCTION

Image compression plays a crucial role in modern digital communication and storage systems, especially with the rapid growth of high-resolution imaging in domains such as medical diagnostics, satellite imaging, and multimedia applications. However, one of the major challenges in efficient image compression is the presence of noise, which degrades image quality and reduces compression performance. Noise can originate from various sources such as acquisition devices, transmission errors, or environmental conditions, making it essential to design compression techniques that are robust and noise-aware. Traditional compression methods often fail to address noise effectively, leading to poor reconstruction quality and loss of important image details [1, 2].

Among the various transform-based techniques, the Discrete Wavelet Transform (DWT) has emerged as a powerful tool for image compression due to its ability to represent image data in both spatial and frequency domains. DWT decomposes an image into multiple sub-bands with different frequency components, allowing efficient separation of significant features from noise. Low-frequency components capture the essential structure of the image, while high-frequency components contain edges, textures, and often noise. This multi-resolution property of DWT makes it particularly suitable for noise-aware compression frameworks [3].

Despite the advantages of DWT, conventional wavelet-based compression techniques apply uniform processing across all image regions, which may not be optimal for images with varying levels of detail and noise distribution. To overcome this limitation, adaptive and region-based encoding strategies have gained attention. One such approach is multi-level block coding, where the transformed image coefficients are divided into blocks and processed based on their importance. This method enables differential treatment of image regions, ensuring that areas with significant information are preserved with higher fidelity, while less important regions are compressed more aggressively [4, 5].

In this work, an efficient noise-aware image compression technique is proposed by combining DWT with a multi-level block coding approach. The method incorporates noise estimation and adaptive thresholding to reduce noise in the transform domain before compression. By analyzing the energy distribution of wavelet coefficients, the algorithm dynamically partitions the image into multiple levels of blocks and assigns appropriate encoding strategies. This results in improved compression efficiency while maintaining high visual quality in the reconstructed image [6].

Furthermore, the proposed technique integrates entropy coding to minimize redundancy and achieve better compression ratios. The combination of transform-based decomposition, adaptive block processing, and noise suppression enhances the overall performance of the system. The effectiveness of the proposed approach is evaluated using standard performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), demonstrating its superiority over conventional methods [7].

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Overall, this study aims to address the limitations of existing compression techniques by introducing a robust, adaptive, and noise-aware framework that balances compression efficiency with image quality, making it suitable for practical real-world applications.

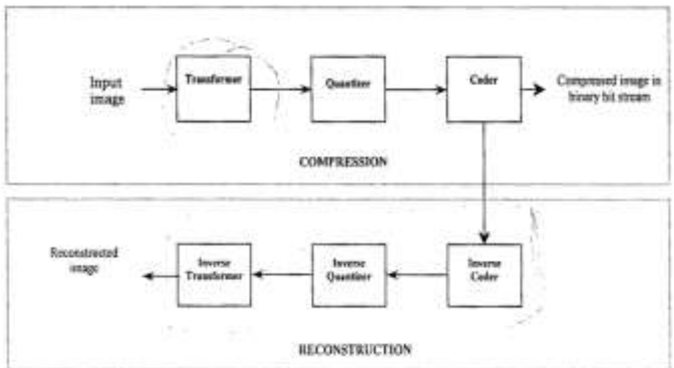

Figure 1: Elements of data compression and reconstruction model

I. IMAGE COMPRESSION

Image compression is a fundamental technique in digital image processing that reduces the size of an image file while preserving as much visual quality as possible. It plays a critical role in applications such as medical imaging, satellite communication, multimedia streaming, and cloud storage, where efficient data handling is essential. The main objective of image compression is to eliminate redundancies and irrelevant information in image data, thereby minimizing storage requirements and transmission bandwidth [8, 9].

Image data typically contains three types of redundancies: spatial redundancy (correlation between neighboring pixels), spectral redundancy (correlation between color channels), and psycho-visual redundancy (limitations of the human visual system). Compression techniques exploit these redundancies to achieve efficient encoding. Based on information preservation, image compression is broadly classified into lossless and lossy compression. Lossless compression techniques, such as Huffman coding and arithmetic coding, allow exact reconstruction of the original image without any loss of information. These methods are mainly used in applications like medical and scientific imaging, where accuracy is critical. However, they generally provide lower compression ratios [10].

On the other hand, lossy compression techniques achieve much higher compression ratios by allowing some loss of information that is often imperceptible to human eyes. Popular lossy methods include transform-based techniques such as Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). DCT is widely used in JPEG compression but suffers from blocking artifacts at high compression levels. In contrast, DWT provides multi-resolution analysis

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and better energy compaction, resulting in smoother image reconstruction and improved visual quality. This makes DWT highly suitable for modern image compression standards like JPEG2000 [11].

The general process of image compression involves several stages: transformation, quantization, and encoding. In the transformation stage, the image is converted into another domain (e.g., frequency domain using DWT or DCT) to concentrate energy into a few coefficients. Quantization then reduces the precision of these coefficients, which introduces controlled loss in lossy compression. Finally, entropy encoding techniques such as Huffman coding or arithmetic coding are applied to further reduce data size by removing statistical redundancy.

DISCRETE WAVELET TRANSFORM

The DWT is appropriate to wide band flag that may not be intermittent. In specific the capacity of the wavelet to concentrate on brief time interims for high recurrence parts and long interims for low recurrence segments improves the examination of the sign. In this manner better is the examination, the more precise is the use of the change to information pressure [8]. A. change that is helpful for information pressure ought to have the following properties.

To make a portrayal for the information that makes less relationship among the changed coefficients esteem. This activity is regularly alluded to as decorrelating the information. Actually, the perfect change is one that makes a zero connection between's the coefficients esteems. The Karhunen-Loeve Transform (KLT) is one of such change, which fulfills the reason. Be that as it may, for all intents and purposes the KLT isn't implementable.

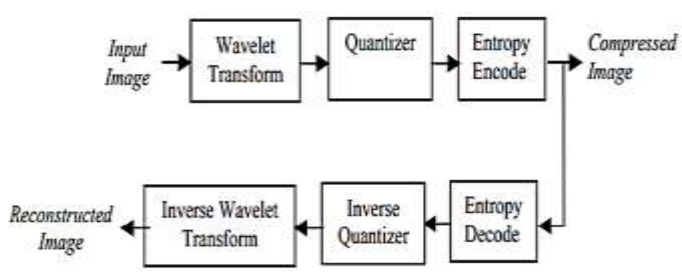

Figure 2: The structure of the wavelet transform based compression

The pressure of information requires a change with autonomous information networks that lessens the relationship among the change coefficients as much as conceivable instead of wiping out the relationship totally. The motivation behind the decorrelation is to diminish the excess, which empowers the client to quantize every coefficient autonomously,

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The change ought to have a portrayal where it is conceivable to quantize various coefficients with various accuracy. That implies the pressure requires a change that focuses the greater part of the vitality of the information signal inside a little number of coefficients.

The steps of compression algorithm based on DWT are described below:

I. Decompose Choose a wavelet; choose a level N. Compute the wavelet. Decompose the signals at level N.
II. Threshold detail coefficients for each level from 1 to N, a threshold is selected and hard thresholding is applied to the detail coefficients.

PROPOSED METHODOLOGY

Transmission and capacity of crude pictures require enormous amount of circle space. Henceforth, there is an earnest need to decrease the extent of picture before sending or putting away.

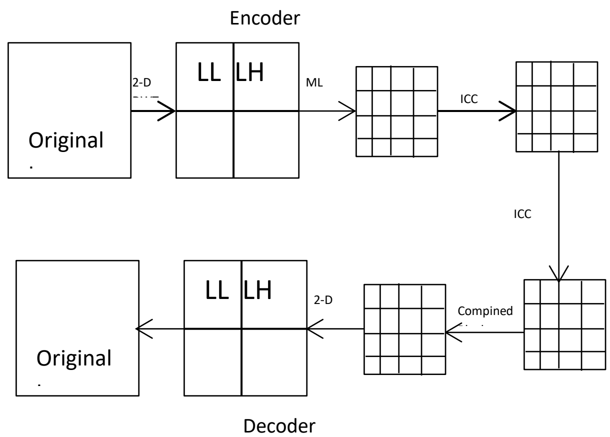

Figure 3: Proposed Methodology

The most ideal answer for the issue is to utilize pressure techniques where the pressure of information on advanced pictures are made to diminish insignificance and repetition of the picture information to have the capacity to proficiently store or transmit information. A large portion of the current pressure systems utilized have their negatives and an improved method which is quicker, successful and memory productive can fulfill the prerequisites of the client.

Inter Color Correlation

Encoder part of the proposed technique shows that the original image is divided into three parts i.e. R component, G component and B component. Each R, G, B component of the image is divided into non overlapping block of equal size and threshold value for each block size is being calculated. Threshold value means the average of the maximum value (max) of 'k × k' pixels block, minimum value (min) of 'k × k' pixels block and m_1 is the mean value of 'k × k' pixels block. Where k represents block size of the color image. So threshold value is:

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$$T = \frac{\max + \min + m_1}{3} \quad (1)$$

Each threshold value is passing through the quantization block. Quantization is the process of mapping a set of input fractional values to a whole number. Suppose the fractional value is less than 0.5, then the quantization is replaced by previous whole number and if the fractional value is greater than 0.5, then the quantization is replaced by next whole number. Each quantization value is passing through the bit map block. Bit map means each block is represented by '0' and '1' bit map. If the Threshold value is less than or equal to the input image value then the pixel value of the image is represent by '0' and if the threshold value is greater than the input image value then the pixel value of the image is represented by '1'.

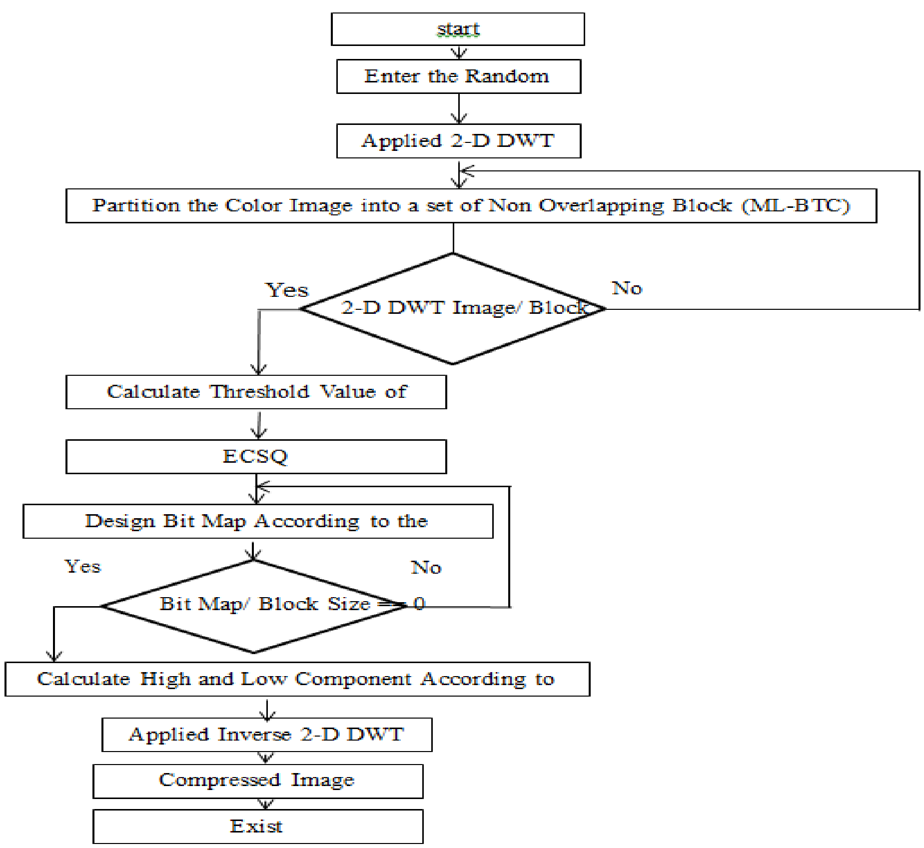

Figure 4: Flow Chart of Proposed Algorithm

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Bit map is directly connected to the high and low component of the proposed decoder multi-level BTC algorithm. High (H) and low (L) component is directly connected to the bit map, bitmap converted the '1' and '0' pixel value to high and low pixel value and arrange the entire block.

$$H = \frac{1}{p}\sum_{i=1}^{p} W_i \quad W_i > T \tag{2}$$

$$L = \frac{1}{q}\sum_{i=1}^{p} W_i \quad W_i \leq T \tag{3}$$

W_i represent the input color image block, q is the number of zeros in the bit plane, p is the number of ones in the bit plane. In the combine block of decoder, the values obtained from the pattern fitting block of individual R, G, B components are combined after that all the individual combined block are merged into a single block. Finally compressed image and all the parameter relative to that image will be obtained.

1. IMAGE QUALITY MEASURES

It is based on the assumption that the digital image is represented as $N_1 \times N_2$ matrix, where N_1 and N_2 denote the number of rows and columns of the image respectively. Also, $f(i, j)$ and $g(i, j)$ denote pixel values of the original image before compression and degraded image after compression respectively.

Mean Square Error (MSE)

$$= \frac{1}{N_1 N_2}\sum_{j=1}^{N_2}\sum_{i=1}^{N_1}(f(i,j) - g(i,j))^2 \tag{4}$$

N_1 = Row Dimension of Image

N_2 = Column Dimension of Image

f(i, j) = Original Image

g(i,j) = De-noising Image

Peak Signal to Noise Ratio (PSNR) in dB

$$= 10 \times \log_{10}\left(\frac{M \times N}{MSE}\right) \tag{5}$$

Evidently, smaller MSE and larger PSNR values correspond to lower levels of distortion. Although these metrics are frequently employed, it can be observed that the MSE and PSNR metrics do not always correlate well with image quality as perceived by the human visual system.

2. SIMULATION RESULT

Shows the building, buildings, sailing, ocean and light house images are implemented MATLAB tool. All the images are divided into three part i.e. original image, resize image and compressed image.

Figure 5; show the Peppers image of 4×4 block pixel. In this figure 5 (a) show the random image of the Peppers image and resized the image of the 512×512 in the Peppers image is shown-in-figure 5 (b). The resize image is passed through 2-D DWT and present in 5 (c). The compressed image of 4×4 block pixel of Peppers image is shown in figure 5 (d) respectively.

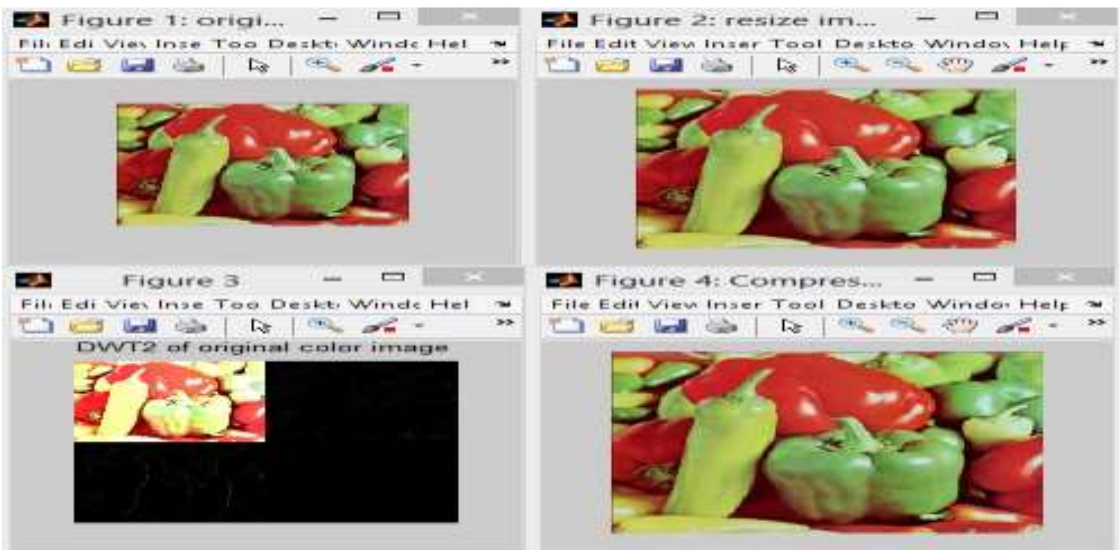

Figure 5: Experiment Result for Peppers Image

Figure 6; show the Flower image of 4×4 block pixel. In this figure 6 (a) show the random image of the Flower image and resized the image of the 512×512 in the Flower image is shown in figure 6 (b). The resize image is passed through 2-D DWT and present in 6 (c). The compressed image of 4×4 block pixel of Flower image is shown in figure 6 (d) respectively.

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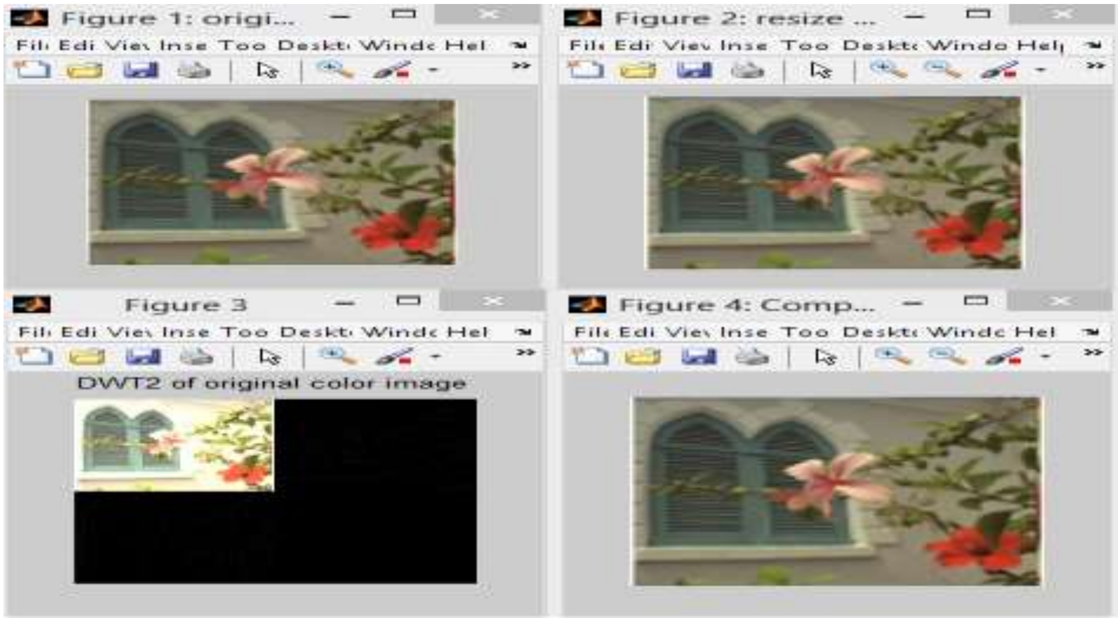

Figure 6: Experiment Result for Flower Image

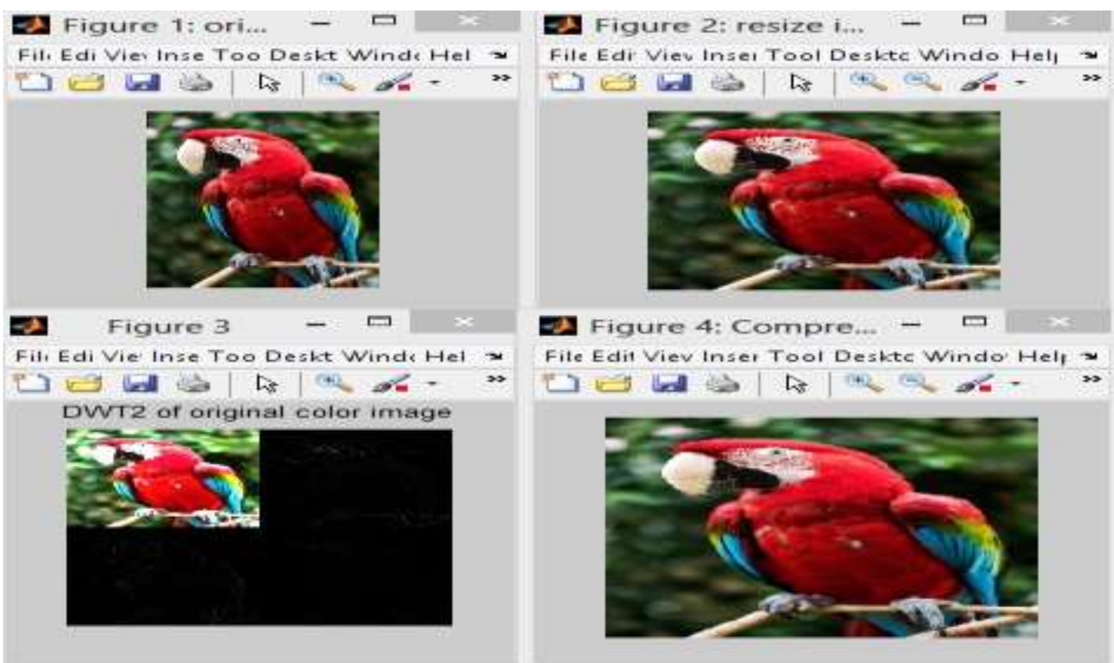

Figure 7: Experiment Result for Parrot Image

Figure 7; show the Parrot image of 4×4 block pixel. In this figure 7 (a) show the random image of the Parrot image and resized the image of the 512×512 in the Parrot image is shown in figure 7 (b). The resize image is passed through 2-D DWT and present in 7 (c). The compressed image of 4×4 block pixel of Parrot image is shown in figure 7 (d) respectively.

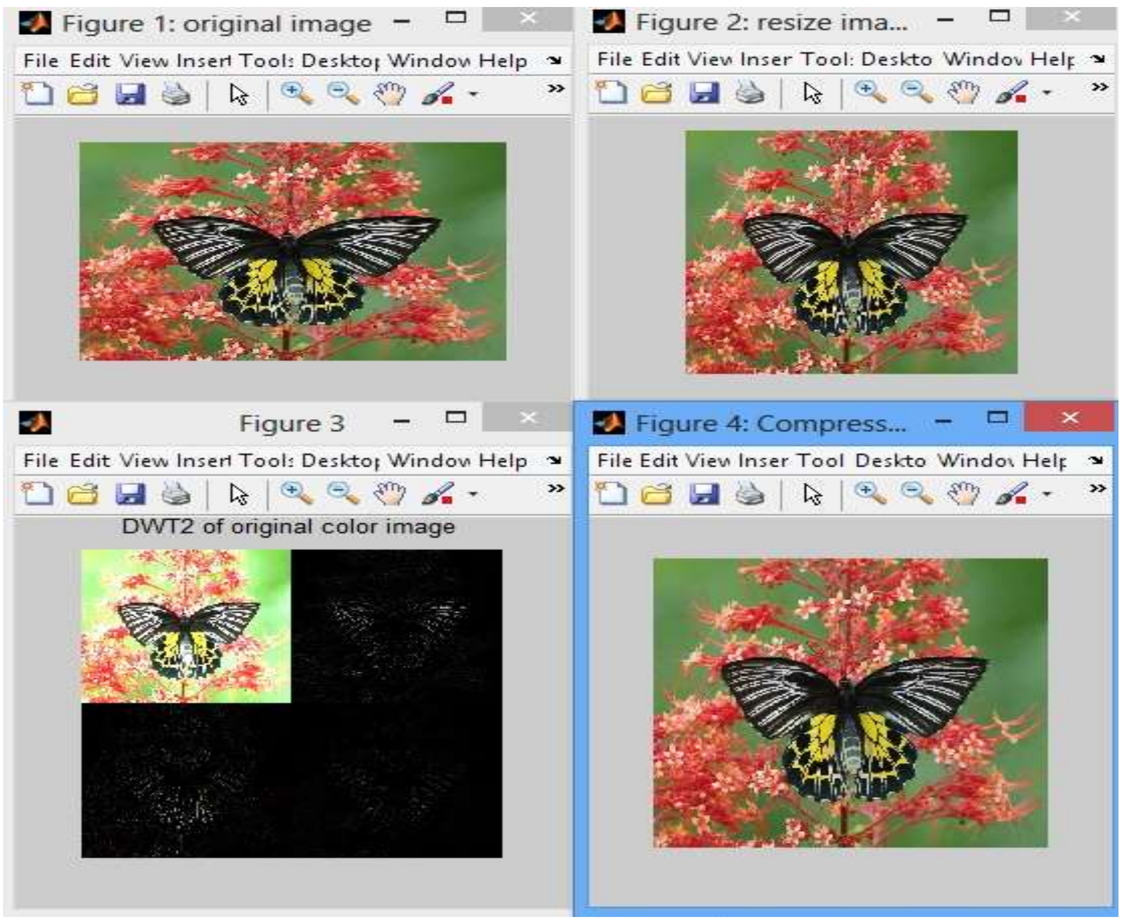

Figure 8: Experiment-Result-for-Butterfly-Image

As shown in table 1 the MSE result are obtained for the proposed Multi-level BTC and DWT algorithm and previous Enhance block truncation code algorithm. From the analysis of the results, it is found that the proposed Multi-level BTC and DWT algorithm gives a superior performance as compared with previous Enhance block truncation code algorithm.

Table 1: Experimental Results for Mean Square Error (MSE)

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Image of Size 512×512	4×4 Block Pixel	8×8 Block Pixel	16×16 Block Pixel	32×32 Block Pixel
Airplane Image	9.431	17.338	29.672	44.543
House Image	4.929	6.136	15.342	23.953
Peppers Image	8.753	18.543	28.553	42.107
Flower Image	4.657	14.556	22.554	37.834
Parrot Image	10.257	21.001	33.512	47.353
Butterfly Image	26.914	33.882	45.771	57.441

Figure 9 shows the graphical illustration of the performance of different methods discussed in this research work in term of MSE. From the above graphical representation, it can be inferred that the implemented algorithm gives the best performance for flower image.

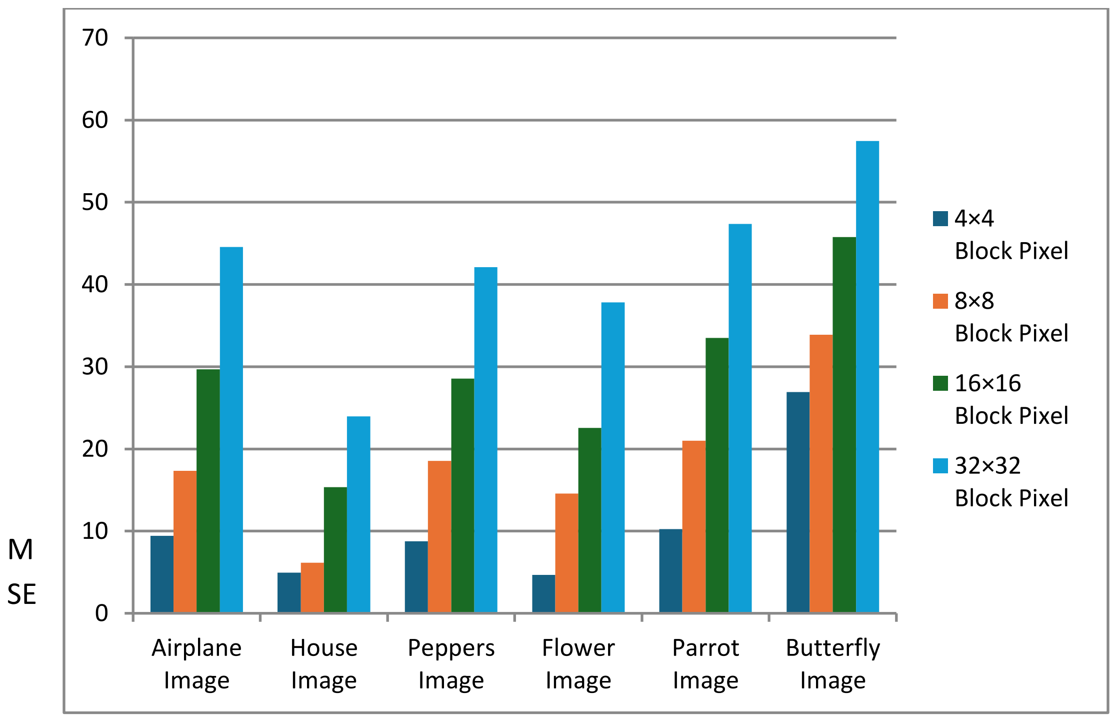

Figure 9: Bar Graph of the MSE for Different Image

As shown in table 2 the PSNR result are obtained for the implemented Multi-level BTC and DWT algorithm and previous Enhance block truncation code algorithm.

Table 2: Experimental Results for Peak Signal to Noise Ratio (PSNR)

Image of Size 512×512	4×4 Block Pixel	8×8 Block Pixel	16×16 Block Pixel	32×32 Block Pixel
Airplane Image	44.44 dB	41.79 dB	38.25 dB	36.50 dB
House Image	50.96 dB	46.32 dB	38.57 dB	40.42 dB
Peppers Image	44.82 dB	42.10 dB	39.86 dB	37.96 dB
Flower Image	47.51 dB	44.56 dB	41.43 dB	38.41 dB
Parrot Image	44.08 dB	42.05 dB	38.89 dB	37.44 dB
Butterfly Image	39.89 dB	38.79 dB	37.95 dB	36.62 dB

From the analysis of the results, it is found that the implemented Multi-level BTC and DWT algorithm gives a superior performance as compared with previous Enhance block truncation code algorithm.

3. CONCLUSION

Image compression is an essential component of modern digital systems, enabling efficient storage, processing, and transmission of large volumes of image data. By reducing redundancy and exploiting the limitations of human visual perception, compression techniques significantly decrease file size while maintaining acceptable image quality. Both lossless and lossy compression methods serve important roles, with lossless techniques ensuring exact reconstruction and lossy methods achieving higher compression ratios for practical multimedia applications.

Among various approaches, transform-based techniques such as Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) have proven to be highly effective. In particular, DWT-based methods offer superior performance due to their multi-resolution analysis, energy compaction, and reduced visual artifacts. When combined with efficient coding strategies like Huffman coding, SPIHT, and EBCOT, these methods provide an optimal balance between compression efficiency and reconstructed image quality.

Despite significant advancements, challenges such as artifact reduction, edge preservation, and computational complexity still exist. Emerging technologies, including machine learning and deep learning-based compression, are opening new avenues for adaptive and intelligent compression systems.

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