Entropy Based Model For Lossy Image Compression Scheme Using Wavelets, Svd, And Two-Channel Coding Techniques

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ABSTRACT
This study introduces a novel image compression technique that leverages wavelet transforms, Singular Value Decomposition (SVD), and two-channel coding methods to achieve high compression ratios while maintaining perceptible image quality. Wavelet transforms offer a multiresolution image representation, preserving essential information while compressing less critical features. SVD further reduces dimensionality by decomposing the image into singular vectors and values, allowing for a customizable balance between image quality and compression ratio. The two-channel coding techniques enhance compression efficiency by separating image statistics into two channels—one dedicated to storing crucial image data and the other to encoding supplementary information. The entropy-based model dynamically allocates bits to each channel, prioritizing the most salient image properties during compression. The method was evaluated using both qualitative and quantitative metrics, including Bits Per Pixel (BPP), Structural Similarity Index (SSIM), and Peak Signal-to-Noise Ratio (PSNR), on benchmark grayscale image datasets. Experimental results demonstrate that the proposed compression scheme outperforms existing methods, showing significant improvements in compression ratio, saving percentage, and bits per pixel, with averages of 40.72%, 31.79%, and 69.35%, respectively, compared to the JPEG method. Additionally, comparative analysis using PSNR, SSIM, and entropy metrics highlights the scheme's superior performance in quality enhancement and visual quality preservation over JPEG. This approach holds promise for applications in clinical imaging, remote sensing, and multimedia communication, contributing to the advancement of lossy image compression techniques and addressing the growing need for efficient compression in a digital-centric world.

Keywords: Image compression, entropy, SVD, Wavelets, image fusion, Compression ratio, saving percentage, bits per pixel, PSNR, SSIM.

1. INTRODUCTION

In trendy virtual era, images are ubiquitous, serving as powerful tacklesfor conversation, statistics dissemination, and inventive expression. Image processingis the sector that empowers us to manipulate, decorate, and examine those visual representations for diverse purposes[1]. It features a extensive range of strategies and algorithms geared toward extracting meaningful data from images, enhancing image visualization, and reducing the size of data for efficient handling of images[2].

The role of image Processing

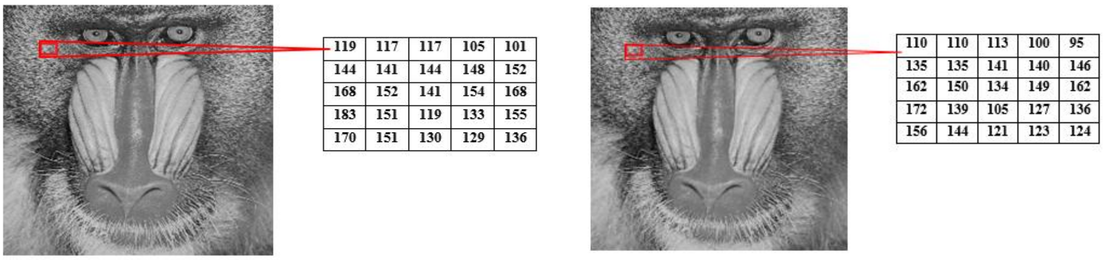
Image processing is not limited to implement in certain domains, its having its role in each every domain with respective current era[3].

1. Medicine: In clinical imaging, it helps in diagnosing sicknesses, making plans surgeries, and monitoring affected person progress through techniques like MRI, CT scans, and X-ray image enhancement.
2. Entertainment:It permits computer graphics, color correction, and photo recuperation, contributing to the visible attraction of movies, video video games, and virtual fact.
3. Security:Image processing is important for tasks like facial reputation, fingerprint analysis, and surveillance, improving protection and law enforcement efforts.
4. Remote Sensing: In environmental science and geography, it helps analyze satellite and aerial snap shots for purposes consisting of weather tracking, land use class, and catastrophe management.

5. Artificial Intelligence:Inside the context of AI and system gaining knowledge, image processing is used for object detection, photograph popularity, and self-sustaining navigation, and others.

Lossyimage coding

One of the fundamental elements of image processing is imagecoding, which includes decreasing the size of image statistics at the same time as retaining as much visible fine as feasible. Lossyimage coding is a crucial subset of image compression[4].Lossy image coding is the technique of encoding and compressing images in a manner that outcomes in a smaller file size however with a few lack of imageinformation[5]. Unlike lossless compression, wherein the unique image may be perfectly reconstructed from the compressed data, lossy compression deliberately discards some statistics that is considered less vital to the human eye.



(a) (b)

Figure 1. a) Original image b) Lossy compressed image

The idea of lossy image coding revolves around the idea that the human visible system is much conscious to certain types of information loss, along with diffused coloration adjustments or minor information, as long as the general visual belief remains high-quality. By strategically eliminating or approximating much less noticeable image content, considerable reductions in file size can be executed without a giant impact on perceived image quality.

In practice, there are manylossy image coding techniques exist, starting from rework-based methods like Discrete Cosine model (DCT) in[6] JPEG to wavelet-based methods[7], and even hybrid methods combining techniques like Singular Value Decomposition (SVD) and quantization[8]. These methods locate programs in multimedia compression, and different fields in which efficient storage and transmission of images are vital.

Research Challenges

Developing an entropy-based model for lossyimage compression using wavelets, Singular value Decomposition (SVD), and two-channel coding strategies affords a number of demanding situations.

1. The combination of wavelet transform, SVD, and coding techniques necessitates the optimization of the algorithms for performance. One foremost hassle is balancing image quality, computational complexity, and compression ratios.
2. There are difficulties in selecting the best wavelet for image compression and in figuring out the high-quality levels of decomposition. For unique image types and compressibility standards, special wavelets carry out differently.
3. Tuning parameters is a necessary part of the SVD, especially with reference to rank reduction. It can be hard to choose the right threshold for SVD although preserving compression ratios and image quality.
4. Creating a successful entropy coding scheme (such Huffman, mathematics, or different entropy coding methods) for compressed coefficients following wavelet decomposition and SVD is important. Here, maintaining a stability between computational complexity and compression ratio is tough.
5. It is tough to evaluate image quality both subjectively and objectively as a way to guarantee that, the compressed snap shots have visible integrity. It's milestone to expand measurements that correspond with human belief.
6. There is a demand to ensure that the compression technique can be adjusted to deal with various image resolutions, sizes, and codecs. It is difficult to obtain scalability without compromising compression efficiency.

The incentive for developing a lossy image compression scheme using Wavelets, SVD, and two channel coding strategies is to cope with the emerging demand for efficient image data transmission and control

throughout various domains. At the same time as compression entails a reduction in data, it is important to keep essential features of image.
The inducement for using wavelet-based fusion lies in its capability to preserve thedata, enhance the image, reduce redundancy, adapt to numerous image content, suppress noise, permit modern transmission, and provide versatility throughout different domains[9].
Singular value Decomposition (SVD) is a powerful method for decreasing the dimensionality of data. Inside the context of image compression, SVD can hold the significant information of the image. With the aid of utilizing SVD, the compression scheme can correctly constitute the image using a reduced set of singular values and vectors, leading to compact information illustration[10].
The combination of image fusion and SVD strategies allows for the preservation of important image capabilities at some stage in compression. That is in particular important in programs like medical imaging, wherein maintaining diagnostic details is essential even at minute sizes[11].
The important thing motivation for employing two-channel adaptive coding in image compression is that, two-channel adaptive coding method leverage the redundancy and correlations found in pictures. By the way of correctly utilizing these correlations between pixels or channels, this method can obtain better compression ratios as compared to standard coding tactics.
This scheme aims to strike a balance among reducing data size and maintaining image quality, making it properly-ideal for extensive domains.
The ever-increasing extent of digital snap shots generated and transmitted throughout numerous platforms, together with the internet, satellite communication, and medical imaging devices, demands green compression strategies. Present image compression strategies often face demanding situations in balancing high compression ratios with the protection of image information with visual quality. Additionally, those methods may not be adaptive sufficient to handle the various traits of various varieties of images, including grayscale and colour, clean textures, and certain styles.
The goal of this research is to design and enforce a novel lossyimage compression scheme that makes use of advanced techniques, inclusive of wavelet transforms, Singular value Decomposition (SVD), and adaptive two-channel coding. The challenge is to address the standard issues together with efficiency and compression ratio, protection of quality, adaptability. Addressing these challenges will make a contribution to the development of a robust and adaptive lossyimage compression scheme that could discover packages in diverse fields, along with telecommunications, medical imaging, remote sensing, and multimedia structures.

The research contributions

The study presents a unique image compression scheme that combines wavelet transforms, single value decomposition (SVD) and dual-channel encoding techniques. This innovative approach provides high compression and preserves important image information.
Wavelet transforms capture the global and local features of an image and provide adaptive bit assignment to different frequency components. SVD is used to reduce dimensionality and control the compression ratio. Dual-channel encoding techniques optimize compression performance and improve image quality.
The study provides a comprehensive performance assessment and shows significant improvements in compression ratio, percentage savings and bits per pixel compared to the JPEG method. Possible applications include medical imaging, remote sensing, and multimedia communication systems.
This study addresses the challenges in developing an entropy lossy image compression model, including algorithm optimization, wavelet selection, parameter tuning in SVD, design of a successful entropy encoding scheme, image quality assessment, and scalability of the compression method. This research contributes to the field of image processing by addressing the need for efficient communication and management of image data in today's digital world.
The paper is prepared as follows, section II discusses about the historical information associated with lossy image coding. Section III discusses approximately the proposed scheme, section IV discusses the system setup and dataset used for the research, section V discusses the outcomes and performance evaluation and finally section IV discusses about conclusion and future work.

2. RELATED WORK

The research work proposed by using Ruihan Yang and Stephan Mandt[12] explores a new technique to lossyimage compression the use of conditional diffusion models. In conventional compression strategies, images are mapped into a latent area for coding and then reconstructed. This research introduces a exceptional paradigm, utilizing conditional diffusion models. On this technique, images are converted into a latent space for entropy coding. The decoder in this machine is a conditional diffusion version, where a "content" latent variable is used for the opposite diffusion process, storing important data approximately the original. The closing "texture" variables, characterizing the diffusion process, are synthesized all through deciphering. The paper probable discusses experiments carried out on numerous datasets and quality metrics. It likely demonstrates that their technique outperforms different present strategies, likely inclusive of GAN-based models, in terms of metrics like FID scores. Moreover, the paper may also emphasize the performance of the proposed method, in particular while using X-parameterization, enabling extremely good reconstructions with a minimal variety of decoding steps.

Leonhard Helminger, AbdelazizDjelouah et al.[13]proposed a compression scheme which explores a brand new method to image compression using normalizing flows, a type of generative version. In contrast to traditional strategies, this approach employs deep gaining knowledge of algorithms to convert the original image into a compressed representation. Those normalizing flows capture complicated styles within the image statistics, allowing for efficient compression. By means of gaining knowledge of the underlying data, the algorithm achieves excessive compression ratios whilst preserving affordable quality. This modern technique gives a promising direction for lossy image compression, leveraging superior generative models to stability compression performance and image fidelity.

ZhihaoDuan, Ming Lu et al.[14] presented an approach for lossyimage compression the usage of VariationalAutoencoders (VAEs). In particular, the method employs quantized hierarchical VAEs, a variation of VAEs designed to address hierarchical representations of images. The method entails encoding images into a decrease-dimensional space using VAEs and quantizing the resulting latent variables. This quantization manner reduces the complexity of the information representation. With the aid of employing hierarchical systems, the model can capture elaborate information efficaciously. The compressed image facts can then be saved or transmitted with a reduced file size, whilst keeping a balance among compression ratio and quality. This modern technique gives a promising performance oflossy image compression, leveraging hierarchical VAEs and quantization to attain efficient compression.

NeelanjanBhowmik, Jack W. Barker et al.[15] investigated the consequences of lossyimage compression on variable size object detection in infrared imagery. Infrared images are frequently compressed to reduce storage and transmission expenses. This work specially makes an impact in the detection of objects with varying sizes within the infrared image. The research explores the alternate-off among compression performance and the accuracy of object detection algorithms. With the aid of analyzing the effect of different compression stages on the detection overall performance, this work presents precious insights into the demanding situations and issues associated with making use of lossy compression strategies in eventualities in which correct object detection is essential, which include infrared surveillance structures.

Yaolong Wang, Mingqing Xiao et al.[16]proposed a lossyimage compression scheme, the research delves into the inherent lack of statistics that happens at some stage in the system of squeezing images. It specializes in developing models and strategies to quantify and recognize this loss. By identifying the trade-off between compression efficiency and the lack of critical image details, the studies offers insights into how different compression techniques impact the content material of the compressed images. Understanding this loss is important for refining compression algorithms, enabling a stability among reducing image size and keeping essential information. The study contributes to optimizing lossy compression techniques, ensuring that vital visible content material is retained, even as accomplishing best compression.

JieyingWang, JiˇríKosinka et al.[17]added a novel technique to lossyimage compression, the use of dense medial descriptors based totally on splines. Medial descriptors are essential in representing the shape and shape of gadgets within an image. This studies makes a speciality of leveraging splines, that are mathematical curves, to create dense medial descriptors. These descriptors capture complex info of the picture, mainly critical for complicated or abnormal shapes. The study achieves efficientlossy image compression. The dense medial descriptors provide a complete illustration of the image content. Even in conditions wherein conventional compression techniques might lose essential information, the use of splines ensures to keep the image shape. This method is specially beneficial in applications in which accurate illustration of gadgets' shapes is vital, which include in clinical imaging or medical evaluation. The usage of spline-based totally dense medial descriptors gives a promising solution for lossy compression whilst keeping the integrity of complex information.

Fabian Mentzer, George Toderici et al.[18]presented an progressive technique for compressing images by retaining visual content . The technique combines generative systems with conventional compression strategies. Generative models, regularly associated with tasks like image synthesis, are hired to seize difficult image details. Integrating these models into the compression process, the approach achieves a high level of fidelity, ensuring that the compressed images preserve a sizeable component and visualization. This study addresses the undertaking of balancing compression performance and image constancy, in particular valuable in domains wherein preserving important information, along with medical images. This technique presents an excessive-fidelity compression, bearing in mind efficient transmission and storage without compromising visible intricacy.

Yash Patel, SrikarAppalaraju et al.[19]presented an innovative method for image compression primarily based on human visible belief. The method carries saliency, which refers back to the visible interest of human observers, to prioritize important image areas. These salient regions, essential for human notion and know-how, are preserved with higher fidelity all through compression, ensuring that the maximum visually substantial components of the images are retained. By using this information, the compression technique optimizes the allocation of bits, focusing on preserving info which might be more likely to capture human interest. This technique outcomes in perceptually optimized compression, wherein the compressed image keeps essential visible data while successfully reducingthe size. This technique is specifically treasured for programs wherein maintaining the perceptual satisfactory of images is vital, which includes in multimedia, video streaming, or clinical imaging.

Ming Lu, Fangdong Chen et al. [20] provided a novel image compression approach. This article presents an innovative method to high-performance lossyimage coding, emphasizing adaptive neighbourhood aggregation with respect to information. This method goals to noticeably compress image information even as preserving a suitable quality. It leverages adaptive strategies to gather necessary elements by considering neighbouring elements of image with moreefficient compression. By doing so, the method achieves higher compression ratios without sacrificing image fidelity. The adaptability in neighborhooddata aggregation ensures that the method can modify to different image content, optimizing the compression system. This technique has the potential to be precious for applications where efficient compression is important even as retaining visual quality.

Lirong Wu, Kejie Huang et al. [21] offered a novel image compression approach utilizing Generative hostile Networks (GANs). GANs are employed because the underlying framework to create a tunable compression system. Not like conventional compression strategies, this work integrates the energy of GANs to optimize the balance among compression ratio and quality. By way of the use of GANs, the model learns the complicated styles and structures in the image. The tunable element indicates that customers can regulate the system in step with specific necessities, enabling a bendy technique to compression. This innovation gives a promising a way of approaching for adaptive compression, wherein the stability among compression and image constancy may be finely tuned based on the application or user alternatives.

Ulacha, G. et al. [22] proposed an approach that allows for rapid decoding times and long-term coding parameter adjustments that impact accomplishment complexity. The other techniques are connected to non-MMSE (minimizing the mean squared error)types, but this traditional method predicts the coefficients based on lowering the MSE. In the data modeling stage, linear and nonlinear predictions are introduced to achieve high compression.

A thorough model was put forth by Amin, M. S., Jabeen et al. [23] to reduce entropy error and raise the compression ratio. In 2-D images, the local context of the pixels is found by the implementation of median edge detection. The Kodak image dataset is used to demonstrate, how well the suggested predictor performs. With various predictor-based lossless compression techniques, the suggested predictor offers a notable improvement in bits per pixel, entropy error, and computational complexity parameters. Future research on 3-D representation of higher resolution images may be used to assess the context of predictor-based lossless compression techniques.

The above related works are summarized and tabulated in the Table.1.

Research gaps

The study highlights several research gaps in image compression methods. These include computational complexity, quality and diversity of training data, handling different types of images, infrastructure limitations, performance across different architectures or compression methods, comparison with the latest compression standards, memory constraints, compatibility issues, learning rate and the algorithm's complexity. Future research should focus on developing more efficient algorithms or leveraging hardware acceleration, addressing the limitations of current models, and improving the iMED predictor's complexity and learning rate for different image types or applications.

Table 1. Summary of related works

Sno	Ref erence	Proposed	Research Findings	Limitations
1	[12]	"Optimized Lossy Image Compression	• Utilizes transform coding paradigm for efficient compression. • Maps image into latent space for	• Computational complexity. • Dependenceon

		Framework”	entropy coding and reconstructs back to data space. • Employs conditional diffusion model as decoder, introducing additional "content" latent variable. • "Texture" variables characterize the diffusion process and are synthesized during decoding.	training data quality and diversity.
2	[13]	“Deep image compression using normalizing flows”	• Proposes a novel approach inspired by traditional image compression techniques. • Leverages normalizing flows to learn a bijective mapping from image space to latent representation. • Allows for a broader range of quality levels, from low bit-rates to near-lossless quality.	• Limited quality levels. • Infrastructure issues: limited storage capacity, network bandwidth. • Common issue in microscopy image analysis.
3	[14]	“Quantization-Aware ResNet VAE (QARV) Method”	• Utilizes hierarchical VAE architecture. • Integrates test-time quantization and quantization-aware training. • Offers broader quality levels than traditional autoencoders.	• Quantization-Induced Artifacts • Complexity and Computational Cost • Tradeoff Between Rate and Quality • Dependency on Hyperparameters
4	[15]	“Integrates lossy image compression on variable size object detection within infrared imagery”	• Examines effects of lossy compression on infrared imagery. • Uses JPEG compression at six discrete levels. • Evaluates impact on Cascade R-CNN, FSAF, and Deformable DETR object detection architectures. • Focuses on varying object sizes in the dataset.	• Quantization-Induced Artifacts • Performance Degradation at Higher Compression Levels. • Sensitivity to Object Sizes.
5	[16]	“Novel approach to lossy image compression”	• Invertible Lossy Compression (ILC) is a deep-learning-based framework to address information loss in image compression. • It introduces an invertible encoding module to produce a low-dimensional informative latent representation. • Lost information is transformed into an auxiliary latent variable, not further coded or stored. • ILC quantizes and encodes the latent representation, ensuring a specified distribution.	• Introduces additional complexity compared to traditional auto-encoders. • Performance sensitive to hyper parameters like quantization levels and distribution constraints.
6	[17]	“Innovative approach to lossy image compression”	• Spline-based Dense Medial Descriptors (SDMD) for Image Compression • Integrates medial descriptors with B-splines for improved compression ratios. • Provides effective vector representation of raster images. • Quantitative evaluation shows higher compression ratios than JPEG technique.	• Integration of B-splines with medial descriptors adds complexity. • Performance depends on hyper parameters like quantization levels and distribution constraints.
7	[18]	“Lossy image compression	• Visually Pleasing Reconstructions • Operates across various bitrates,	• Complexity • Hyper parameter

		using combination of GANs and learned compression”	allowing flexibility in compression levels. • Unlike previous methods, can be applied to high-resolution images.	Sensitivity • Generalization
8	[19]	“A novel approach for lossy image compression”	• Incorporates perceptual similarity metric, specifically learned for image compression. • Leverages saliency information in images to prioritize important regions during compression. • Employs hierarchical auto-regressive model to capture dependencies within image data.	• Performance heavily depends on saliency detection quality. • Inaccurate estimation could affect compression results. • Compression ratio and visual quality may trade-offs.
9	[20]	“High-Efficiency Lossy Image Coding Through Adaptive Neighborhood Information Aggregation”	• Proposes a Content-Adaptive Transform using Integrated Convolution and Self-Attention (ICSA) unit. • Introduces Multistage Context Model (MCM) for improved probability estimation. • Implements End-to-End Learning using ICSA and MCM under a VariationalAutoEncoder (VAE) architecture.	• Effectiveness relies on saliency detection and neighbourhoodmodeling quality. • Real-world deployment and scalability considerations not addressed.
10	[21]	“Lossy Image Compression with Quantized Hierarchical VAEs”	• Utilizes Generative Adversarial Network (GAN) to reconstruct non-important regions in content-based compression. • Incorporates multiscale pyramid decomposition in encoder and discriminator for global compression of high-resolution images.	• Doesn't address real-world deployment challenges or scalability. • Multiscale pyramid decomposition and tunable compression scheme effectiveness vary.
11	[22]	“A novel approach for lossless image compression”	• Coder parameters can be fine-tuned based on specific requirements, enhancing practical usability. • Compares non-MMSE prediction coefficients, crucial in compression process. • The data modeling stage combines linear and non-linear predictions. • The prediction error coding uses an adaptive Golomb code and a binary arithmetic code.	• Shorter decoding times and lower bit averages compared to JPEG-LS codec. • Non-MMSE prediction coefficients' effectiveness depends on image characteristics and algorithms' quality.
12	[23]	“A new Median Edge Detection (iMED) predictor for lossless image compression”	• Incorporates K-means clustering for better context modeling. • Uses learning rates (μ_i) to update cluster weights, minimizing prediction errors. • Significant improvement in entropy error, bits per pixel, and computational running time.	• Lacks Real-World Deployment and Scalability Considerations • Enhancements like k-means clustering, DDx20, weight updates may vary across image types and datasets.

3. Proposed Compression Scheme

JPEG is one of the most used image compression that which uses lossy image compression in order to minimize the size of the image file. The compression process includes converting image from RGB to

YCbCrcolor space followed by down sampling of chrominance components, division of image into blocks of size 8*8 blocks, applying Discrete Cosine Transform (DCT) and quantizing this transform coefficients and lastly using entropy coding to construct the compressed bit stream. However, JPEG compression reduces the image quality and the loss of details, formation of block structure and ringing effects are common problems at high compression ratio. These problems become more apparent in images with high contrast, or areas of flat colour – the so called edges of the image and regions dominated by high frequencies, like clear-cut text or logos. Also, JPEG has following disadvantages: absence of transparency layer, only 8-bit palette, and the degradation of the image's quality after multiple operations. However, the proposed compression scheme avoids such shortcomings because it incorporates wavelet transforms and Singular Value Decomposition (SVD) in order to better capture the most important details of an image in order to allow for relatively high compression ratios. An entropy-based model is applied, distributing the bits based on the importance of image properties, and also minimizes such JPEG artefacts as they are. This approach is ideal to offer enhanced quality preservation and it is thus preferred in applications that require high image accuracy such as clinical imaging and remote sensing.
The proposed scheme integrates standards of wavelets based fusion, Singular value Decomposition (SVD), and two-channel coding strategies which are discussed below.

Wavelet based fusion
Wavelet transforms are essential in image compression because of their capability to successfully represent images in both spatial and frequency domains[24]. This method combines information from more than one assets right into a single fused image with the use of wavelet transforms. This process guarantees that essential capabilities are retained within the fused image, decreasing redundant information. The fusion system optimizes data, removing needless repetition and enhancing compression efficiency. The fused image regularly has superior visible interpretability, making it extra meaningful and without any problems[25].
Key standards and steps involved in wavelet-based fusion encompass decomposition, choice of sub bands, reconstruction, subsequent processing, and evaluation. The inverse wavelet transform (IDWT) is used to reconstruct the final fused image, and subsequent processing steps can be implemented to betterment the quality of the fused image. The improved fused image is commonly evaluated by the use of objective metrics consisting of signal-to-noise ratio (SNR), structural similarity index (SSIM), and visible inspection through human observers[26]. Wavelet based fusion is widely used in diverse fields, consisting of remote sensing, scientific imaging, surveillance and protection, multispectral and hyperspectral imaging, robotics, and self-directed systems.
The proposed scheme uses Haar wavelets for image fusion process. In the process of wavelet decomposition, each image is broken down into four subbands: LL, LH, HL, and HH. Figure.2 illustrates this two-level wavelet decomposition.

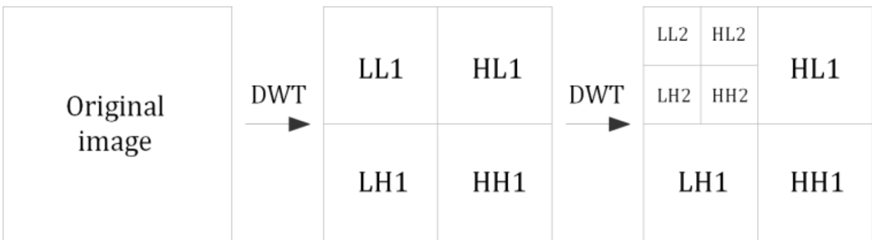


Figure 2. Two-level wavelet decomposition

The fusion process involves combining the LL parts of each image to generate the final LL subband. The same procedure is applied to the other subbands (HL, LH, and HH), resulting in their respective final subbands. These final subbands are then used for inverse decomposition using the Haar wavelet, ultimately producing the fused image.
The fusion rules governing the generation of final subbands in image fusion are defined by equations (1) and (2). Specifically:
Equation (1) represents the fusion rule for the approximate coefficient subband (LL), where the maximum value from the two inputs is chosen.
Equation (2) represents the fusion rule for the detailed coefficients subbands (LH, HL, and HH), where the minimum value from the two inputs is selected.

$$I_{LL}^{f} = max(I_{LL}^{1}, I_{LL}^{2}) \quad (1)$$
$$I_{E}^{f} = min(I_{E}^{1}, I_{E}^{2}) \quad (2)$$

Here $I_{LL}^1, I_{LL}^2, and\ I_{LL}^f$ denotes the approximate subband coefficients of image 1, image 2 and fused image, $I_E^1, I_E^2, and\ I_E^f$ denotes the detailed subband coefficients of image 1, image 2 and fused image (here E is substituted with LH, HL and HH). In the proposed scheme Haar wavelet is used for transformation, and is defined in equation (3). The Haar transform y_n of an n-input function x_n is

$$y_n = H_n x_n \quad (3)$$

Here y_n indicates the Haar wavelet transformed image, x_n indicates the input image and H_n indicates the Haar wavelet transformation matrix.
The Haar transform is derived from the Haar matrix. An example of a 4x4 Haar transformation matrix[27] is shown below.

$$H4 = \frac{1}{2}\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ \sqrt{2} & \sqrt{-2} & 0 & 0 \\ 0 & 0 & \sqrt{2} & -\sqrt{2} \end{bmatrix} \quad (4)$$

and the inverse Haar transform is defined as in equation (5).

$$x_n = H^T y_n \quad (5)$$

Here H^T denotes the inverse Haar transformation matrix.
In this step, entropy is computed with respect to a reference image to estimate the visual quality of the image fusion scheme[28]. The impact of visual quality is represented in the Figure.3.

Significance of wavelet based fusion in image compression

Wavelet-based fusion is a critical method in compression, improving compression performance and also enhancing the quality. It permits to retain important capabilities from multiple sources by decreasing redundancy and noise.The fused image carries consolidated and optimized facts, making it more suitable for compression algorithms like JPEG or JPEG 2000. It additionally offers customizable compression. Fused images are greater sturdy to noise and artifacts, making them more resilient to degradation. This technique is specifically useful in remote sensing and medical imaging, where retaining crucial information and reducing data size are important. It also reduces complexity constraints with respect to time and space, permits adaptive compression, and improves interpretability. Standard, wavelet-based fusion is a valuable technique in compression, which maintains appropriate quality and reduction of redundancy. Figure.4 shows the wavelet based fused image.

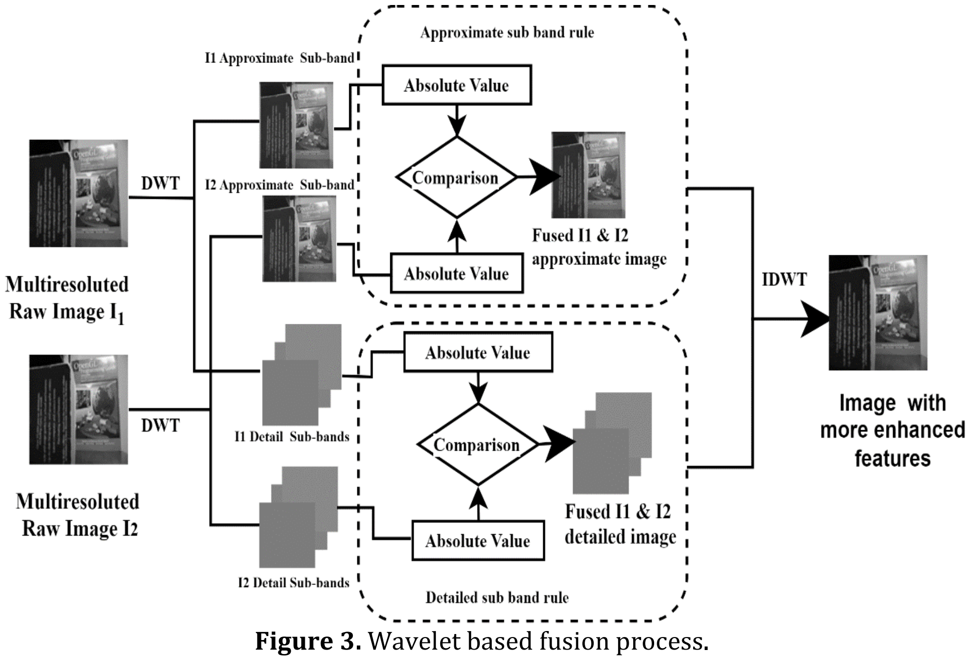


Figure 3. Wavelet based fusion process.

(a) (b) (c)

Figure 4. a) Left blurred image b) Right blurred image c) Fused image

Singular value Decomposition (SVD)

Finding approximations of an image using the fewest terms of the diagonal matrix in the decomposition is the primary objective of researching the SVD of an image (matrix of $m \times n$).Since images may be thought of as matrices, with each pixel representing an element of a matrix, the foundation of image compression using SVD is this approximation of the matrix.

For the factorization of real or complex rectangular matrices, the linear algebra of the SVD method of a matrix is a crucial tool in mathematics.

Let A be a matrix with m rows and n columns, rank r, and $r \leq n < m$. After that, A can be divided into three matrices: U, Σ, and V^T, so that $A = U\Sigma V^T$, where Σ is a diagonal matrix, U and V are orthogonal, and $U \Sigma V^T$ is the rank K approximation that is closest to A. The decomposition of matrix is shown in Figure.5.

To approximate matrix A with significantly fewer entries than in the original matrix, matrix A is transformed into $U\Sigma V^T$. We eliminate the superfluous data (the dependent elements) by applying a matrix's rank. For the purpose of compressing images, SVD can be utilized to produce the best lower-rank approximation to matrix A.

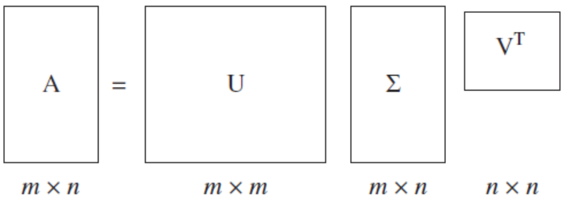


Figure 5. Decomposition of a matrix

SVD is used for various areas, such as size reduction, pseudoinverse computation, compression, and collaborative filtering in recommendation models[11]. It reduces dataset dimensions through retaining sizable singular values, compresses images, and predicts lacking values in big sparse matrices. SVD can be computed the usage of numerical algorithms just like the Golub-Reinsch[29] set of rules or iterative techniques just like the Lanczos algorithm[30]. Effect of SVD for different ranks is shown in Figure.6.

(a) (b) (c) (d) (e)

Figure 6. a) Original Image, SVD Rank images b) rank=20 c) rank=30d) rank=50e) rank=100

Two-Channel Adaptive coding

Two-channel coding, is a technique utilized in compression to divide the content into two separate channels: information table and a bit table. This approach helps correctly represent and save information, allowing for effective compression and decompression processes. Here's a detailed clarification of two-channel coding and how it divides the content.

Information table:The information table in two-channel coding carries the vital information required to reconstruct the image, typically includes details about the image, inclusive of pixel values, colour statistics, or depth values. The statistics table represents the essential visual elements of the image and serves as a basis for accurate reconstruction.

Bit table:The bit table includes the extra information essential for encoding. This information comprises the binary data representing the image content. The bit table encodes the image in a compact way, taking into consideration for transmission as well as storage.

Contents of information table and the bit table go through compression using suitable algorithms. Huffman entropy coding approach is hired here to compress the image information table and bit table.The two-channel coding divides the content material right into ainformation table containing essential additives and a bittable containing additional binary statistics. This separation lets in for effective compression, storage, and transmission of snap shots, aims to improved compression ratios and reconstruction rate.The precise steps concerned are represented in the following Figure.7.

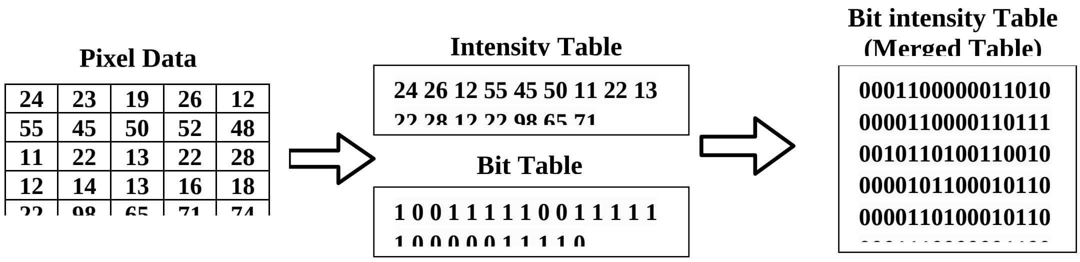


Figure 7. Two channel adaptive encoding process

The operation of a two-channel adaptive coding scheme described as follows. The system is depicted in Figure.7as two tables categorised intensity table and bit table. The raster scan method is followed to choose pixel values. First, pick out the pixel from the pixel data table; the pixel value is entered into the intensity table, and a binary bit 1 is entered into the bit table. The next pixel is selected from the pixel data; if the difference between current pixel and its previous pixel in between -4 to +4 (scalar threshold) then, current pixel is replaced with previous pixel and in the bit table bit 0 is written and nothing is written in the intensity table; If the selected pixel value is not in the range of scalar threshold (-4 to +4) then, the current pixel value is written into the pixel intensity table, and binary bit 1 is written into the bit table. This operation is performed until the end of the pixel is reached. Finally, the merged table is produced by combining the values of the intensity and the bit tables, and it is further represented as an intermediate compressed table of two-channel adaptive coding.

Huffman Coding

Huffman coding is a lossless information compression method evolved via David A. Huffman in 1952. It assigns variable-length codes to characters based on their frequency band on input information[31]. The process entails frequency calculation, constructing a Huffman tree, assigning codes, and generating codes. The tree is a binary tree with leaves representing characters and a unique route from the basis to every individual. The codes are then generated by using mapping characters to their corresponding Huffman codes[32].Huffman coding is a lossless compression method that reduces storage and transmission necessities via assigning shorter codes to common symbols.

Example: For example the subsequent characters and their frequencies shown in Figure.8(a).Huffman coding will assign shorter codes to more frequent characters and longer codes to less common characters. After constructing the Huffman tree and generating the codes shown in Figure.8(b).

Character	Frequency
a	5
b	9
c	12
d	13
e	16
f	45

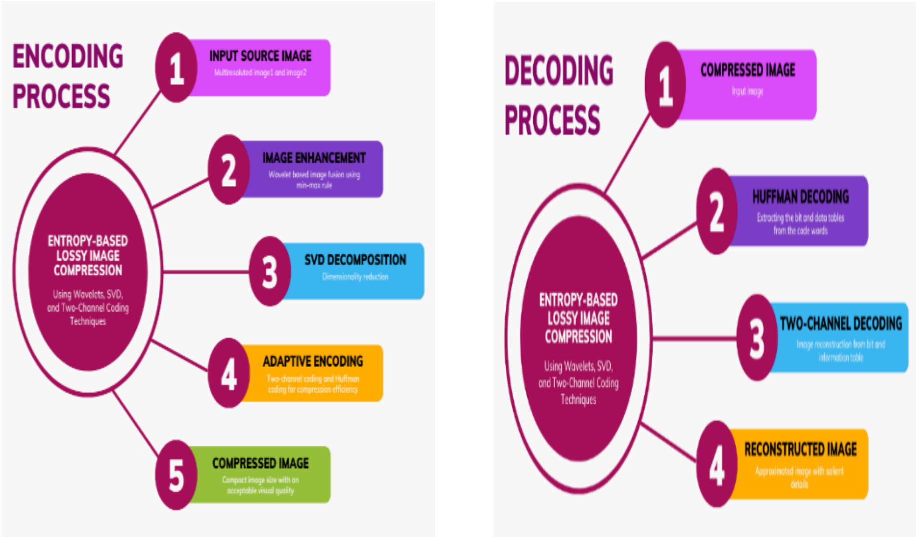
(a)

Character	Huffman Code
f	0
c	100
d	101
a	1100
b	1101
e	111

(b)

Figure 8. a) Characters and their frequencies b) Generated Huffman codes

So, in this case, the individual 'f' receives the shortest code, and 'b' and 'a' have longer codes.In case of textual information certain times a character may more frequently occurred then Huffman plays a vital role. It is an efficient data compression approach when compared with other algorithms used to achieve substantial reduction in file size by maintaining original content.



(a) Encoding process (b) Decoding process

Figure 9. Diagram representing the proposed compression scheme

Compression procedure

The proposed scheme of compression starts with two Multiresoluted images i.e left half blurred and right half blurred of the same input image. A fused image with more enhanced features is generated by applying the wavelet decomposition process. Further, the dimensionality of the fused image is reduced by the SVD. Adaptive entropy coding methods, such as two-channel encoding followed by Huffman coding, are applied for generating the compressed image which is shown in Figure.9(a).

Decompression procedure

The decompression technique starts off evolved with the compression of the facts. To be able to get better the authentic data table and bit tables, the compressed information is decoded utilising the best entropy reconstructing strategies. The information table, which contains the vital additives of the image, is hired inside the initial reconstruction process. In addition information is furnished through the bit table improves the precision and visual clarity of the reconstructed image. Through the integration of information from both tables data, an specific reconstruction of the authentic image is carried out. The process of above procedure is shown in Figure.9(b).The flow of operations of the encoding process and decoding process of the proposed compression scheme described in Figure.9.The outline of encoding process of the proposed scheme are described below.

1. Input Source Image: Get multiresolution images.
2. Image Enhancement: Enhance the image using wavelet-based fusion with a min-max rule.
3. SVD Decomposition: Reduce the dimensionality of the enhanced image using SVD.
4. Adaptive Encoding: Encode the decomposed image using two-channel coding and then Huffman coding for compression efficiency.
5. Compressed Image: Generate the compressed image with acceptable visual quality.

The outline of decoding process of proposed scheme are described below.

1. Compressed Image: Get the compressed image as input.
2. Huffman Decoding: Extract the bit and data tables from the code words of the compressed image.
3. Two-Channel Decoding: Extract the data matrix from the bit and information table.
4. Reconstruct Image: Generate an approximated image with salient details from the data matrix.

The detailed process of compression and decompression schemesare given in Algorithm 1 and Algorithm 2 respectively.

Algorithm 1: Compression scheme

Input: Grayscale Multiresoluted images I_L and I_R
Output: $I_{COMPRESSED}$ the compressed file.
1. Read Multiresoluted input images I_L and I_R
2. Generate the enhanced image using wavelet based fusion process.
   a. Apply the wavelet transformation on I_L and I_R and generate detailed and approximate coefficient subbands
      LL_L, LH_L, HL_L and HH_L =DWT(I_L)
      LLR, LH_R, HL_R and HH_R = DWT(I_R)
   b. Using maximum rule generate the fused detailed subbands
      LH_{FUSED}=max(LH_L,LH_R)
      HL_{FUSED}=max(HL_L,HL_R)
      HH_{FUSED}=max(HH_L,HH_R)
   c. Using minimum rule generate the fused approximate subbands
      LL_{FUSED}=min(LL_L,LL_R)
   d. Apply inverse wavelet transform to generate the fused image
      I_{FUSED}←IDWT(LL_{FUSED}, LH_{FUSED}, HL_{FUSED} and HH_{FUSED})
3. Generate the rank approximation image I_{Rank} to matrix I_{FUSED}using SVD Decomposition
      [U, I_{Rank}, V]= SVD(IFUSED)
4. Generate the Intesity table I_{Table} and Bit Table B_{Table}using Two-channel encoding
   [I_{Table}, B_{Table}]= Two_channel_encoding(I_{Rank})
5. Merge I_{Table} and B_{Table} and generate the BI_{Table}
BI_{Table} = Merge(I_{Table}, B_{Table})
6. Apply Huffman encoding and generate the final compressed image file $I_{COMPRESSED}$.
$I_{COMPRESSED}$= Huffmanencode(BI_{Table})

The definition of functionTwo_channel_encoding as shown below.

Function: Two_channel_encoding (BI_{Table})

Input: Bit intensity table
Return: Bit vector Bit and Intensity value vectorIv
function Two_channel_encoding(BI_{Table})
   1.InitializeBit=1 and Iv=first value ofBI_{Table}
   2. Read next valueIvalfromBI_{Table}in sequential order
   3. If currentIval>= (Ipval-4) and Ival<= (Ipval+4) as with previousIpvalofBI_{Table}
         Bit={Bit, 0}
   else
   Iv={Iv, I_{val}}
   Bit={Bit, 1}
   5. Repeat steps 2 and 3 for all the values ofBI_{Table}
   6. Return Bit, Iv vectors
end function

Algorithm 2: Decompression scheme

Input: Compressed file $I_{COMPRESSED}$
Output: Decompressed image I_{Rec}.
1. Read the compressed file $I_{COMPRESSED}$
2. Apply the Huffman decoding and generate the encoded BI_{Table}
   BI_{Table}= Huffmandecode($I_{COMPRESSED}$)
3. Extract I_{Table} and $B_{Table}$from the BI_{Table}
4. Apply Two-channel decoding on B_{Table}, I_{Table} and generate the D_{Matrix}
   D_{Matrix}=Two_channel_decoding (B_{Table}, I_{Table})
5. Construct the image $I_{Rec}$from data matrix D_{Matrix}

The definition of function Two_channel_decoding as shown below.

Function: Two_channel_decoding (BI_{Table}, I_{Table})

Input: Bit intensity table BI_{Table} and Intensity table I_{Table}
Return: Decoded image matrix D_{Matrix}
function Two_channel_decoding(B_{Table}, I_{Table})
1. Initialize $D_{Matrix,}$={ }, CB=B_{Table} , CV=I_{Table}
2. add CV to D_{Matrix}={ $D_{Matrix,}$ CV}
3. Read the next bit from B_{Table} and assign to CB
   CB=B_{Table}
4. If CB=1
   CV=I_{Table}
   D_{Matrix}={ $D_{Matrix,}$ CV}
5. If CV=0
   D_{Matrix}={ $D_{Table,}$ CV}
6. Repeat steps 3 to 5 for all the bits in B_{Table}
7. Return D_{Matrix}
end function

The outcome of proposed lossy compression scheme uses wavelets, SVD, and two-channel coding strategies for efficient data reduction and also it offers customizable compression settings,in real world domain specific applications.

5. System Setup and Data Used For the Study

This study uses an Intel Core i5-7200U CPUwith main frequency is 2.50 GHzand 8GB RAM for efficient image processing, and Java 8 for software development. The system uses the Java Advanced Imaging API for image processing, and can use additional libraries for wavelet transforms, Singular Value Decomposition, and coding techniques for complex compression algorithms.The waterloofractal coding and analysis group database [33], is a widely used benchmark database in computer vision used for experimentation and evaluation in this study, focusing on grayscale images from various categories.The image repository is categorized into three sets. Grayscale Set 1 consists of 12 small greyscale images, all measuring 256x256 in size. Grayscale Set 2 contains 12 medium greyscale images, including several renowned examples from the image processing literature, which are sized at 512x512. Additionally, this set includes some images with non-standard dimensions. Lastly, the Color Set comprises 8 large full color images.The images in the dataset are available in RAW, TIFF, PGM, GIF and TGA formats. RAW format, allowing direct access to pixel intensity values without compression or encoding. The study aims to shorten the experimental process while preserving visual content.

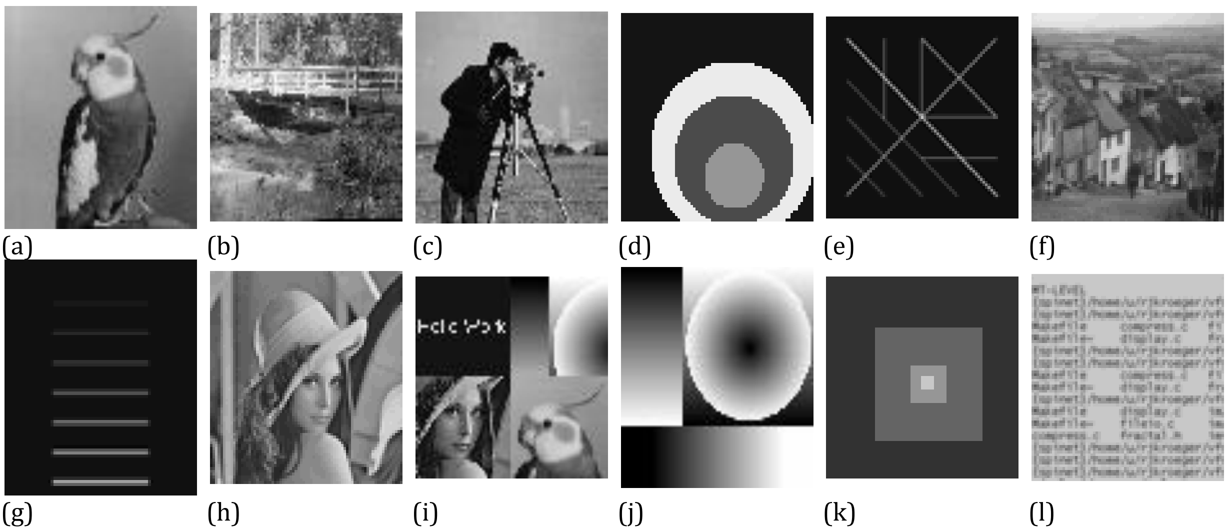
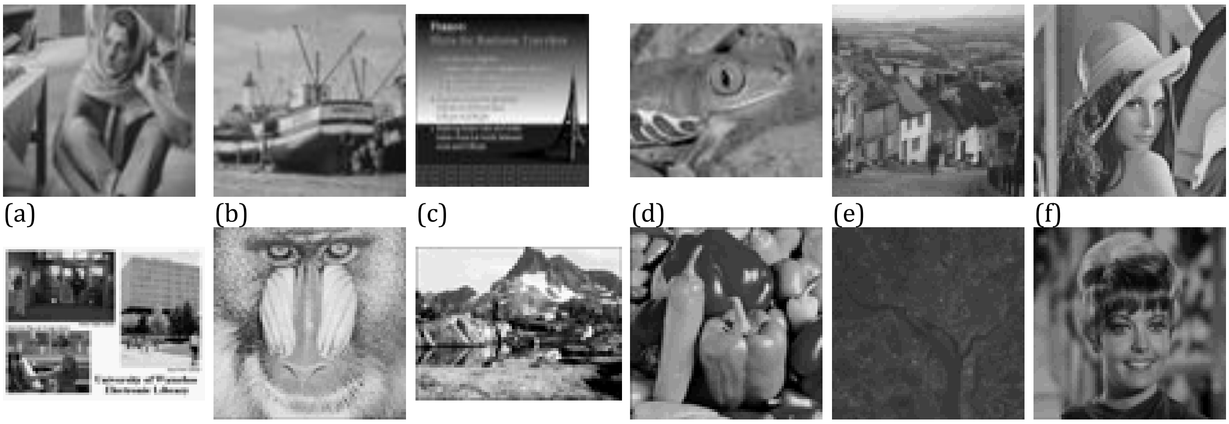


Figure 10. Greyscale Set 1 images of size 256x256 of 1st Waterloo dataset.



(a) (b) (c) (d) (e) (f)
(g) (h) (i) (j) (k) (l)

Figure 11. Greyscale Set 2 images of 2ndWaterloo dataset.a-b)512x512 c) 672x496 d) 621x498 e-f) 512x512 g)464x352 h) 512x512 i) 640x480 j-l) 512x512.

6. RESULTS AND DISCUSSION

The proposed method has evaluated with the original grayscale images available in .raw format included in the 1st Waterloo and 2nd Waterloo datasets [33]. Sample test images are shown in Figure.10 and Figure.11. The analysis of severalmeasures for the suggested and related works is presented in the sectionthat follows.

A variety of metrics can be used to analyze the lossy image coding performance and evaluate the quality of the compressed image[34]. These criteria is used to evaluate the trade-off between compression ratio and compressed image quality[35][36]. The criteria considered to evaluate the performance of proposed work are compressed size (CS), compression ratio(CR), bits per pixel(BPP), saving percentage(SP), peak signal to noise ratio (PSNR), and structural similarity index (SSIM)[37].

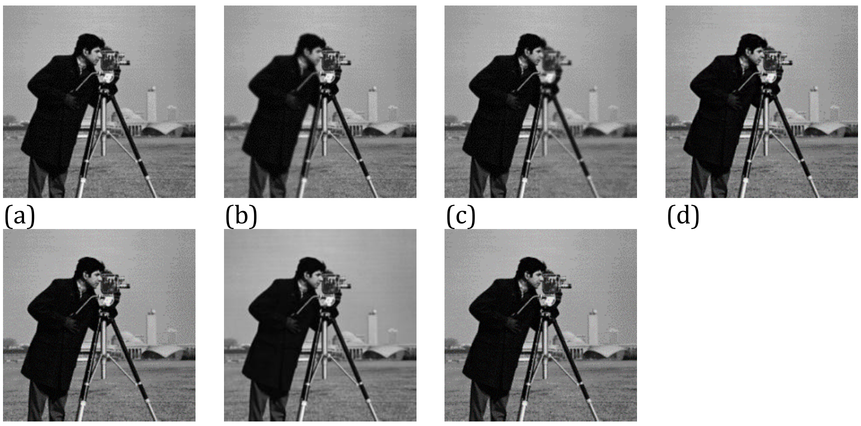
$$Compression\ Ratio(CR) = \frac{No.\ of\ bits\ before\ compression}{No.\ of\ bits\ after\ compression} \quad (6)$$

$$Saving\ Percentage\ (SP) = \frac{Original\ size - Compressed\ size}{Original\ size}\ \% \quad (7)$$

$$Bits\ Per\ Pixel(BPP) = \frac{size\ of\ compressed\ image}{Total\ number\ of\ pixels} * 8 \quad (8)$$

$$Peak\ Signal\ to\ Noise\ Ration(PSNR) = 10\ \log_{10}\left(\frac{m^2}{MSE}\right)\ [dB] \quad (9)$$

$$\text{Structural Similarity Index}\ \ SSIM(x,y) = \left(\frac{(2\mu_x\mu_y + C_1)(2\sigma_x\sigma_y + C_2)}{(\mu_x^2+\mu_y^2+1)(\sigma_x^2+\sigma_y^2+C_2)}\right) \quad (10)$$



(a) (b) (c) (d)
(e) (f) CR=1.19 (g) CR=2.36

BPP=6.7085 BPP=3.3917
SP=16.1438 SP=57.6035

Figure 12. a) Original Cameraman image (256x256) from 1st Waterloo dataset b) Left blurred image c) Right blurred image d) Fused image with enhanced features e) SVD decomposed image with rank=175 f) JPEG image g) Reconstructed image with proposed method.

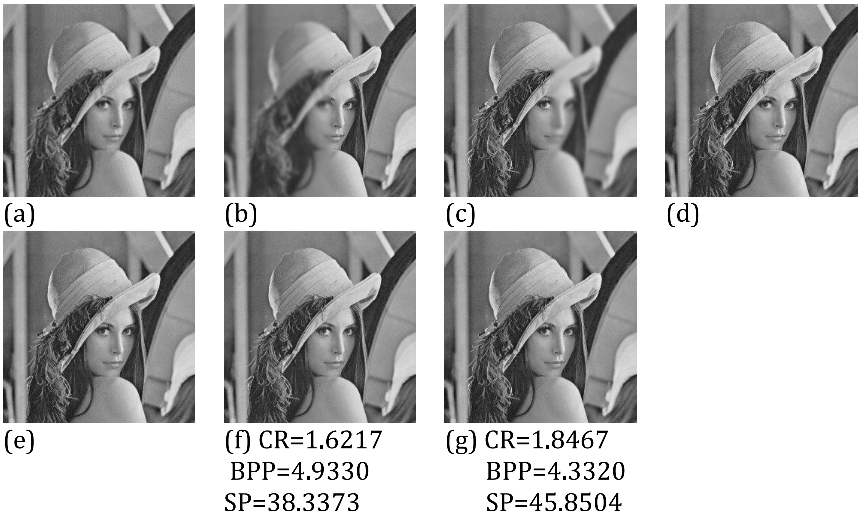


Figure 13. a) Original Lena image (512x512) from 2nd Waterloo dataset b) Left blurred image c) Right blurred image d) Fused image with enhanced features e) SVD decomposed image with rank=175 f) JPEG image g) Reconstructed image with proposed method.

Figure.12. and Figure.13 showing the results of proposed scheme and JPEG method for Cameraman and Lena images. The following part showing the image compression performance for different methodologies, which are based on objective image quality indexes (PSNR, SSIM, CR, and BPP) and visual quality evaluation. Two parameters, specifically some typical features of image compression. The compressed image's quality is shown by the PSNR and SSIM. While higher compression ratios and lower bitrates suggest superior image compression, greater PSNR and SSIM values indicate better image reconstruction.The proposed scheme is evaluated with different standard input images collected from the specified image data source. The parameters CS, CR, SP, BPP, PSNR andSSIMare evaluated for the proposed method and JPEG method and are tabulated in Tables2to 5. The graphical analysis of the parameter evaluation is shown in Figures 14 to 18.

Table 2. CS, CR, BPP and SPof JPEG vs. Proposed Methodfor the images of the 1st Waterloo grayscale dataset.

S.No	Image (256x256)	Compressed Size (CS) (in bytes)		Compression Ratio(CR)		Bits per pixel (BPP)		Saving Percentage(SP)	
		Existing JPEG	Proposed Method	Existing JPEG	Proposed Method	Existing JPEG	Proposed Method	Existing JPEG	Proposed Method
1	bird.raw	43,282	22,616	1.51	2.90	5.2834	2.7607	33.9569	65.4907
2	bridge.raw	72,562	50,014	0.90	1.31	8.8577	6.1052	-10.7208	23.6847
3	camera.raw	54,956	27,785	1.19	2.36	6.7085	3.3917	16.1438	57.6035
4	circles.raw	24,811	1,971	2.64	33.25	3.0287	0.2406	62.1414	96.9925
5	crosses.raw	32,348	16,138	2.03	22.14	3.9487	1.9700	50.6409	75.3754
6	goldhill.raw	64,064	42,201	1.02	1.55	7.8203	5.1515	2.2461	35.6064
7	horiz.raw	16,230	3,363	4.04	61.42	1.9812	0.4105	75.2350	94.8685
8	lena.raw	57,271	40,708	1.14	1.61	6.9911	4.9692	12.6114	37.8845
9	montage.raw	41,513	24,608	1.58	2.66	5.0675	3.0039	36.6562	62.4512
10	slope.raw	28,731	15,821	2.28	4.14	3.5072	1.9313	56.1600	75.8591
11	squares.raw	10,847	4,755	6.04	50.84	1.3241	0.5804	83.4488	92.7444
12	text.raw	86,721	6,717	0.76	9.76	10.5861	0.8199	-32.3257	89.7507
Average		**44,445**	**21,392**	**2.0942**	**16.1617**	**5.4254**	**2.6112**	**32.1828**	**67.3593**

Table 3. PSNR and SSIM of JPEG vs. Proposed Method for the images of the 1st Waterloo grayscale dataset.

S.No	Image	PSNR(dB)		SSIM	
		Existing JPEG	Proposed Method	Existing JPEG	Proposed Method
1	bird.raw	52.0151	40.2380	0.9695	0.6410
2	bridge.raw	53.4378	30.4382	0.9991	0.9778
3	camera.raw	53.5316	41.7098	0.9770	0.7321
4	circles.raw	61.1661	32.6933	0.9147	0.5452
5	crosses.raw	59.7395	49.3668	0.9057	0.3313
6	goldhill1.raw	52.6691	40.6928	0.9960	0.9481
7	horiz.raw	65535.00	61.9732	1.0000	0.8890
8	lena1.raw	52.7967	41.2222	0.9922	0.8962
9	montage.raw	55.6001	42.9921	0.9868	0.7311
10	slope.raw	59.0789	41.5234	0.9982	0.8905
11	squares.raw	65535.0000	58.2194	1.0000	0.9365
12	text.raw	52.7269	38.8835	0.9589	0.8699
Average		**10968.5635**	**43.3294**	**0.9748**	**0.7824**

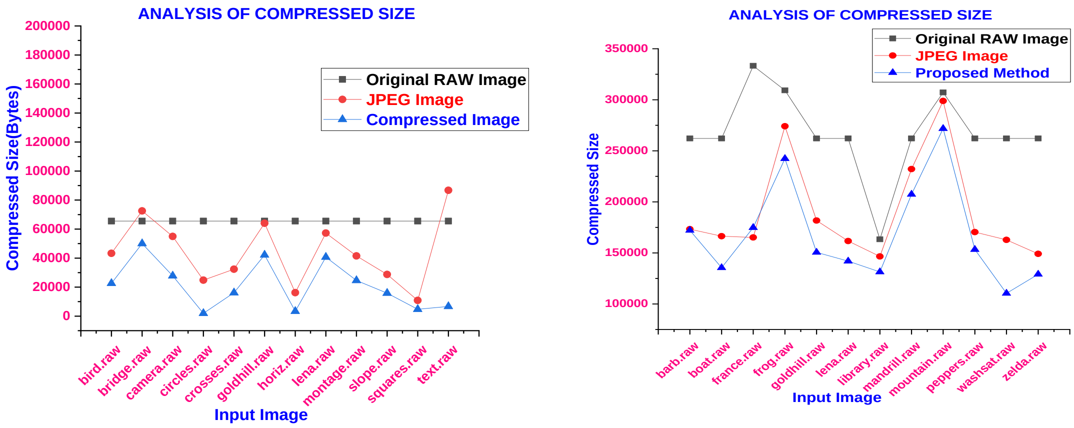
Table 4. CS, CR, BPP and SP of JPEG vs. Proposed Method for the images of the 2nd Waterloo grayscale dataset.

S.No	Image (512x512)	Compressed size (in bytes)		CR		BPP		SP	
		Existing JPEG	Proposed Method	Existing JPEG	Proposed Method	Existing JPEG	Proposed Method	Existing JPEG	Proposed Method
1	barb.raw	1,73,242	1,72,159	1.5132	1.5227	5.2869	5.2539	33.9134	34.3266
2	boat.raw	1,66,432	1,35,487	1.5751	1.9348	5.0791	4.1347	36.5112	48.3158
3	*france.raw (672x496)	1,65,140	1,74,845	2.0184	1.9063	3.9636	4.1965	50.4548	47.5431
4	*frog.raw (621x498)	2,74,070	2,42,405	1.1284	1.2758	7.0897	6.2706	11.3782	21.6172
5	goldhill2.raw	1,81,690	1,50,592	1.4428	1.7408	5.5447	4.5957	30.6908	42.5537
6	lena2.raw	1,61,645	1,41,950	1.6217	1.8467	4.9330	4.3320	38.3373	45.8504
7	*library.raw (464x352)	1,46,520	1,31,390	1.1147	1.2431	7.1767	6.4356	10.2909	19.5545
8	mandrill.raw	2,32,113	2,07,380	1.1294	1.2641	7.0835	6.3287	11.4559	20.8908
9	*mountain.raw (640x480)	2,98,834	2,71,839	1.0280	1.1301	7.7821	7.0791	2.7233	11.5107
10	peppers.raw	1,70,417	1,53,355	1.5383	1.7094	5.2007	4.6800	34.9911	41.4997
11	washsat.raw	1,62,767	1,10,450	1.6105	2.3734	4.9673	3.3707	37.9093	57.8667
12	zelda.raw	1,49,096	1,29,065	1.7582	2.0311	4.5500	3.9388	43.1244	50.7656
Average		**1,90,164**	**1,68,410**	**1.4566**	**1.6649**	**5.7214**	**5.0514**	**28.4817**	**36.8579**

Table 5. PSNR and SSIM of JPEG vs. Proposed Method for the images of the 2nd Waterloo grayscale dataset.

S.No	Image (512x512)	PSNR(dB)		SSIM	
		Existing JPEG	Proposed Method	Existing JPEG	Proposed Method
1	barb.raw	52.8020	32.0751	0.9917	0.9725
2	boat.raw	52.7949	35.6870	0.9832	0.8725
3	*france.raw (672x496)	58.6299	17.0169	0.9804	0.4740

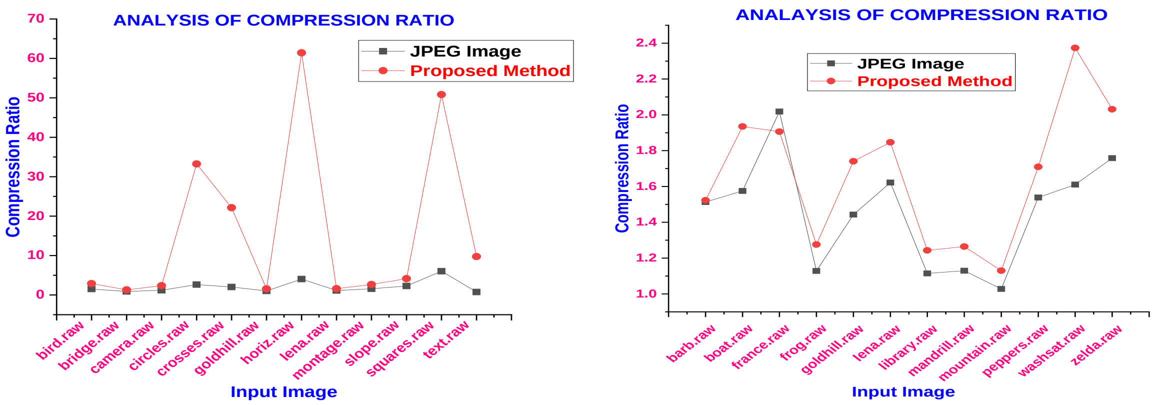
4	*frog.raw (621x498)	53.3722	24.9642	0.9992	0.9035
5	goldhill2.raw	52.6680	35.6577	0.9937	0.8900
6	lena2.raw	53.0569	34.9530	0.9887	0.9708
7	*library.raw (464x352)	54.3665	13.5338	0.9852	0.7598
8	mandrill.raw	52.4688	25.5743	0.9987	0.9432
9	*mountain.raw (640x480)	53.4452	14.5120	0.9956	0.6924
10	peppers.raw	52.4384	23.5369	0.9915	0.9540
11	washsat.raw	52.8572	33.2369	0.9920	0.8538
12	zelda.raw	50.6904	35.2833	0.9910	0.9800
Average		**53.2992**	**27.1693**	**0.9909**	**0.8555**



(a) (b)

Figure 14. Analysis of compressed size between JPEG image and proposed method for a) 1st Waterloo dataset images b) 2nd Waterloo dataset images.

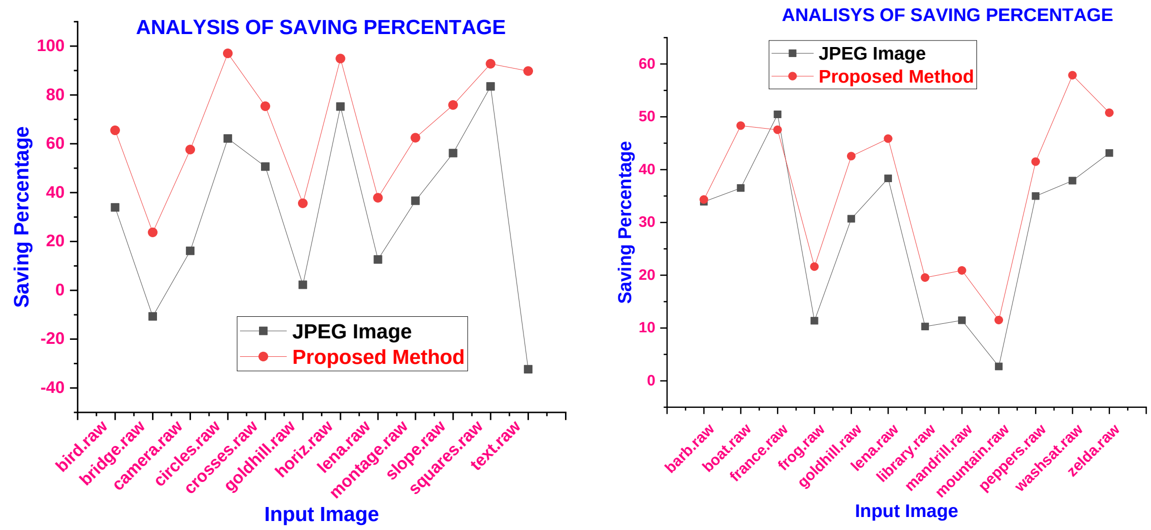
In the above Figure.14, size of the compressed image size is compared with different input images between proposed method and JPEG technique. In most of the cases, the proposed method is giving compressed images with smaller size when compared with JPEG.It is observed that proposed method is showing 51.86% and 11.44% of improvement when compared with existing JPEG method in terms of compressed size comparisons.



(a) (b)

Figure 15. Analysis of compression ratio between JPEG image and proposed method for a) 1st Waterloo dataset images b) 2nd Waterloo dataset images.

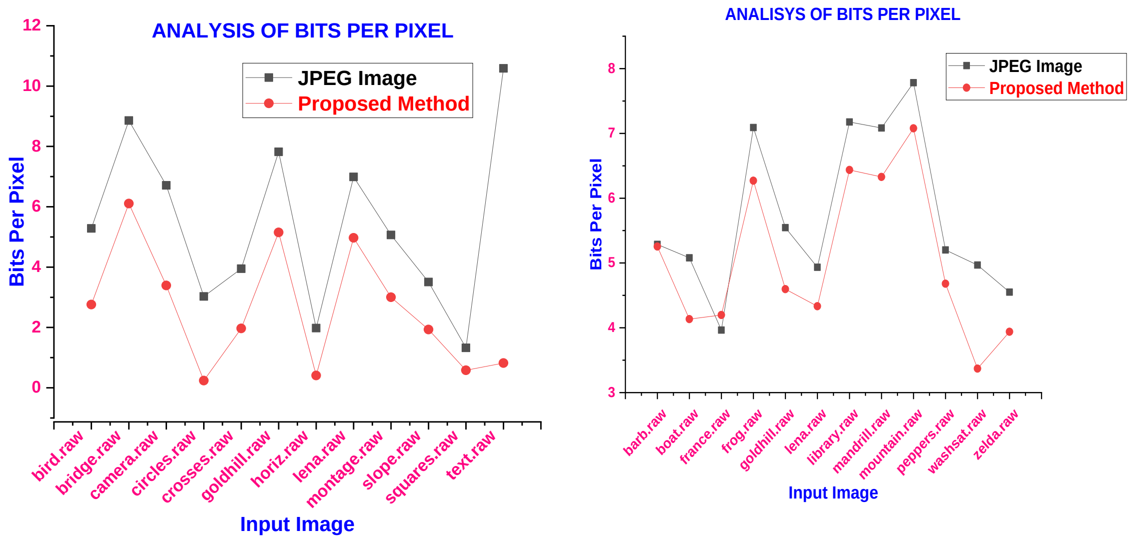
Graphical analysis of the performance evaluation parameter compression ratio (CR) between proposed method and JPEG is shown in Figure.15 for different input size images. In most of the cases, the proposed method attaining high compression ratios compared with JPEG method. At an average 61.74% and 14.30% of improvement in this parameter is observed in proposed method than JPEG method for 1st waterloo and 2nd waterloo dataset images respectively.This improvement indicates that proposed method is highly compressing the images than JPEG.



(a) (b)

Figure 16. Analysis of saving percentage between JPEG image and proposed method for a) 1st Waterloo dataset images b) 2nd Waterloo dataset images.

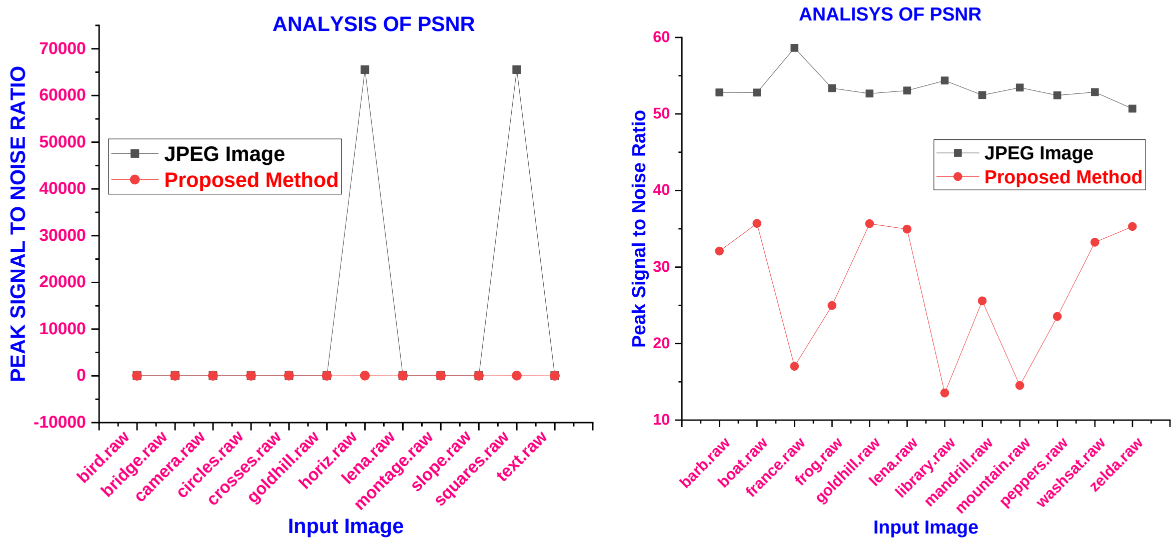
The performance evaluation parameter saving percentage (SP) graphical analysis between proposed method and JPEG is shown in Figure.16 for different input images. In most of the cases, the proposed method is allowing more storage space saving compared with JPEG method. At an average 87.87% and 27.40% of improvement in this parameter is observed over proposed method than JPEG method for 1st waterloo and 2nd waterloo dataset images respectively. High saving percentage indicates that compressed image requires less storage space.



(a) (b)

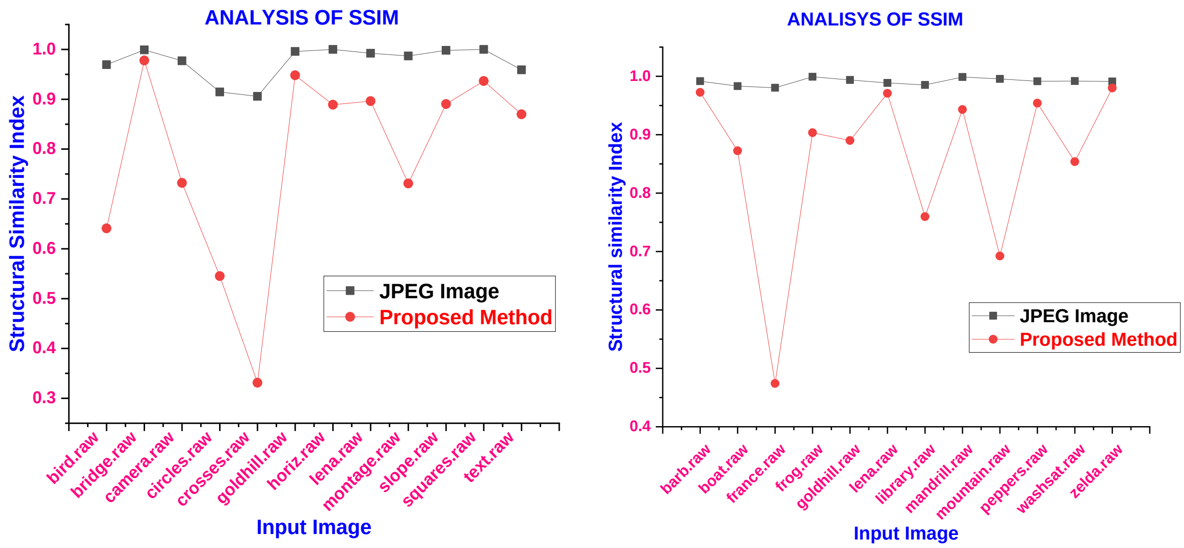
Figure 17. Analysis of bits per pixel between JPEG image and proposed method for a) 1st Waterloo dataset images b) 2nd Waterloo dataset images.

The performance evaluation parameter bits per pixel (BPP) graphical analysis between proposed method and JPEG is represented in Figure.17 for different input images. While representing the image, the number of bits, i.e BPP parameter is having its role. It is ensured that the proposed method having a significant 51.86% and 11.71% of improvements for overall 1st waterloo and 2nd waterloo datasets images. Here, the significant indicates that, the BPP is considering 51.86% and 11.71% less number of bits with respect to the JPEG image storing the images of 1st waterloo and 2nd waterloo datasets.



(a) (b)

Figure 18. Analysis of PSNR between JPEG image and proposed method for a) 1st Waterloo dataset images b) 2nd Waterloo dataset images.



(a) (b)

Figure 19. Analysis of SSIM between JPEG image and proposed method for a) 1st Waterloo dataset images b) 2nd Waterloo dataset images.

The parameters PSNR and SSIM are quality metrics, used to compare the image compression quality. Figure.18 and Figure.19 showing the graphical analysis of PSNR and SSIM values between proposed method and JPEG methods. Lower the PSNR value, lower the image quality. Before compressing the image, in prior quality enhancement is taken place in the proposed method, so that there is a possibility of huge differences in the pixel intensities between original and compressed images. This is the reason why PSNR values are low when compared with the JPEG method. In the proposed method, lowPSNR values are observed due to prior enhancement before compression when compared to JPEG method, automatically low PSNR values occur in the proposed method than that of JPEG method.

The graphical analysis of SSIM parameter is shown in Figure.19. Structural similarity index (SSIM) is a metric for image quality. SSIM measures the structural similarities between the input image and the reference image. Better quality image is observed when its value is closer to 1. The proposed method's

SSIM parameter values are lesser than that of JPEG method's SSIM values due to the enhancement of image by fusion process before compression.

Comparison with baseline model

The Tables numbered from 6 to 9 represents the evaluation of performance measures with the model implemented using wavelet coefficients andHuffman coding[38], the performance metrics of the model obtained by implementing discrete wavelet transformation along with Huffman coding and the proposed method performance metrics are obtained by using wavelets, SVD, Two-channel coding. Further, it is identified that highest compression ratio and space saving are obtained by the proposed method on average of 1.7230 than that of 1.4078, and 0.4036 than that of 0.2796 respectively for traditional test images. Similarly, the highest compression ratio and space saving values 5.4860 than that of 2.7104 and 0.5715 than that of 0.4558 are for standard test images respectively. At an average there is 62.39% of improvement in compression ratio and 34.87% of improvement in space saving is observed in from both standard and traditional test datasets by the proposed method than the baseline method.

In case of objective quality measures such as PSNR and SSIM, due to the enhancement of original image using fusion, the improvement in the respective parameters showing less, because the difference between original image and enhanced image is more then automatically the value of the PSNR will be decreased, with respect to SSIM visual quality will be increase in fusion based decompressed image, some structural properties may not match with the original due to the disappearance in the original image with respect to images of traditional and standard test images.

Table 6. Analysis of proposed method vs baseline method (wavelet coefficients and Huffman coding integrated method) on traditional images of size 512x512.

S.No	**Image (512x512)**	**Base line method** [38]			**Proposed method**		
		Compression Ratio	**Uncompressed/ Compress**	**Space Saving**	**Compression Ratio**	**Uncompressed/ Compress**	**Space Saving**
1	Mandrill	1.1635	0.8595	0.1405	1.30	0.7715	0.2285
2	Girl	1.4895	0.6714	0.3286	1.87	0.5334	0.4666
3	Lena	1.5186	0.6585	0.3415	1.84	0.5420	0.4580
4	Pepper	1.5336	0.6521	0.3479	1.71	0.5857	0.4143
5	Tiffany	1.575	0.6349	0.3651	2.14	0.4674	0.5326
6	Zelda	1.6164	0.6186	0.3814	2.03	0.4932	0.5068
7	Barb	1.2992	0.7697	0.2303	1.52	0.6573	0.3427
8	Boat	1.4087	0.7099	0.2901	1.66	0.6035	0.3965
9	Gold hill	1.3441	0.744	0.256	1.86	0.5381	0.4619
10	Baboon	1.1295	0.8853	0.1147	1.30	0.7715	0.2285
Average		**1.4078**	**0.7204**	**0.2796**	**1.7230**	**0.5964**	**0.4036**

Table 7. Values of PSNR and SSIM for the proposed method against baseline method (wavelet coefficients and Huffman coding integrated method) on traditional test images.

S.No	**Image (512x512)**	**Base line method**[38]		**Proposed method**	
		PSNR	**SSIM**	**PSNR**	**SSIM**
1	Mandrill	54.3074	0.9995	26.0096	0.7713
2	Girl	54.2676	0.9989	33.4527	0.8181
3	Lena	54.1541	0.9987	34.5148	0.7344
4	Pepper	54.2209	0.9989	21.3561	0.6825
5	Tiffany	54.2801	0.9985	23.4902	0.6551
6	Zelda	54.2838	0.9984	34.3329	0.7943
7	Barb	54.2514	0.9983	31.0867	0.8565
8	Boat	54.1609	0.9983	32.2703	0.7825
9	Gold hill	54.2011	0.9989	32.7679	0.8252
10	Baboon	54.0736	0.9986	26.0096	0.7713
Average		**54.22009**	**0.9987**	**29.52908**	**0.76912**

Table 8. Analysis of proposed method vs baseline method (wavelet coefficients and Huffman coding) on standard test images of size 256x256.

S.No	Image (256x256)	Base line method[38]			Proposed method		
		Compression Ratio	Uncompressed/ Compress	Space Saving	Compression Ratio	Uncompressed/ Compress	Space Saving
1	Bird	1.6557	0.604	0.396	2.62	0.381	0.619
2	Bridge	1.1571	0.8642	0.1358	1.27	0.7899	0.2101
3	Camera	1.4027	0.7129	0.2871	2.08	0.4799	0.5201
4	Circles	6.3076	0.1585	0.8415	6.1	0.1639	0.8361
5	France	2.2754	0.4395	0.5605	2.53	0.3949	0.6051
6	Gold Hill	1.2357	0.8093	0.1907	1.49	0.6719	0.3281
7	Lena	1.3442	0.7439	0.2561	1.55	0.6461	0.3539
8	Montage	1.7678	0.5657	0.4343	2.25	0.4454	0.5546
9	Slope	2.4328	0.4111	0.5889	3.57	0.2798	0.7202
10	Squares	7.5251	0.1329	0.8671	31.4	0.0318	0.9682
Average		**2.7104**	**0.5442**	**0.4558**	**5.4860**	**0.4285**	**0.5715**

Table 9. Values of PSNR and SSIM for the proposed method against baseline method (wavelet coefficients and Huffman coding integrated method) on standard test images.

S.No	Image (256x256)	Base line method [38]		Proposed method	
		PSNR	SSIM	PSNR	SSIM
1	Bird	54.2754	0.9981	34.9433	0.6321
2	Bridge	54.2816	0.9996	26.0641	0.9244
3	Camera	54.2694	0.9985	31.7558	0.7033
4	Circles	71.6418	1.0000	33.1889	0.3676
5	France	65.4749	1.0000	24.7019	0.7809
6	Gold Hill	54.3225	0.9993	32.8182	0.9153
7	Lena	54.2754	0.9989	31.0447	0.8568
8	Montage	55.25	1.0000	31.1188	0.6828
9	Slope	56.386	0.9993	32.4447	0.7802
10	Squares	58.9237	0.9995	29.1219	0.7302
Average		**57.9101**	**0.9993**	**30.7202**	**0.7374**

6. CONCLUSION

This work presents a revolutionary technique to lossy compression the usage of wavelets, singular value decomposition (SVD), and two-channel coding techniques. This scheme reduces image sizes even as preserving excessive photograph quality, making it appropriate for various applications. The model's effectiveness was proven thru experiments and critiques, displaying competitive compression ratios whilst retaining picture quality. The computational complexity of the proposed scheme also analyzed, making it sensible for both real-time and resource-constrained applications. But, overall performance of proposed scheme based on characteristics of source image. When the results are equated to JPEG method, the compression ratio, saving percentage, and bits per pixel are all increased significantly on an average by 40.72%, 31.79%, and 69.35% respectively. Comparative analysis with qualitative metrics MSE, PSNR, SSIM and entropy shows a remarkable performance in terms of quality improvement and preservation of visual quality over the JPEG method.

Limitations

In conclusion, the future of image compression research lies in addressing the trade-offs between compression ratio and quality, advancing subjective quality assessment methodologies, and mitigating compression artifacts. By leveraging advancements in coding techniques, perceptual modelling, and machine learning, researchers can pave the way for next-generation image compression systems that deliver superior compression performance and perceptual quality. These efforts will not only benefit traditional applications such as multimedia streaming and storage but also enable new and emerging applications in virtual reality, augmented reality, and remote sensing.

Future work

The proposed scheme concentrates on lossy image compression scheme based on wavelets, SVD, and two-channel coding which encompasses future advancements. This work also includes other methodologies which optimizes the performance of compression scheme in different domains. In future, this model may enhance for energy efficient compression schemes by utilizing IoT based devices, it may also provide compression schemes which allows a progressive transmission that enables enhancing the resolution in remote sensing domain with the combination of deep learning methods, it is essential to investigate to protect the compressed information from intentional attacks or manipulations during the transmission with the help of different cryptographic algorithms. Further compression schemes may explore in legal and ethical considerations by ensuring privacy and fairness. Finally, this research may enhance the reliability, flexibility and efficiency in image compression algorithms in various domains.

Data Availability

The images utilized during the implementation of the proposed work are available inthe "Waterloo Fractal Coding and Analysis Group"https://links.uwaterloo.ca/Repository.html.

Conflict-of-Interest Statement

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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