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Original Article

Multi-Resolution Contextual Image Fusion and Compression Using PCA Features, SVM Classification, and Hybrid Entropy Encoding

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Abstract *- With the rapid growth of digital imaging applications, efficient image compression has become increasingly important for reducing storage requirements and enabling faster transmission, particularly in bandwidth-constrained environments. Healthcare, remote sensing, multimedia, and scientific analysis digital images must be highly compressed, with important visual and structural information retained. In this work, a new system of multi-resolution contextual image fusion and compression is introduced with the use of Principal Component Analysis (PCA), Support Vector Machine (SVM)-based adaptive patch classification and hybrid entropy encoding. The approach proposed uses a patch-based representation in overlapping patches to maintain continuity and consistency of context across space. The aim of PCA is to reduce the dimensions of data and preserve the main features of the image, which allows compact and informative representation of patches. To enhance adaptive compression, image patches are categorized into important and non-important ones by an SVM trained on features based on variance. Critical areas are more faithfully recreated, whilst less crucial areas are more severely compressed to achieve better storage performance. A further refinement of the reconstructed image is done with the help of Gaussian filtering and the Haar wavelet-based multi-resolution fusion to get a higher quality of preservation of edges, and also a better perceptual quality. The fused image is coded with a hybrid entropy coding scheme, two-channel bit-plane coding and Huffman encoding. It has been experimentally shown that the proposed method always performs better on the compressed size, compression ratio, saving percentage, compression gain, bits per pixel and coding efficiency compared to the traditional BMP, TIFF, LZW and baseline compression methods. The framework has compression ratios of 2.655, storage savings of 62.34 and reduced bit rates with high reconstruction quality. These findings prove the usefulness of the suggested framework to the efficient image storage and transmission applications demanding high-quality reconstruction as well as better compression performance.*

Keywords *- Adaptive compression, Haar wavelet fusion, Principal Component Analysis (PCA), Support Vector Machine (SVM), Two-channel bit-plane coding.*

1. Introduction

The high rate of development of digital imaging technologies has resulted in a geometric growth of the production and use of images in a wide range of fields, including healthcare, remote sensing, surveillance, multimedia and scientific research. The increase in image data specifically requires effective storage and transmission systems, and thus image compression is an essential provision in contemporary digital systems. But it is a problem of great difficulty [1] to obtain high compression ratios and still maintain perceptual quality and important structural information.

Traditional image compression algorithms, such as transform-based image compression tools like Discrete Cosine Transform (DCT) and wavelet-based image compression [2], generally compress the entire image by an equal amount. Although these techniques are useful in decreasing data size, they do not usually take into consideration the difference in significance of different parts of the image, resulting in loss of details of important features, particularly in high detail regions.

New technologies in machine learning and signal processing have facilitated more adaptive and intelligent compression schemes [3]. Specifically, patch-based representations with dimensionality reduction algorithms like Principal Component Analysis (PCA) provide an effective method to extract salient image features [4]. Also, classification methods like Support Vector Machines (SVM) can be used to draw a line between the areas of different significance to allow selective retention of important data [5].

This study introduces a multi-resolution contextual image fusion and compression system, which combines the PCA-based feature extraction, SVM-based adaptive patch classification, and hybrid entropy encoding to show better compression efficiency and reconstruction quality.

1.1. Motivation

The rationale behind this study is the increasing demand of smart image compression mechanisms that are capable of changing according to the contents and context of pictures. In most practical uses, like medical imaging and remote sensing, fine details and structural integrity are vital for correct interpretation and analysis. The traditional compression techniques tend to treat all parts the same, and this may lead to the loss of diagnostically or contextually significant information. Moreover, as the necessity to transmit and optimize data transmission and storage grows, there is a need to find ways to not only minimise data size, but also ensure high visual fidelity. Introducing the compression pipeline with machine learning tools can provide a chance to develop adaptive systems that can make decisions based on data regarding information preservation and reduction. The current study is driven by the premise of integrating feature extraction, smart classification and fusing in multiple resolutions to create a powerful compression system that transcends the constraints of traditional practices.

1.2. Research Gap

While many image compression methods have been proposed, most of the existing compression methods focus on independently either transform domain compression or machine learning-based feature extraction. The conventional compression methods like JPEG, JPEG2000, TIFF and LZW compress the entire image using the same compression method, without taking into account the context significance of the image areas. As a result, higher compression ratios typically see a significant loss of information in high-frequency regions, at edges and in terms of structural detail.

However, reconstruction quality has been improved with recent deep learning and wavelet-based compression methods, requiring generally large training datasets, high memory consumption and extensive computational resources. Similarly, there have been fewer works related to using PCA-based dimensionality reduction and SVM-based classification together in a novel incorporation for adaptive image compression based on multi-resolution image fusion and hybrid entropy coding.

Besides, most of the current image fusion methods are directed toward the improvement of image quality but not compression efficiency. In the same way, entropy coding techniques are usually used following the image transformation, without taking into account any contextual information coming from a smart region classification. Hence, there is still a great deal of research work to be done for the realization of an adaptive compression framework, where the contextual features extraction, intelligent image region classification, multi-resolution image fusion, and efficient entropy encoding are all implemented in one single framework.

In order to address these drawbacks, this paper presents a Multi-Resolution Contextual Image Fusion and Compression Framework which combines PCA-based image Feature Extraction, SVM-based Adaptive Patch Classification, Haar wavelet-based image fusion, and Hybrid entropy-based image coding for enhanced compression performance while maintaining good perceptual image quality.

The rest of this work will be structured in the following manner. Section II provides a literature review of related work and existing techniques of image compression. Section III outlines the suggested fusion and compression model, such as PCA feature extraction, adaptive processing by the SVM, Haar wavelet fusion and hybrid entropy encoding. Section IV has the experimental findings and the performance analysis. Lastly, Section V wraps up the research and gives possible future research directions.

2. Background Study

Background study is an important aspect of research since it gives a comprehensive knowledge of what has been already done in terms of research, methodologies and technological developments in regards to the research problem. It assists the researchers to recognize the gaps in research, limitations and uncharted fields that need to be investigated. The literature review provides a theoretical and methodological basis of the proposed study through a critical analysis of the literature in the field. It also helps in choosing the appropriate algorithms, models, evaluation metrics, and experimental procedures that are pertinent to the research objectives. Moreover, a properly organized literature review justifies the originality and importance of the proposed methodology by comparing it with the current methods. Research on image fusion and compression, it fosters the creation of effective and powerful frameworks by isolating the existing issues and new trends in the area.

Kusuma and Meer [6] suggested a hybrid medical image fusion model based on Singular Value Decomposition (SVD) and PCA in terms of maintaining the spatial and spectral details in multimodal images. The primary study goal was to enhance the quality of fusion and reduce the amount of information that is redundant. The methodology consisted of PCA-based feature extraction and SVD-based coefficient optimization to be fused. The experimental results revealed better entropy, PSNR and edge preservation than the traditional fusion methods. The proposed model, however, had weaknesses of higher computation and noise sensitivity in low contrast images.

A hybrid context-based multi-prior entropy model of lossless image compression was proposed by Fu et al. [7]. It aimed at enhancing compression efficiency by taking advantage of cross-channel and contextual dependencies. The algorithm integrated the hybrid local context modeling, hyperprior estimation and entropy coding in YUV color space. The results of the research showed better compression and low redundancy in comparison to the available entropy models. However, with high-resolution images, the model demanded a lot of memory and increased encoding time.

Al-Khafaji et al. [8] introduced a hybrid deep-learning model that combines Stationary Wavelet Transform (SWT), Stacked Denoising Autoencoders (SDAE), and GLCM features to compress medical images. The key goal was to obtain scalability of compression without losing diagnostic information. The algorithm was multiresolution decomposition, texture extraction, clustering and adaptive encoding. It was shown that experimental results achieved greater PSNR and compression ratio than JPEG2000 and traditional wavelet methods. The framework was, however, highly complex in terms of training and reliant on massive annotated datasets.

An entropy-based multi-level feature fusion network that is efficient in image retrieval and fusion applications was proposed by Lavanya et al. [9]. The study had the objective of improving the accuracy of retrieval and relevance of features through adaptive entropy-based fusion of features. It was done using deep belief networks, entropy-based weighting, and multi-feature adaptive fusion strategies. Results demonstrated better feature ranking and retrieval performance in the heterogeneous image sets. The constraints were the processing time, and efficiency were lower with large-scale real-time systems.

Lyu et al. [10] developed a hybrid dimensionality reduction and classification system that combines the Sparse PCA and SVM classifiers. This was aimed at minimizing the computational complexity and enhancing image classification accuracy. The techniques were sparse feature extraction, dimensionality reduction using PCA, and classification using SVM. The findings of the research assured the enhancement of classification accuracy as the size of features decreased. However, tuning of kernel parameters had a great influence on model performance and stability.

Mangalapalli, Vamsi Krishna et al. [11] suggested a work on region-based lossless image compression, which suggested an Integer Wavelet Transform (IWT) and entropy coding system on region-of-interest compression. Its purpose was to save significant parts of the images but minimize redundancy during encoding. This was done by segmenting ROI, multiresolution wavelet decomposition and entropy-based encoding. Results showed better compression ratio and reconstruction compared to traditional lossless techniques. Manual ROI generation, however, added complexity to processing and decreased the ability to automate.

The review of multimodal medical image fusion methods by Goswami et al. [12] concentrated on contextual and multiresolution fusion methods. The aim was to examine scalable and clinically pertinent techniques of fusion in medical diagnosis. The analysis conducted the assessment of fusion methodologies in terms of modality integration, feature extraction, and quantitative assessment measures. Results have indicated the contextual and adaptive fusion methods greatly enhanced the diagnostic visualization. However, there was a lot of reviewed models that were not robust, could not be scaled up and could not be implemented in real-time.

Ogbuanya et al. [13] created a hybrid-based optimization multimodal medical image fusion model to enhance the accuracy of diagnosis. The aim was to speed up the process of multimodal image fusion without compromising structural and contextual information. The approach combined the optimization algorithms with adaptive multimodal fusion techniques. The results of the experiment proved a high degree of fusion accuracy and visual clarity of medical images. The optimization process, however, consumed a lot of computational resources with large-scale data.

Lu et al. [14] proposed a dictionary-based cross-attention entropy model for learned image compression. The goal of the research was to enhance the entropy and rate-distortion performance of learned compression. The methodology comprised of hyperprior-entropy modelling, contextual attention mechanisms and adaptive latent representation learning. Results showed that the BD-rate can be reduced considerably and the coding efficiency can be increased compared to conventional codecs. However, the model complexity and training requirements hampered the use of such models in resource-constrained systems.

Wang et al. [15] gave a detailed analysis of infrared-visible image fusion based on contextual and cross-modal fusion strategies. The aim was to enhance the scene representation and object visibility with heterogeneous image integration. The methodology used in this work comprised multi-scale decomposition, learning of contextual features and adaptive fusion mechanisms. The results of the research showed that the spatial resolution was improved, as well as the interpretability and detection performance. Issues still persisted with dealing with illumination variations and real-time implementation.

Li et al. [16] have also developed a scalable medical image compression system based on hybrid wavelet compression and contextual encoding. The goal was to get a high compression rate with no loss of diagnostic data. Multiresolution decomposition, adaptive feature retention and scalable coding mechanisms were used for methodology. Results showed the improvement in the compression efficiency and edge information preservation of CT and MRI images. However, the framework showed higher computational delay in case of large medical datasets.

Li et al. [17] proposed a multi-feature weighted fusion and PCA-SVM Framework for remote sensing image classification. The goal was to enhance detection accuracy of ships in complex background. The methodology used was a combination of HOG and LBP feature fusion, PCA dimensionality reduction and SVM classification. The experimental results demonstrated that the proposed classifiers outperformed the conventional ones in both accuracy of detection and reduction of false positives. But for very low-resolution and noisy RS images, the performance of the system dropped.

A multifocus image fusion framework suggested by Danyal et al. [18] combines Marr-Hildreth edge detection, DCT, SWT and DWT. This was aimed at maintaining focused areas and edge data in the fusion of images. The technique was edge-based focus detection, with multiresolution transform-domain fusion. The results of the research showed increased sharpness, entropy and quality of visual perception. Nonetheless, the proposed system generated minor ringing artifacts at the edges of high frequencies when there is noise.

Table 1. Summary of literature review

Author(s) & Year	Technique / Methodology	Objective	Key Findings	Limitations
Kusuma and Meer (2024) [6]	Hybrid SVD-PCA-based medical image fusion	Optimise the quality of fusion and minimise redundant information.	Better entropy, PSNR and edge preservation compared to conventional methods.	Computationally complex and affected by noise in low-contrast images
Fu et al. (2024) [7]	Hybrid context-based multi-prior entropy model	Increase the effectiveness of lossless image compression.	Better compression ratio and less redundancy.	More memory usage and encoding time for images at high resolutions
Al-Khafaji et al. (2025)[8]	SWT + SDAE + GLCM-based hybrid deep learning compression	Compress medical images in a scalable manner without compromising any diagnostic information.	Higher PSNR and compression ratio than JPEG2000 and wavelet methods	Complicated training procedure and need for extensive labelled datasets
Lavanya et al. (2026)[9]	Entropy-guided multi-level feature fusion network	Enhance image retrieval accuracy and feature relevance	Better feature ranking and retrieval.	Decreased efficiency for large-scale real-time systems
Lyu (2024) [10]	SPCA-GA-SVM classification framework	Minimize computation and enhance image classification	High dimensionality reduction and high accuracy of classification.	Very sensitive to tuning of kernel parameters
Mangalapalli et al. (2025)[11]	Region-based lossless compression using IWT and entropy coding	Maintain Return on Investment data with least amount of duplication	Increased compression ratio and reconstruction quality.	Manual ROI selection decreased automation capability.
Goswami et al. (2025) [12]	Review of multimodal medical image fusion techniques	Examine clinically and scalable fusion techniques	The adaptive fusion and the contextual fusion improved the visualization of the diagnosis.	Scalability and real-time implementation were not possible for many of the reviewed methods.
Ogbuanya et al. (2025) [13]	Hybrid optimization-based multimodal image fusion	Enhance the speed and precision of the diagnostics and fusion process	Accurate fusion and higher image clarity.	Expensive to compute for large data sets

Lu et al. (2025) [14]	Dictionary-based cross-attention entropy model	Enhancing Rate-Distortion in Learned Image Compression	Reduced BD-rate and improved coding efficiency	The complexity of the model and training needs are high.
Wang et al. (2025) [15]	Infrared-visible image fusion using contextual and cross-modal strategies	Improve scene representation and facilities for viewing objects.	Higher spatial resolution and detection performance	Challenge of dealing with changes in lighting and near-real-time processing
Li et al. (2025) [16]	Hybrid wavelet compression with contextual encoding	Compress medical images to large scales.	More compression efficiency and edge retention.	Increased computation delay for large medical datasets
Li et al. (2025) [17]	Multi-feature weighted fusion with PCA-SVM	Enhance ship detection in remote sensing images	Increase detection rates and reduce false positives.	Noise/low-resolution images are less effective.
Danyal et al. (2025) [18]	Multifocus image fusion using DCT, SWT, DWT, and Marr-Hildreth edge detection	Maintain and retain areas of interest and edge detail.	Greater image sharpness, entropy and image quality.	There were ringing artefacts in high-frequency noisy areas.

2.1. Research Gap Identified

A literature survey shows that a lot of research work has been done in image fusion, transform domain compression, deep learning-based image coding and entropy coding. But most reported methods only cover individual stages of compressing the pipeline. Most of the current methods include no contextual adaptation for the detection of critical image areas before compression. Moreover, lots of cutting-edge methods are either very time-consuming, require a lot of data for training, or demand a lot of memory, which hinders their usefulness.

So far, only a few papers have considered the combination of PCA-based feature extraction and machine learning based adaptive classification, multi-resolution image fusion, and the hybrid entropy encoding in a single compression framework. To this end, this research paper focuses on filling such a gap by proposing an intelligent contextual image compression model that is able to retain the important structural information and significantly improve its compression performance.

3. Proposed Methodology

The proposed framework combines the patch-based representation, dimensionality reduction, classification by machine learning and adaptive reconstruction to obtain efficient image compression for perceptual quality. The overall workflow is divided into four main steps: patch extraction, PCA-based feature extraction [19], SVM-based adaptive classification [20] and reconstruction with adaptive component allocation.

3.1. Main Contributions

The key advances of the proposed research are presented below.

- An innovative contextual image compression method based on PCA feature extraction, Support Vector Machine (SVM) classification, Haar wavelet fusion and hybrid entropy encoding.
- Implementation of an adaptive patch classification mechanism considering the contextual information that helps in distinguishing the important and non-important image regions.
- Adding a multi-resolution Haar wavelet fusion method for structural and edge information preservation in the beginning of entropy encoding
- Design of hybrid entropy coding scheme for efficient compression using two-channel bitplane coding and Huffman coding.
- Extensive experimental results and validation when compared to a number of standard Waterloo benchmark image databases, which show superior compression ratio, storage savings, coding efficiency and reduced bits-per-pixel when compared to BMP, TIFF and LZW compression methods.

The proposed framework is different from the current ones that have taken a step-by-step approach to feature extraction, feature fusion or entropy coding, by combining all these steps into a single adaptive compression framework.

3.2. Patch-based Image Representation

Suppose that the input image is $I \in \mathbb{R}^{H \times W}$. First, the image is normalized and symmetrically padded to deal with boundary conditions. The padded image I_p is divided into overlapping patches, each with a size of $p \times p$, with stride s. Every patch is taken out like:

$$P_k = I_p(i: i + p - 1, j: j + p - 1) \quad (1)$$

Where P_k is the patch index. Each patch is then vectorised into a column vector $x_k \in \mathbb{R}^{p^2}$. The complete set of patches is represented as:

$$X = [X_1, X_2, \cdots X_N]^T \quad (2)$$

where N is the total number of patches.

3.3. PCA-based Feature Extraction

Principal Component Analysis (PCA) is used to minimize the redundancy and generate meaningful features from the set of vectorized patches [19]. First, the average of all patches is calculated, and the data is re-centered. The mean vector of all patches is computed as:

$$\mu = \frac{1}{N}\sum_{k=1}^{N} x_k \quad (3)$$

The data is mean-centered: $\tilde{X}_k = X_k - \mu$.

The covariance matrix is given by:

$$C = \frac{1}{N}\sum_{k=1}^{N} \tilde{x}_k \tilde{x}_k^T \quad (4)$$

Next, PCA is done to get orthogonal components accounting for the largest variance of the data set. Based on the cumulative variance retained (e.g., 99 – 99.5%), a subset of the principal components is chosen in a way that most of the important information is retained with greatly reduced dimensionality. This results in compact and efficient feature vectors, as necessary for classification and reconstruction of the original patches.

3.4. SVM-based Adaptive Patch Classification

Patches are classified by a Support Vector Machine (SVM) classifier [20] as to their importance, so as to enable adaptive compression. Labels are generated using a variance-based criterion, in which patches with larger variance are deemed to be information-rich (important) and those with smaller variance are considered less important. A variance-based labeling is used to classify patches by importance:

$$\sigma_k^2 = \frac{1}{p^2}\sum_{i=1}^{p^2}\left(x_{k,i} - \bar{x}_k\right)^2 \quad (5)$$

where $\bar{x}_k$ is the mean intensity of patch k.

The actual label is defined as:

$$y_k = \begin{cases} 1, & if\ \sigma_k^2 > T \\ 0, & otherwise \end{cases} \quad (6)$$

where T is a threshold (e.g., median variance).

The PCA features extracted are used to train the SVM model, which learns the difference between important patches and non-important patches. After training, the model will output the score of each patch, which allows to perform region-specific processing. The SVM classifier learns a decision function:

$$f(f_x) = sign\left(\sum_{i=1}^{M} \alpha_i y_i K(f_i, f_k) + b\right) \quad (7)$$

where:

- α_i are learned coefficients,
- K(·,·) is the kernel function (e.g., RBF),
- b is the bias term.

Each patch has a predicted label $\hat{y}_k$, which determines its importance. This classification step adds intelligence into the compression framework since it enables the differential treatment of image regions.

3.5. Adaptive Reconstruction Strategy

The adaptive reconstruction mechanism is used, based on the predicted labels. Important patches are reconstructed by a larger number of principal components to preserve finer details, while less important patches are reconstructed by a smallest number of principal components to gain higher compression. The number of principal components used for the reconstruction is varied according to the prediction label:

$$\hat{x}_k = \begin{cases} V_{dh} f_k^{(h)} + \mu, & \hat{y}_k = 1 \\ V_{dl} f_k^{(l)} + \mu, & \hat{y}_k = 1 \end{cases} \quad (8)$$

where:

- d_h = number of components for important patches,
- d_l = number of components for less important patches ($d_l < d_h$).

The reconstructed patches are returned to their original location. Multiple values can be stored for a pixel because of overlap. These are averaged as:

$$\hat{I}(i,j) = \frac{\sum_{k\in\Omega i,j} \hat{I}_k(i,j)}{|\Omega_{i,j}|} \quad (9)$$

Where $\Omega_{i,j}$ is the set of patches covering pixel (i,j).

Finally, Gaussian filtering is applied for smoothing:

$$I_{final} = G_\sigma * \hat{I} \quad (10)$$

where G_σ is a Gaussian kernel and ∗ denotes convolution operation.

This adaptive reconstruction strategy is an effective compromise between compression efficiency and quality of the image, taking into account the importance of each region. This approach allows for a compression process that is aware of the content and can compress the data in an intelligent way to preserve the critical information, but still reduce the data significantly.

3.6. Haar Wavelet-based Multi-Resolution Image Fusion

To enhance the perceptual quality and preserve structural details, the reconstructed image is fused with the original image with the help of a multi-resolution fusion technique using Haar wavelet [22]. This is based on both spatial and frequency information to achieve better edge preserving and visual effect. Let I and $\hat{I}$ be the original and reconstructed images, respectively. Both images are decomposed to four subbands using a single-level Haar Discrete Wavelet Transform (DWT):

$$\{LL, LH, HL, HH\} \tag{11}$$

where:

- LL: Approximation (low-frequency component)
- LH: Horizontal detail
- HL: Vertical detail
- HH: Diagonal detail

The Haar transform is expressed as:

$$W = (I * g \downarrow 2, I * h \downarrow 2) \tag{12}$$

where g and h are low-pass and high-pass filters, and ↓ denotes downsampling.

3.6.1. Fusion of Approximation Subband

The entropy of each approximation subband is computed as:

$$H = -\sum_i p_i \, log2(p_i) \tag{13}$$

The fused approximation subband is obtained using entropy-based weighted fusion:

$$LL_f = \frac{w_1 LL_1 + w_2 LL_2}{w_1 + w_2 + \varepsilon} \tag{14}$$

3.6.2. Fusion of Detail Subbands

For preserving edges and information about texture, the detail subbands are merged by maximum absolute selection:

$$D_f(x, y) = \max(|D_1(x, y)|, |D_2(x, y)|) \tag{15}$$

Where $D \in \{LH, HL, HH\}$.

3.6.3. Inverse Wavelet Reconstruction

The final fused image is reconstructed using the inverse DWT:

$$I_f = IDWT(LL_f, LH_f, HL_f, HH_f) \tag{16}$$

The fusion method proposed in this study can not only maintain the global intensity information and edge details, but also preserve the structural characteristics and avoid the reconstruction artefacts, and it also has the characteristics of less computation.

3.7. Hybrid Entropy Encoding

To achieve efficient compression of the fused image, a hybrid entropy encoding scheme is employed that combines two-channel bit-plane coding [23] with Huffman encoding. This approach exploits both spatial redundancy and statistical redundancy, resulting in improved compression performance while maintaining reconstruction fidelity.

3.7.1. Two-Channel Adaptive Coding

The fused image is named as $I_f \in ¡^{H \times W}$, and it is initially converted to an 8-bit integer image:

$$I_f(i,j) \in \{0,1,\ldots,255\}$$

Structured code tables are used to represent information in this coding technique. The first table is the level of intensity of the source given and is called the intensity table. The second table shows the associated binary symbols (0s and 1s) and is called the bit table. Both these tables are then merged together and referred to as a bit–intensity table. The overall encoding procedure is illustrated in Figure 1.

The two-channel adaptive coding scheme works like this. The scheme comprises of two tables: an intensity table and a bit table, as shown in Figure 1. The pixel data is rather scanned in raster mode. Consider the input image as a series of intensities of its pixels: $X=\{x_1, x_2, x_3, \ldots, x_N\}$ where N is the total number of pixels.

The encoding process generates two sequences:

- *Intensity table:* $I=\{i_k\}$
- *Bit table:* $B=\{b_n\}$

The first pixel is always encoded as: $i_1=x_1$, $b_1=1$

For $n=2,3,\ldots, N$, the encoding rule is defined as:

$$b_n = \begin{cases} 0, & if\ X_n = X_{n-1} \\ 1, & if\ X_n \neq X_{n-1} \end{cases}$$

The intensity table is updated only when a change occurs:

$$I = \{x_n | b_n = 1\}$$

Merged Bit-Intensity Representation

The final compressed representation is the combination of the bit table and intensity table, $C = (B, I)$; Where $B= \{b_1, b_2, \ldots, b_N\}$ and $I=\{i_1,i_2,\ldots,i_M\}$, $M \leq N$. In this case, M is the number of transitions (i.e., the number of times $b_n = 1$).

Interpretation

- bn=1 represents a new intensity value, this value is stored in I.
- If bn=0, then there is no change, and the previous intensity is maintained.

The scheme thus effectively represents runs of identical pixel values, which reduces the amount of redundant data.

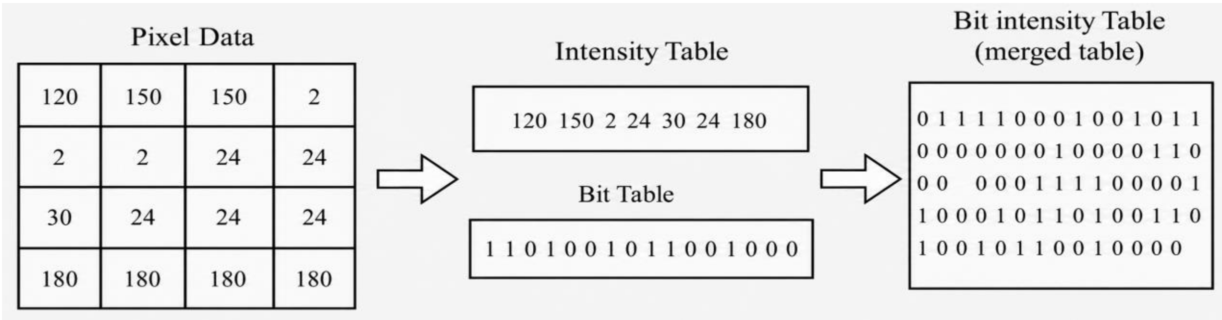


Fig. 1 Two-channel adaptive coding process

Huffman Encoding

Huffman coding [24] is used individually for each channel (MC and SC) to make use of statistical redundancy. The entropy of a source is given by:

$$H(X) = -\sum_i p(x_i) log2p(x_i) \quad (17)$$

When Huffman coding is used, the average code length L is such that: $H(X) \leq L < H(X) + 1$

Let C(xi) be the codeword for symbol xi. The encoded bitstream is organised as:

$$Bitstream = \bigcup_b C(s_b) \quad (18)$$

To achieve the highest coding efficiency, a separate Huffman dictionary is kept for each channel.

Final Compressed Bitstream Formation

The output bitstream is created by joining the encoded output of both channels and the required side information:

$$B_{final} = Bitstream \parallel metadata \quad (19)$$

where metadata includes:

- Image dimensions
- Two-channel adaptive split index k
- Huffman code tables

3.8. Decoding Process

The decompression steps are the reverse of the compression steps:

1. Huffman decoding of each channel
2. Reconstruction of bit-planes
3. Recombination of bit-planes:

$$\hat{I}_f(i,j) = \sum_{b=0}^{B-1} \hat{B}_b(i,j) \cdot 2^b \quad (20)$$

This guarantees loss-less recovery of fused image encoded. The proposed encoding scheme takes advantage of both the structural and statistical redundancies by dividing the significant and less significant bit planes to enhance the performance of the compression. In addition, the mutual entropy across each channel is also smaller, which increases the efficiency of Huffman coding and also gives freedom to choose the bit-plane split between compression ratio and the reconstructed image quality. Figure 2 shows the entire workflow.

The hybrid entropy encoding scheme is able to increase the image compression efficiency and retain the necessary information of the images overall, so it is suitable for high-performance image compression. In Algorithm 1, the steps to be carried out in the encoding process are represented.

Algorithm 1. Encoder (Proposed Compression Framework)

Input: Raw Image I
Output: Compressed bitstream B_{final}

1. Acquire and pre-process the input image.
2. Divide the image into overlapping local regions to be analyzed.
3. Extracting representative features by dimensionality reduction techniques.
4. Explore local texture/statistical properties of each zone.
5. Train and use a machine learning model for region classification according to the significance.
6. Reconstruct image regions adaptively based on variable feature representations based on classification results.
7. Reconstructed the image after aggregating the reconstructed areas and applied spatial filtering to the reconstructed image.
8. Do the wavelet decomposition for both the original image and the reconstructed image at multi-resolution levels.
9. Adaptive fusion of the approximation and detail coefficients.
10. Perform the inverse wavelet transformation to obtain the fused image.
11. Use two-channel adaptive coding for structural and intensity information.
12. Do the entropy-based encoding for the compact representation of the coded data.
13. Produce the output compressed bitstream and necessary metadata.
14. Return the compressed output $B_{final.}$

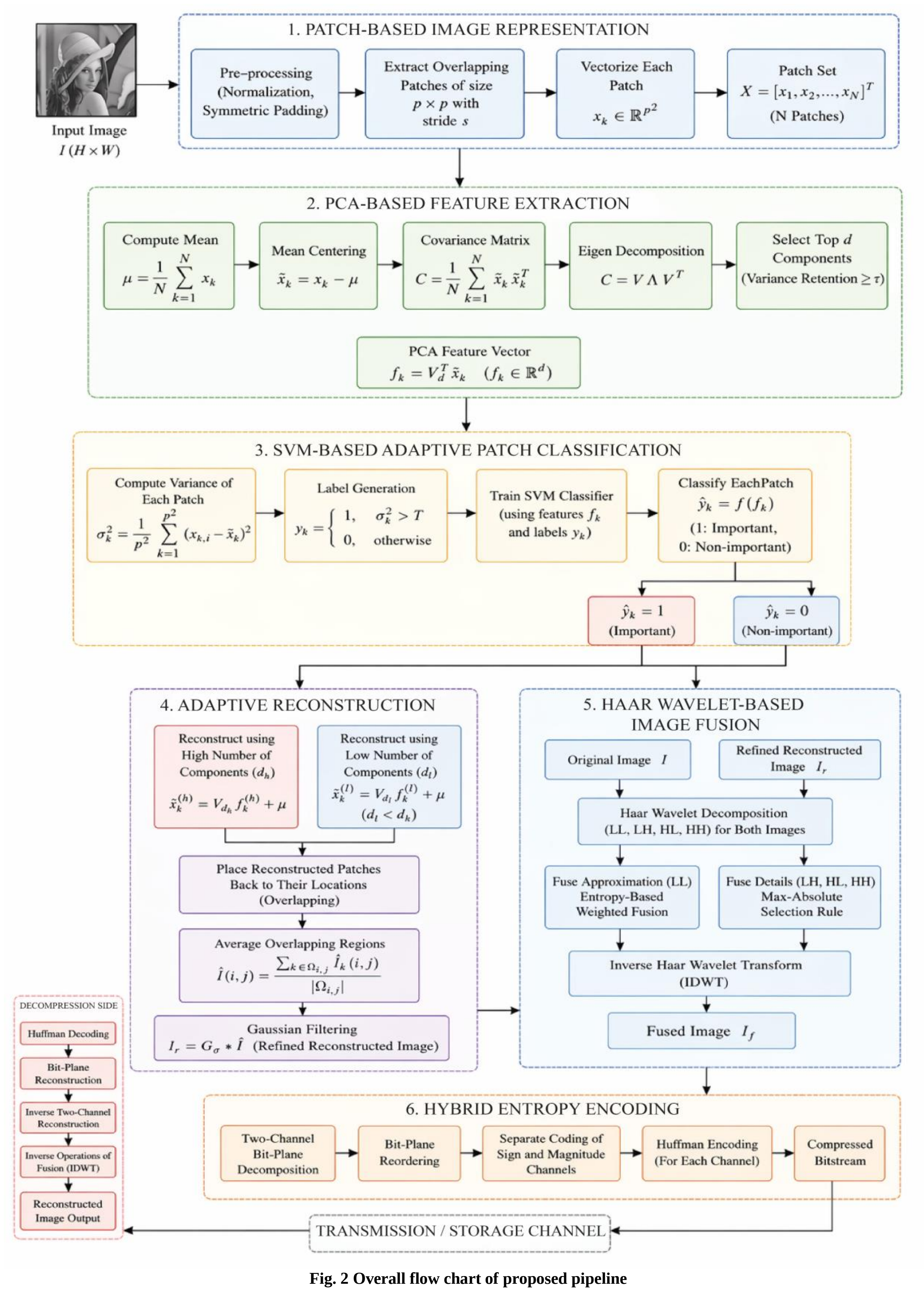


Fig. 2 Overall flow chart of proposed pipeline

4. Experimental Results and Discussion

4.1. Dataset Description

The University of Waterloo Image Repository dataset is a standard image data set of grayscale and colored images, which are commonly used in the field of image processing, image fusion, image segmentation, image enhancement and image compression [25]. The repository is split into three sets: Greyscale Set 1 (12 small grayscale images) (See Figure 3), Greyscale Set 2 (12 medium grayscale images) (See Figure 4) and a Color Set (8 large color images). The dataset comprises some common benchmark images in different formats like GIF, PGM, RAW, TGA and TIFF for testing different image processing algorithms. These images feature a wide range of textures, edges, structural details, and intensity variations, which can be used for quantitative analysis using metrics such as PSNR, SSIM, entropy, and compression ratio. Due to its standardized image quality and benchmarking capability, the repository is widely used for research and development in image fusion, transform-domain processing, entropy encoding and compression performance evaluation.

In this section, the performance of the proposed multi-resolution contextual image fusion and compression framework has been evaluated. The method is tested on the standard grayscale benchmark images 256×256 and 512×512. The performance is measured by the quality of reconstruction and compression efficiency.

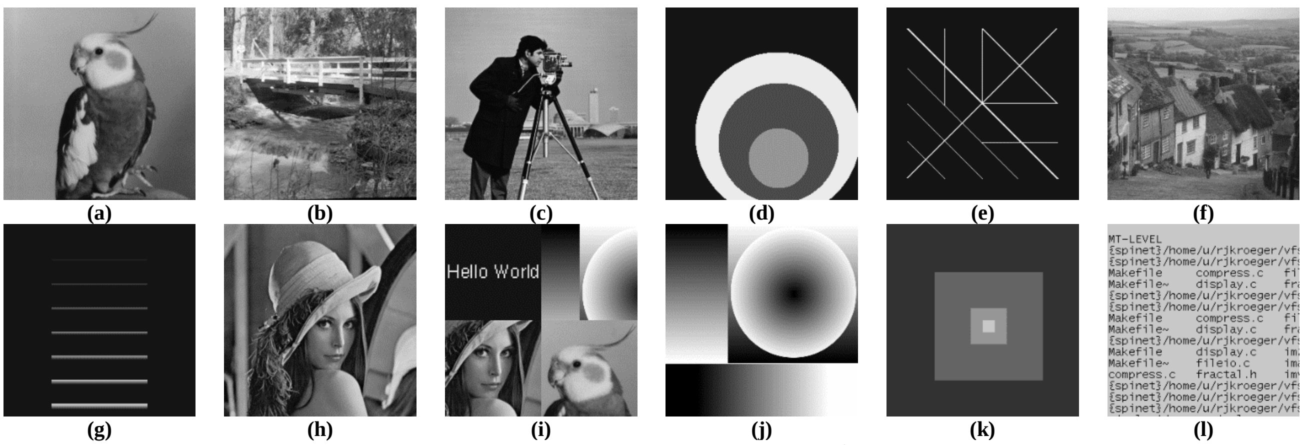


Fig. 3 Greyscale Set 1 images of size 256x256 of 1st Waterloo dataset

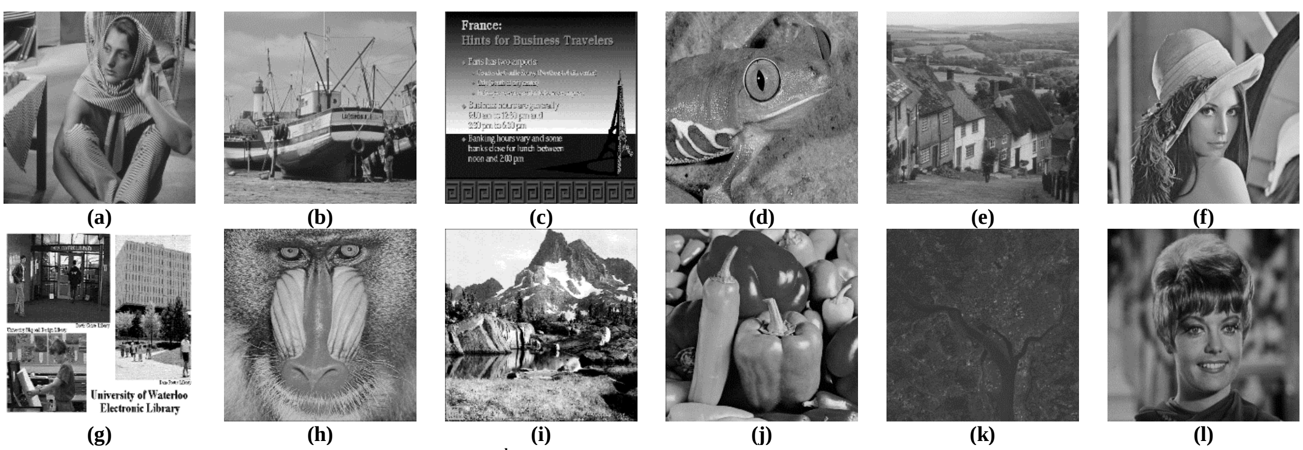


Fig. 4 Greyscale Set 2 images of 2nd Waterloo dataset. a-b)512x512 c) 672x496 d) 621x498 e-f) 512x512 g) 464x352 h) 512x512 i) 640x480 j-l) 512x512.

4.2. Performance Evaluation Metrics

Several compression performance metrics are used as an evaluation of the performance of the proposed image compression framework. The performances of the proposed method are quantitatively measured by these metrics, which can be used to evaluate the compression capability, storage reduction, coding efficiency, and bitrate characteristics. The chosen measures are Compressed Size (CS), Compression Ratio (CR), Saving Percentage (SP), Compression Gain (CG) and Coding Efficiency (CE) [26]. All these measures taken together give a complete overview of the compression performance and allows a comparison with conventional compression methods to be made.

1. Compression Ratio (CR)

$$CR = \frac{Original\ Image\ Size}{Compressed\ Image\ Size} \tag{21}$$

2. Bits Per Pixel(BPP)

$$BPP = \frac{S_c \times 8}{M \times N} \tag{22}$$

3. Saving Percentage (SP)

$$SP = \left(1 - \frac{S_c}{S_o}\right) \times 100 \tag{23}$$

4. Coding Efficiency (CE)

$$CE = \frac{-\sum_{i=1}^{N} p(x_i) log2p(x_i)}{L_{avg}} \tag{24}$$

5. Compression Gain (CG)

$$CG = 10log_{10}\left(\frac{S_O}{S_C}\right) \tag{25}$$

4.3. Experimental Setup

To obtain a good compression efficiency, image reconstruction quality, and computational performance, the proposed image fusion and compression framework was tested with the carefully selected set of parameters.

- Patch size: 8×8
- Stride: 4 (overlapping patches)
- PCA variance retention: 99.5%
- SVM kernel: Radial Basis Function (RBF)
- Split index for bit-planes: k=4
- Gaussian filter: σ=0.5

The selected configuration above provides the preservation of important structure information, at the same time, it provides efficient dimensionality reduction and entropy coding.

4.4. Results Analysis and Discussion

The proposed framework is consistently outperforms conventional image compression solutions as it integrates intelligent feature extraction, adaptive region classification, multi-resolution image fusion and hybrid entropy encoding into a single compression pipeline.

PCA is able to extract the non-redundant information, and the most important feature of the image. The SVM is used to classify patches as high information to more accurately reconstruct them, while smooth patches are compressed more aggressively. As a result, the significant structure, including edges and textures, can be maintained with minimal visual distortion.

Combining low-frequency approximation and high-frequency coefficients by entropy-based weighted averaging and maximum absolute selection, respectively, further improves the quality of reconstructed images by the Haar wavelet-based fusion. This is a fusion method that retains the fine details of the image and reduces the reconstruction artifacts.

Lastly, the two-channel hybrid entropy encoding presented is efficient in making use of the statistical redundancies of both intensity values and bit plane representations. Thus, the proposed framework gets a lower compressed size, higher compression ratio, better coding efficiency, lower bits per pixel, and better storage savings than BMP, TIFF and LZW compression techniques.

Table 2. Performance analysis for standard methods vs proposed method

SNO	Image and Size	Performance Metric	BMP	TIFF	LZW	Proposed Method	Improvement
1	Barb 512×512 (262144 Bytes)	CS	263224	273256	300997	213928	↓ 49,296
		CR	0.99	0.95	0.87	1.22	↑ 0.23
		SP	-0.41	-4.24	-14.82	18.39	↑ 18.80
		CG	-0.018	-0.18	-0.6	0.883	↑ 0.901
		BPP	8.033	8.339	9.186	6.529	↓ 1.504
		CE	-0.41	-4.24	-14.82	18.39	↑ 18.80
2	Boat 512×512 (262144 Bytes)	CS	263224	273640	286213	190823	↓ 72,401
		CR	0.99	0.95	0.91	1.37	↑ 0.38
		SP	-0.41	-4.39	-9.18	27.21	↑ 27.62
		CG	-0.018	-0.186	-0.381	1.379	↑ 1.397
		BPP	8.033	8.351	8.735	5.823	↓ 2.210
		CE	-0.41	-4.39	-9.18	27.21	↑ 27.62
3	Bridge 256×256 (65536 Bytes)	CS	66616	78528	80052	56819	↓ 9,797
		CR	0.98	0.83	0.81	1.15	↑ 0.17
		SP	-1.65	-19.92	-22.15	13.3	↑ 14.95
		CG	-0.071	-0.785	-0.869	0.62	↑ 0.691
		BPP	8.132	9.586	9.772	6.936	↓ 1.196

		CE	-1.65	-19.92	-22.15	13.3	↑ 14.95
4	Camera 256×256 (65536 Bytes)	CS	66616	76340	73666	47212	↓ 19,404
		CR	0.98	0.85	0.88	1.38	↑ 0.40
		SP	-1.65	-16.49	-12.41	27.96	↑ 29.61
		CG	-0.071	-0.663	-0.508	1.424	↑ 1.495
		BPP	8.132	9.319	8.992	5.763	↓ 2.369
		CE	-1.65	-16.49	-12.41	27.96	↑ 29.61
5	Lena2 512×512 (262144 Bytes)	CS	263224	273356	294883	188173	↓ 75,051
		CR	0.99	0.95	0.88	1.39	↑ 0.40
		SP	-0.41	-4.28	-12.49	28.22	↑ 28.63
		CG	-0.018	-0.182	-0.511	1.44	↑ 1.458
		BPP	8.033	8.342	8.999	5.743	↓ 2.290
		CE	-0.41	-4.28	-12.49	28.22	↑ 28.63
6	Mandrill 512×512 (262144 Bytes)	CS	263224	274756	331267	233359	↓ 29,865
		CR	0.99	0.95	0.79	1.12	↑ 0.13
		SP	-0.41	-4.81	-26.37	10.98	↑ 11.39
		CG	-0.018	-0.204	-1.016	0.505	↑ 0.523
		BPP	8.033	8.385	10.109	7.122	↓ 0.911
		CE	-0.41	-4.81	-26.37	10.98	↑ 11.39
7	Peppers2 512×512 (262144 Bytes)	CS	263224	273572	283894	188050	↓ 75,174
		CR	0.99	0.95	0.92	1.39	↑ 0.40
		SP	-0.41	-4.36	-8.3	28.26	↑ 28.67
		CG	-0.018	-0.185	-0.346	1.443	↑ 1.461
		BPP	8.033	8.349	8.664	5.739	↓ 2.294
		CE	-0.41	-4.36	-8.3	28.26	↑ 28.67
8	Zelda 512×512 (262144 Bytes)	CS	263224	272372	251070	178141	↓ 85,083
		CR	0.99	0.96	1.04	1.47	↑ 0.48
		SP	-0.41	-3.9	4.22	32.04	↑ 32.45
		CG	-0.018	-0.166	0.187	1.678	↑ 1.696
		BPP	8.033	8.312	7.662	5.436	↓ 2.597
		CE	-0.41	-3.9	4.22	32.04	↑ 32.45

4.4.1. Comparing to the Existing Methods

The proposed method can approximately achieve smaller compressed data size and a higher compression rate than traditional lossless compression, like BMP, TIFF and LZW compression. The adaptive contextual processing allows to allocate image data efficiently based on the importance of the region, saving visually important structures without increasing the storage volume.

In contrast to the traditional compression scheme using transform, the proposed scheme has the ability to selectively reconstruct the important part of the image using a larger number of principal components, and reconstruct the less important part using a higher compression ratio. This adaptive strategy is an effective way of enhancing perceptual image quality.

Furthermore, the proposed framework uses multi-resolution image fusion and hybrid entropy coding, which can help to achieve better coding efficiency and lower bit rate as compared to recently reported PCA-SVM and wavelet-based approaches. Experiments test the proposed framework with various benchmark images and show that the overall compression performance is better with high reconstruction fidelity.

The compressed size analysis, as shown in Table.2 and Figure.5, indicates that compression is obtained by the proposed method is better than BMP, TIFF and LZW techniques. For all the test images, the proposed framework achieves smaller compressed files.

In the Zelda (512×512) image, for example, the proposed method compresses the image to 178,141 Bytes while BMP, TIFF and LZW compress it to 263,224 Bytes, 272,372 Bytes, and 251,070 Bytes, respectively. Likewise, the compressed size of Camera (256×256) image is reduced to 47,212 Bytes. The results shows the effectiveness of the proposed framework to reduce the redundant image information while maintaining important image details.

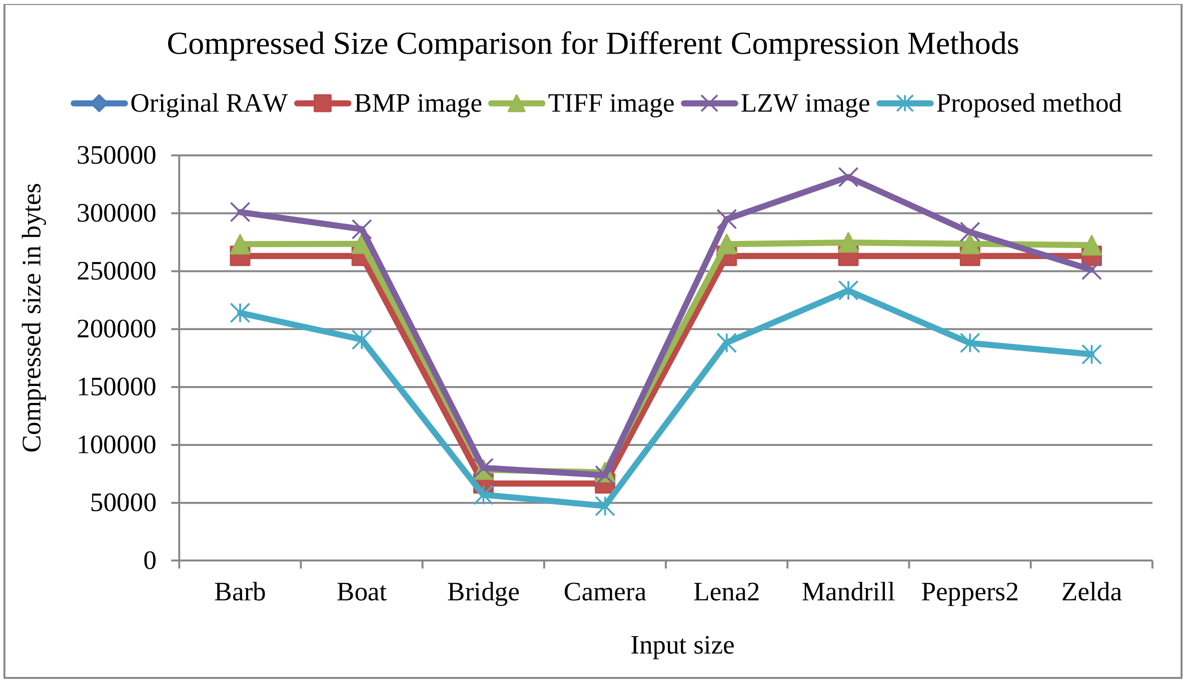


Fig. 5 Compressed Size (CS) performance evaluation across different image compression techniques

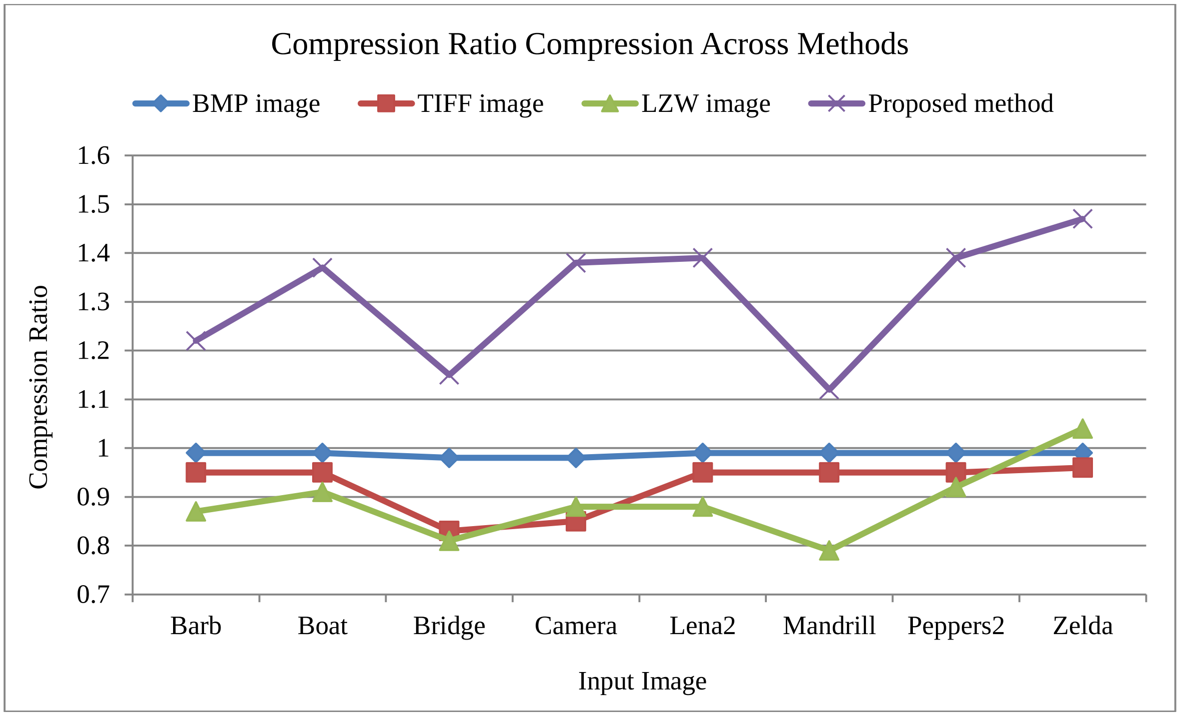


Fig. 6 Compression Ratio (CR) performance evaluation across different image compression techniques

The compression ratio analysis, as shown in Table.2 and Figure.6, proves that the proposed method is more efficient in compression. The proposed framework consistently provides CR > 1 for all test images, which helps to effectively reduce the data. The maximum CR is achieved for the image of Zelda with 1.47, followed by Lena2 with 1.39 and Peppers2 with 1.39. However, with BMP and TIFF, the CR values are less than 1, reflecting the poor compression performance of these two methods. LZW has moderate performance for some images, but its compression performance is still not as good as the proposed method. These improvements are made possible by the use of PCA-based dimensionality reduction and efficient entropy coding.

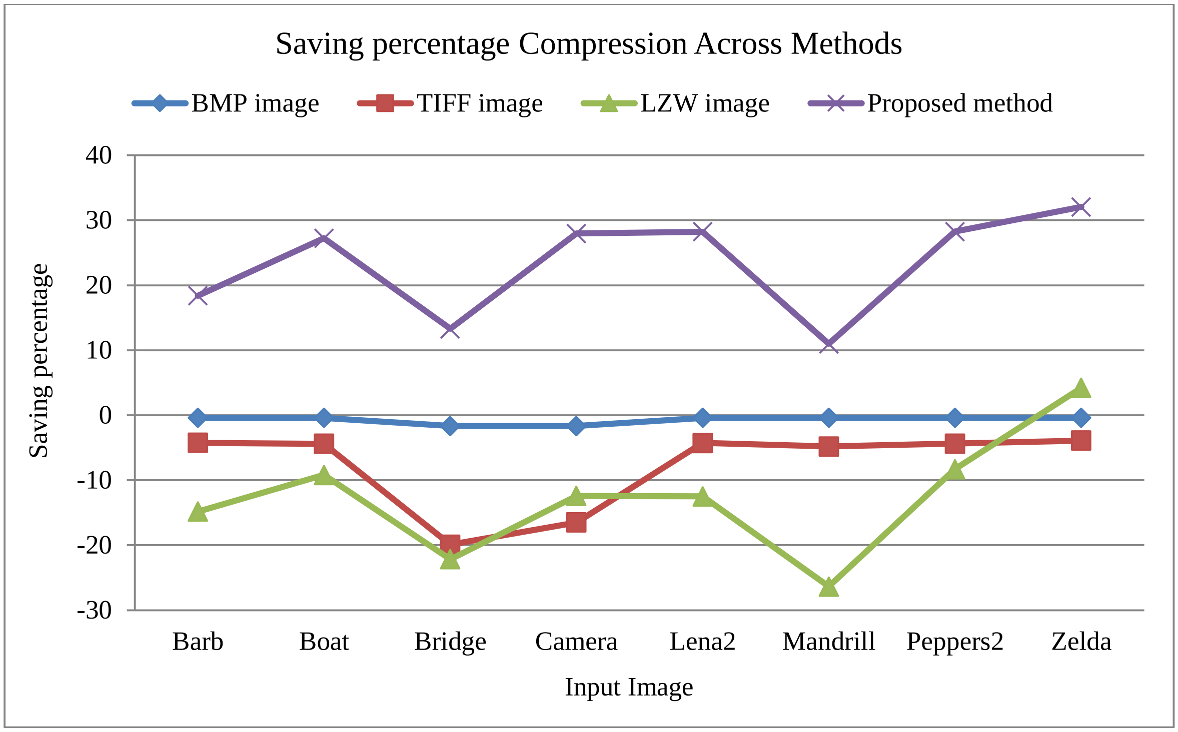


Fig. 7 Saving percentage (SP) performance evaluation across different image compression techniques

Based on the analysis performed in Table.2 and Figure.7, it is observed that the proposed method is able to consistently yield positive saving percentages for all test images, hence the method shows effective storage reduction over BMP, TIFF and LZW methods. The largest Savings of 32.04% is achieved for the Zelda image, followed by 28.26% for Peppers2 and 28.22% for Lena2. On the other hand, BMP and TIFF create negative saving percentages, which means that the file size will get larger. The positive savings from LZW are restricted to certain images. The lower saving percentage for the Mandrill has been attributed to the higher texture of the content, which lessens the compressibility.

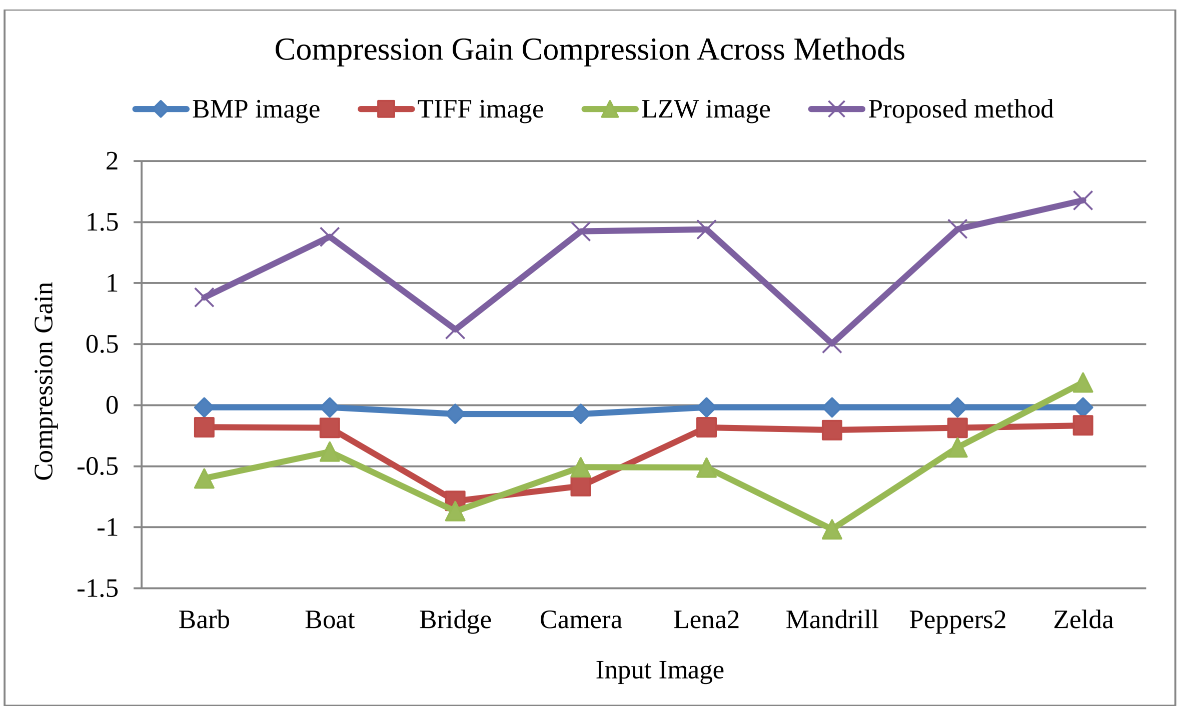


Fig. 8 Compression Gain (CG) performance evaluation across different image compression techniques

From the results, it is seen that the proposed framework is able to achieve positive values for the compression gain of all images, which is confirmed by the numerical and graphical analysis of CG using Table.2 and Figure.8, respectively. Zelda has the highest gain of 1.678 dB, followed by Peppers2's gain of 1.443 dB, and Lena2's gain of 1.440 dB. The negative gain values for BMP and TIFF methods are a sign of bad compression performance; LZW produces inconsistent results. Mandrill's lower gain is due to its complicated texture properties.

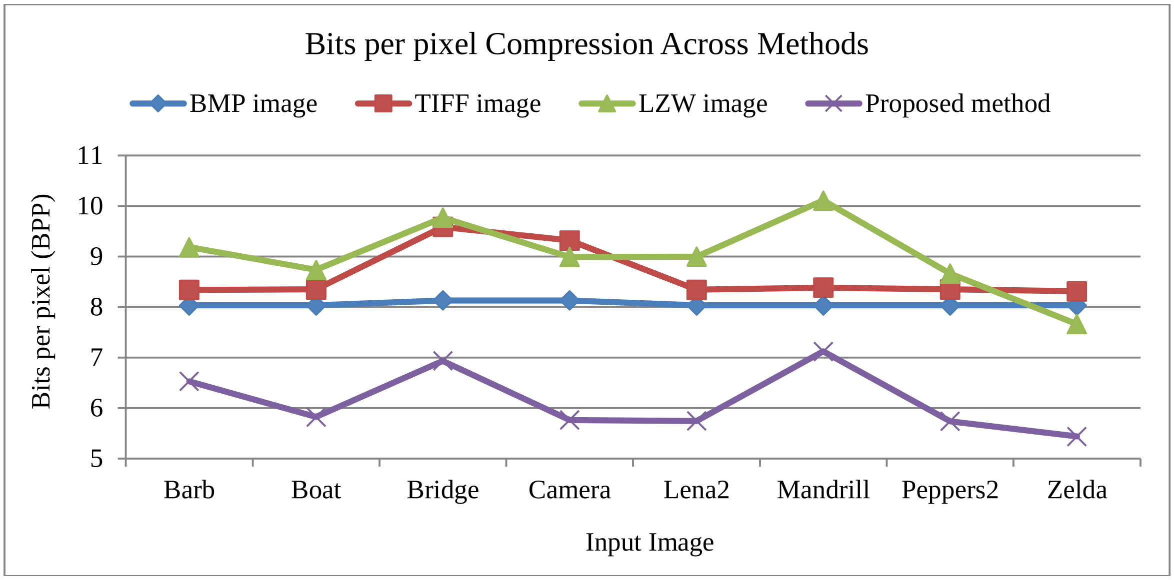


Fig. 9 Bits per pixel (BPP) performance evaluation across different image compression techniques

The numerical and graphical observation of BPP (as tabulated in Table.2 and plotted in Figure.9, respectively) shows that the proposed method gives lower BPP values than BMP, TIFF and LZW methods, which means utilizing less bit value and less storage space. The minimum BPP value is 5.436 for Zelda, 5.739 for Peppers2 and 5.743 for Lena2. BMP and TIFF, on the other hand, have BPP close to or equal to 8 bits, which means that they have a limited compression ability. The high-frequency texture complexity of the Mandrill explain the higher BPP values.

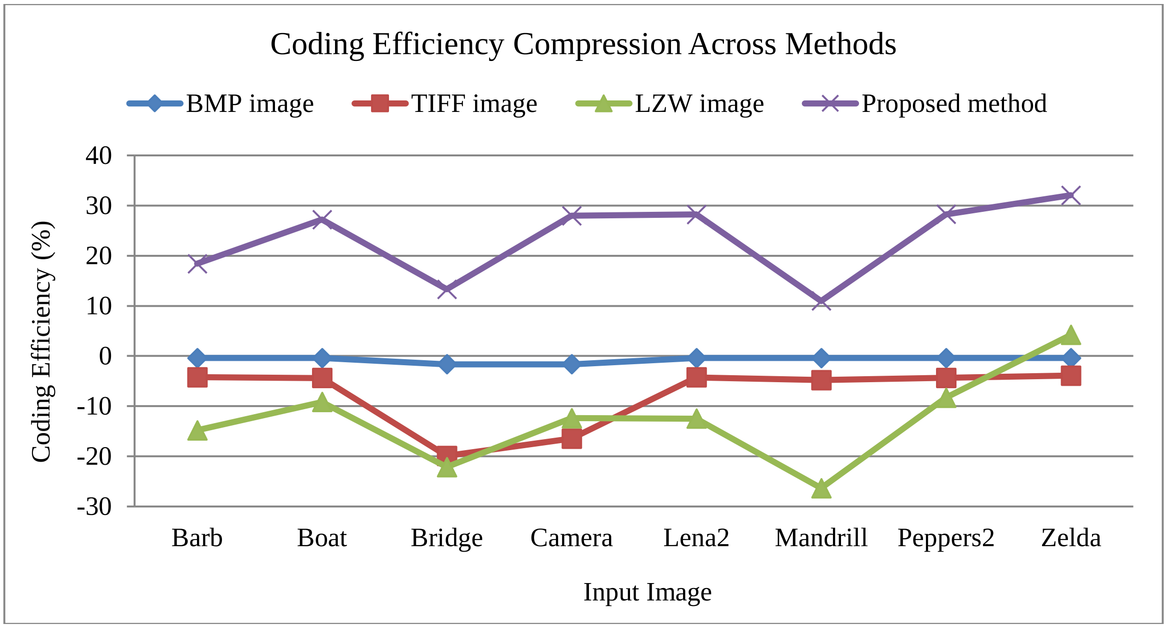


Fig. 10 Coding Efficiency (CE) performance evaluation across different image compression techniques

Based on the results obtained from Coding Efficiency in Table.2 and Figure.10, it is concluded that the proposed framework has a significantly higher coding efficiency as compared to conventional methods. The highest efficiency of 32.04 % is obtained for Zelda, followed by 28.26 % for Peppers2 and 28.22 % for Lena2. The efficiency value is negative for BMP and TIFF, that means they can't effectively reduce the redundancy, and moderate for LZW, only for some images. Overall, the proposed method can be shown to have higher coding efficiency because of adaptive feature extraction and hybrid entropy coding.

In overall, the proposed adaptive PCA–SVM-based compression framework shows better coding efficiency by using the effective feature extraction, adaptive reconstruction, and hybrid entropy coding mechanisms.

Table 3. Performance analysis for existing method vs proposed method

SNO	Image and Size	Performance Metric	Existing Method[23]	Proposed Method	Improvement
1	Barbara 150×150 (22500 Bytes)	CS	21085	19341	↓ 1744
		CR	1.0671	1.1633	↑ 0.0962
		SP	6.29	14.04	↑ 7.75
		CG	6.496	15.129	↑ 8.633
		BPP	7.497	6.877	↓ 0.620
		CE	6.29	14.04	↑ 7.75
2	Cameraman 256×256 (65536 Bytes)	CS	51728	45913	↓ 5815
		CR	1.2669	1.4274	↑ 0.1605
		SP	21.07	29.94	↑ 8.87
		CG	23.661	35.586	↑ 11.925
		BPP	6.314	5.605	↓ 0.709
		CE	21.07	29.94	↑ 8.87
3	ChestXray 135×135 (18225 Bytes)	CS	12848	12640	↓ 208
		CR	1.4185	1.4419	↑ 0.0234
		SP	29.5	30.64	↑ 1.14
		CG	34.962	36.594	↑ 1.632
		BPP	5.64	5.548	↓ 0.092
		CE	29.5	30.64	↑ 1.14
4	KneeJoint 135×135 (18225 Bytes)	CS	12043	11078	↓ 965
		CR	1.5133	1.6452	↑ 0.1319
		SP	33.92	39.21	↑ 5.29
		CG	41.432	49.785	↑ 8.353
		BPP	5.286	4.863	↓ 0.423
		CE	33.92	39.21	↑ 5.29
5	CT1 400×400 (160000 Bytes)	CS	65525	62610	↓ 2915
		CR	2.4418	2.5555	↑ 0.1137
		SP	59.05	60.87	↑ 1.82
		CG	89.277	93.828	↑ 4.551
		BPP	3.276	3.131	↓ 0.145
		CE	59.05	60.87	↑ 1.82
6	CT3 225×225 (50625 Bytes)	CS	28213	27584	↓ 629
		CR	1.7944	1.8353	↑ 0.0409
		SP	44.27	45.51	↑ 1.24
		CG	58.468	60.723	↑ 2.255
		BPP	4.458	4.359	↓ 0.099
		CE	44.27	45.51	↑ 1.24
7	CT4 512×512 (262144 Bytes)	CS	107275	98735	↓ 8540
		CR	2.4437	2.655	↑ 0.2113
		SP	59.08	62.34	↑ 3.26
		CG	89.353	97.648	↑ 8.295
		BPP	3.274	3.013	↓ 0.261
		CE	59.08	62.34	↑ 3.26
8	LenaGray 512×512 (262144 Bytes)	CS	213164	182756	↓ 30408
		CR	1.2298	1.4344	↑ 0.2046
		SP	18.68	30.28	↑ 11.60
		CG	20.684	36.075	↑ 15.391
		BPP	6.505	5.577	↓ 0.928
		CE	18.68	30.28	↑ 11.60

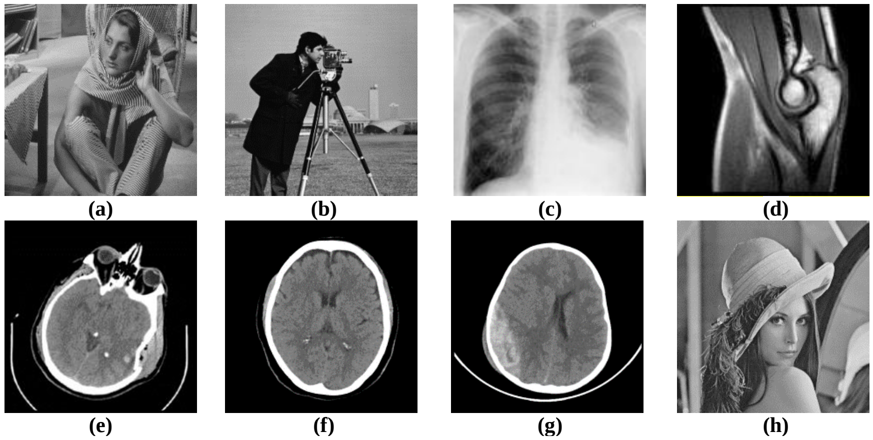
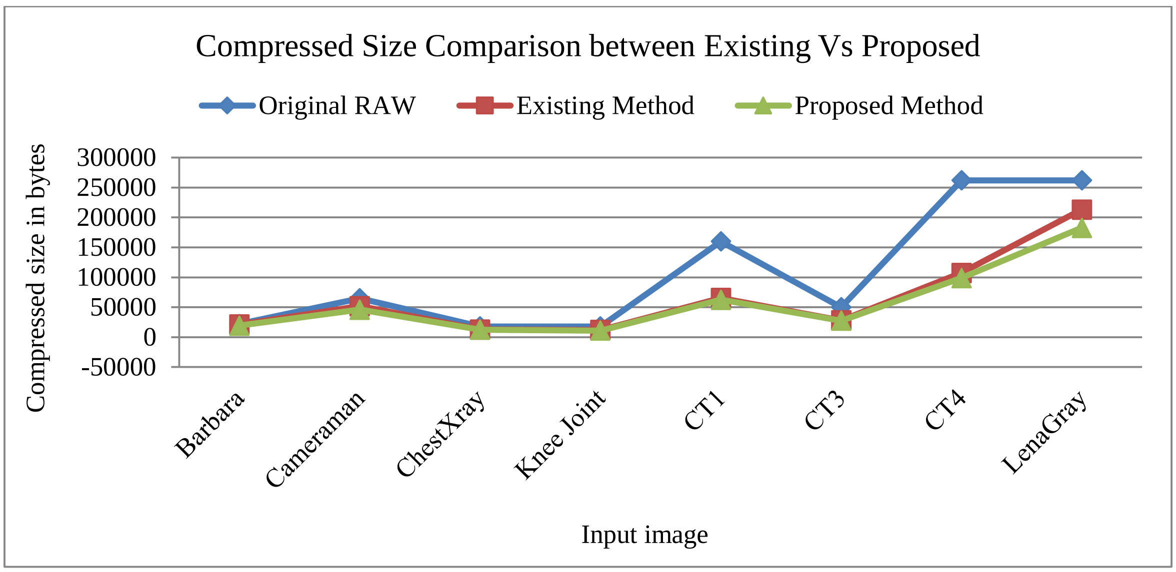
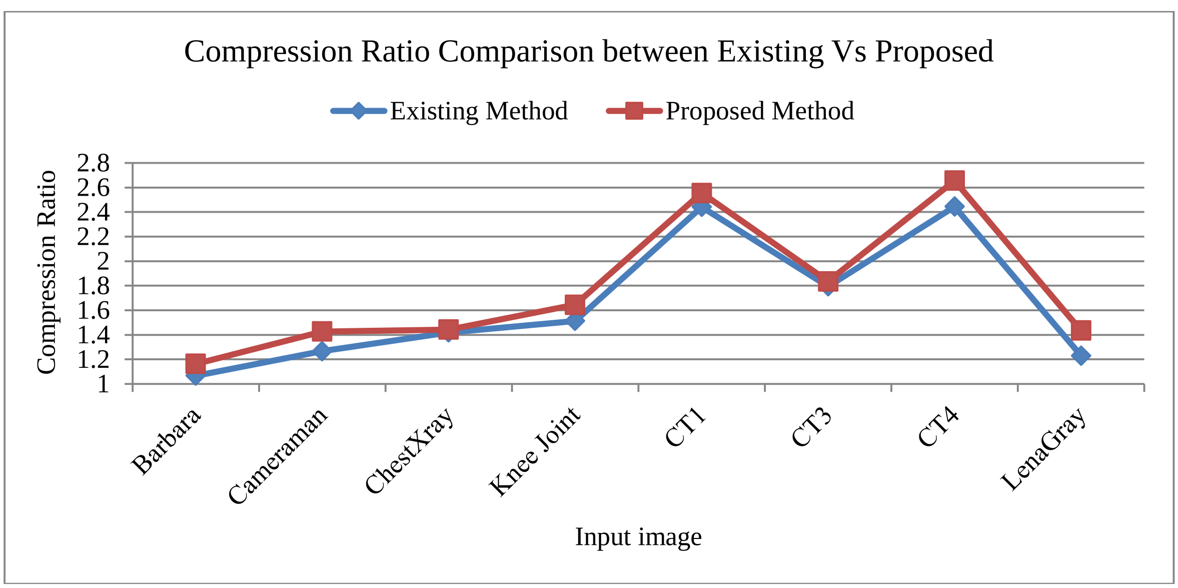


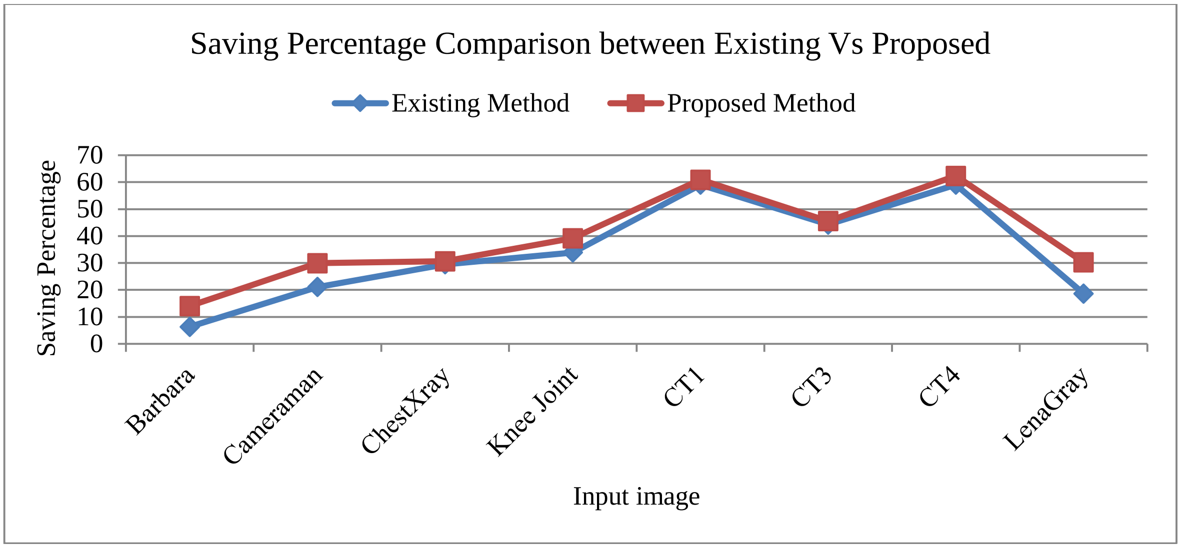
Fig. 11 Existing method Grayscale images a) Barbara b) Cameraman c) ChestXray d) KneeJoint e) CT1 f) CT3 g) CT4 h) Lena.



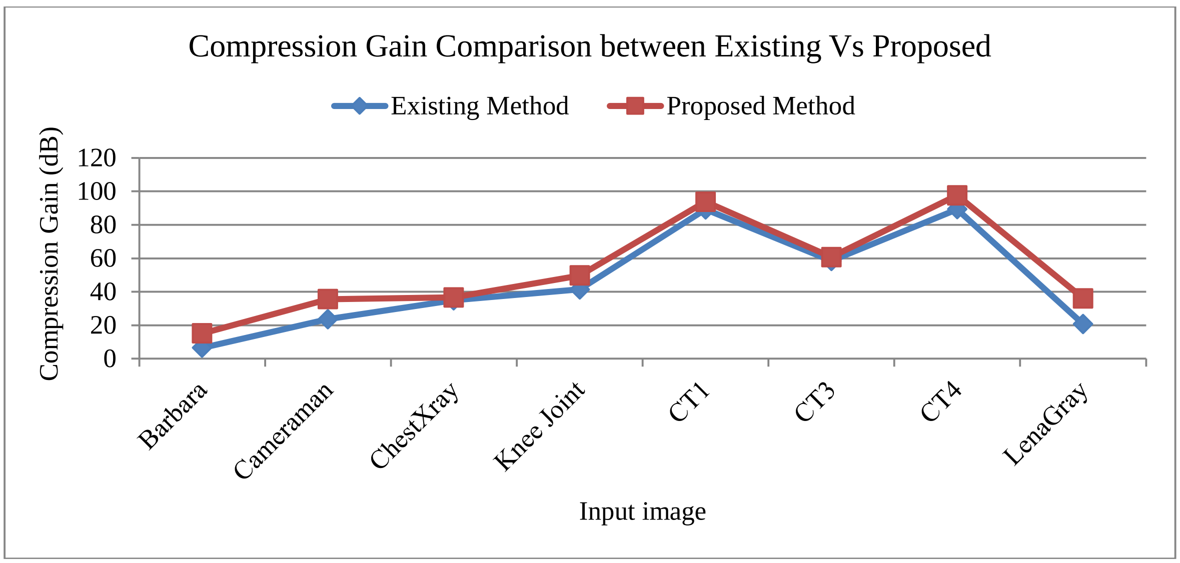
(a)



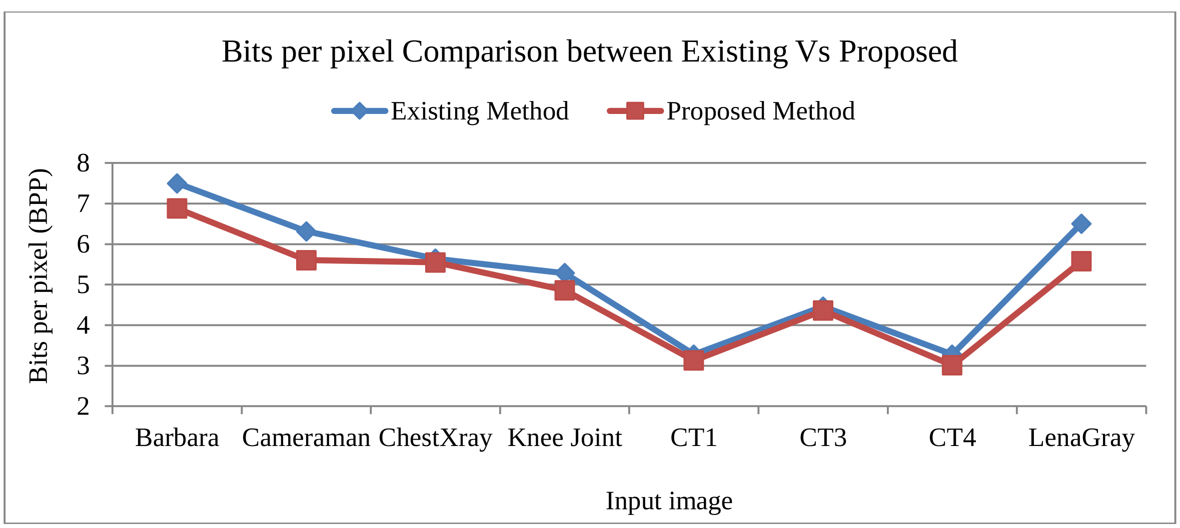
(b)


Saving Percentage Comparison between Existing Vs Proposed
Existing Method
Proposed Method
Saving Percentage
0
10
20
30
40
50
60
70
Barbara
Cameraman
ChestXray
Knee Joint
CT1
CT3
CT4
LenaGray
Input image

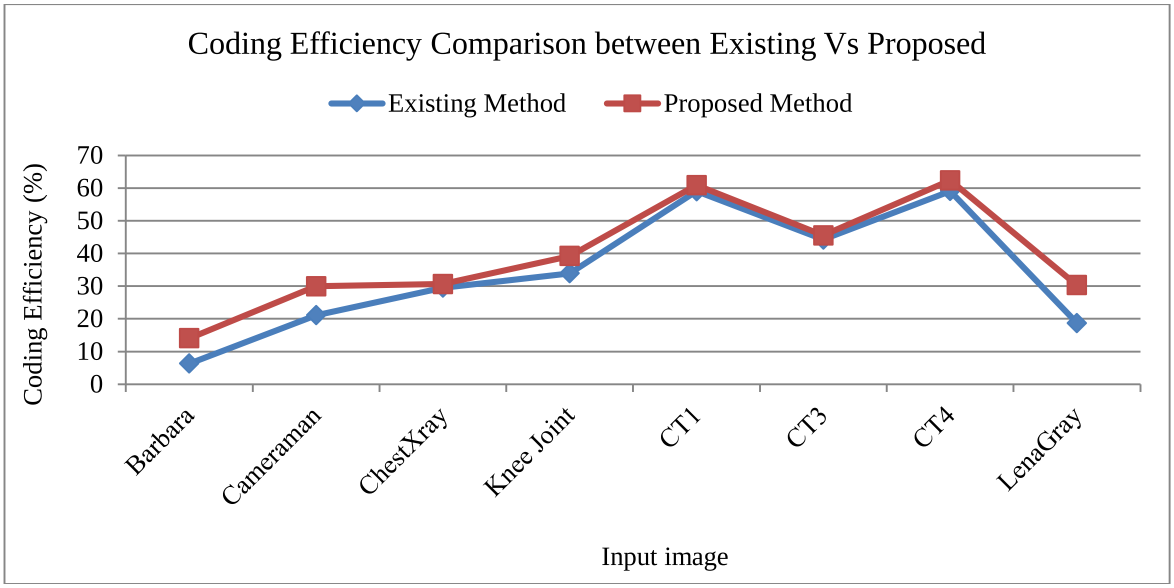
(c)


Compression Gain Comparison between Existing Vs Proposed
Existing Method
Proposed Method
Compression Gain (dB)
0
20
40
60
80
100
120
Barbara
Cameraman
ChestXray
Knee Joint
CT1
CT3
CT4
LenaGray
Input image

(d)


Bits per pixel Comparison between Existing Vs Proposed
Existing Method
Proposed Method
Bits per pixel (BPP)
2
3
4
5
6
7
8
Barbara
Cameraman
ChestXray
Knee Joint
CT1
CT3
CT4
LenaGray
Input image

(e)



(f)

Fig. 12 a) Compressed Size b) Compression Ratio c) Saving Percentage d) Compression Gain e) Bits per pixel and f) Coding Efficiency analysis between existing vs Proposed methods.

Images used for evaluating the existing method and the proposed method are shown in Figure 11. Table 3 and Figure.12 shows the comparative analysis of the proposed image compression framework with BMP, TIFF, LZW and the existing method [23] with respect to all evaluation metrics. The proposed method always produces the smaller compressed sizes and higher compression ratios for all test images.

For instance, the compressed size of the CT4 (512×512) image is 98735 bytes, and it has the highest compression ratio of 2.6550, which is better than the baseline and conventional method. In the same way, Lena Gray (512×512) image and CT1 (400×400) image shows significant reduction in storage.

It is also found that the proposed framework has a higher percentage of saving and compression gain values as well as coding efficiency when compared to other methods. It can be seen that the maximum saving percentage and coding efficiency of 62.34% are achieved for the CT4 (512×512) image, and also the highest compression gain is 97.648 dB for the same image. The negative saving and efficiency values for most images, on the other hand, are obtained by the BMP and TIFF methods, which show poor compression performance.

Moreover, the proposed method always yields lower BPP values, which indicates efficient use of bits and less storage requirement. The minimum BPP value of 3.013 is achieved for CT4 (512×512). From these results, it can be seen that the proposed adaptive PCA–SVM-based compression framework achieves higher compression efficiency and good redundancy reduction with the preservation of image quality overall.

5. Conclusion

This paper introduced a new Multi-Resolution Contextual Image Fusion and Compression framework, which integrated PCA-based feature extraction, SVM-based adaptive patch classification, Haar wavelet-based image fusion and hybrid entropy coding for efficient image compression. The proposed method can not only select the significant image area intelligently, but also reconstruct the image adaptively and fuse the wavelets in the wavelet domain and encode them with two-channel entropy coding to remove the statistical redundancy effectively.

Tested on some of the well-known benchmark images from the Waterloo image library, the experimental results show that the proposed framework always exhibits better compression ratio, storage savings, coding efficiency and lower bits-per-pixel than BMP compression and TIFF compression, as well as LZW compression. Adaptive integration of contextual analysis and multi-resolution processing helps to preserve the quality of the visual information while performing efficient data reduction.

Future research will focus on feature extraction using deep learning techniques, adaptive arithmetic coding, and lightweight neural entropy models for further compression efficiency improvement and for real-time application to large size images.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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