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ORIGINAL

RIFD-LZW: A Hybrid Approach for Lossy Image Compression Using Intensity Rounding, Division, and Lempel-Ziv-Welch Encoding

RIFD-LZW: Un enfoque híbrido para la compresión de imágenes con pérdida mediante redondeo de intensidad, división y codificación Lempel-Ziv-Welch

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ABSTRACT

This research presents RIFD-LZW, a new hybrid lossy image compression algorithm designed for both color and grayscale images across varying resolutions. The method integrates the Rounding the Intensity and Dividing (RIFD) technique with Lempel-Ziv-Welch (LZW) encoding to enhance compression efficiency while preserving high image quality. The RIFD stage reduces data redundancy through intensity quantization and scaling, while LZW applies efficient lossless dictionary-based encoding to the transformed data. Comprehensive experiments were conducted on four benchmark datasets EPFL, Kodak, Waterloo, and HQ-50K to evaluate the performance of the proposed method. The results demonstrate that RIFD-LZW consistently outperforms traditional RIFD, LZW, and standard compression algorithms including JPEG2000, JPEG-LS, and RIFD-Huffman. On average, RIFD-LZW achieved a compression efficiency of 7,51 Bits Per Pixel (BPP) for color datasets, representing a 49,93 % improvement over RIFD and 62,49 % over LZW. For grayscale images, RIFD-LZW attained an average BPP of 1,92, significantly outperforming RIFD (5,00) and LZW (4,74), with an improvement exceeding 59 %. The RIFD-LZW algorithm delivers high visual quality despite being lossy, achieving average PSNR values 38,36 dB with minimal visible distortion. It effectively reduces file sizes while preserving acceptable image quality, making it well-suited for applications that require efficient compression with good visual retention.

Keywords: Lossy Image Compression; RIFD-LZW; Lempel-Ziv-Welch (LZW); Image Quality; Bits Per Pixel (BPP); PSNR.

RESUMEN

Esta investigación presenta RIFD-LZW, un nuevo algoritmo híbrido de compresión de imágenes con pérdida, diseñado para imágenes en color y en escala de grises con distintas resoluciones. El método integra la técnica de Redondeo de Intensidad y División (RIFD) con la codificación Lempel-Ziv-Welch (LZW), con el fin de mejorar la eficiencia de compresión mientras se preserva una alta calidad visual. La etapa RIFD reduce la redundancia de datos mediante cuantificación de intensidad y escalado, mientras que LZW aplica una codificación sin pérdida basada en diccionario de manera eficiente sobre los datos transformados.Se llevaron a cabo experimentos exhaustivos en cuatro conjuntos de datos de referencia: EPFL, Kodak, Waterloo y HQ-50K, para evaluar el rendimiento del método propuesto. Los resultados demuestran que RIFD-LZW supera de manera consistente a los métodos tradicionales como RIFD, LZW y algoritmos estándar de compresión, incluidos JPEG2000, JPEG-LS y RIFD-Huffman. En promedio, RIFD-LZW logró una eficiencia de compresión de 7,51 bits por píxel (BPP) en conjuntos de datos a color, representando una mejora del 49,93 % sobre RIFD y del 62,49 % sobre LZW. Para imágenes en escala de grises, RIFD-LZW alcanzó un BPP promedio de 1,92, superando significativamente a RIFD (5,00) y a LZW (4,74), con una mejora superior al 59 %. El algoritmo RIFD-LZW proporciona alta calidad visual a pesar de ser con pérdida, alcanzando valores promedio de PSNR de 38,36 dB con distorsión visible mínima.

Reduce de manera efectiva el tamaño de los archivos mientras preserva una calidad de imagen aceptable, lo que lo hace adecuado para aplicaciones que requieren compresión eficiente con buena retención visual.

Palabras clave: Compresión de Imágenes con Pérdida; RIFD-LZW; Lempel-Ziv-Welch (LZW); Calidad de Imagen; Bits por Píxel (BPP); PSNR.

INTRODUCTION

The rapid proliferation of digital imagery across domains such as photography, medical imaging, and remote sensing has created a growing need for efficient image compression techniques to manage the storage and transmission of high-resolution images. Traditional lossless methods preserve image quality but often deliver limited compression efficiency, while lossy methods achieve higher compression by allowing some loss of visual information. This study presents a hybrid compression approach, RIFD-LZW, which combines Rounding and Intensity-Frequency Division (RIFD) with Lempel-Ziv-Welch (LZW) encoding. The proposed method effectively reduces redundancy and enhances compression performance while maintaining visually acceptable image quality.[1,2]

Background and Motivation

The exponential growth of image data has created an increasing demand for effective compression techniques. High-resolution images, while offering excellent visual quality, consume substantial bandwidth and storage space.[3] In domains where maintaining image integrity is essential such as medical imaging and satellite observation, traditional lossy methods often fall short. This highlights the need for advanced lossy compression techniques that can significantly reduce file size while preserving high visual quality. The motivation behind this work stems from the necessity to develop a method that achieves higher compression ratios than conventional techniques without compromising perceptual image quality.[4]

The Importance of Lossy Image Compression

Lossy image compression techniques aim to significantly reduce file sizes by allowing a controlled loss of image data, striking a balance between compression efficiency and acceptable visual quality. Unlike lossless methods that preserve every bit of the original data, lossy approaches discard less perceptually important information, enabling much higher compression ratios. This is particularly valuable in applications such as online image sharing, multimedia storage, and certain types of medical imaging where perfect reconstruction is not essential, but high visual quality is still required. By strategically reducing data, lossy compression can achieve substantial savings in storage and bandwidth without severely affecting the image's usability or perceptual appearance.[5,6]

Current Methods and Their Constraints

Many image compression algorithms have been created, but their ability to find a balance between compression and quality has varied. Huffman and LZW encoding are used by lossless approaches like Graphics Interchange Format (GIF) and Portable Network Graphics (PNG) to retain all of the original image information, however they frequently produce moderate compression ratios. Although lossy techniques, such as Joint Photographic Experts Group (JPEG), significantly reduce file size, they can also generate observable artifacts, especially at higher compression levels. Despite their best efforts, hybrid techniques such as RIFD-Huffman are unable to preserve a high degree of compression without compromising visual quality. These drawbacks emphasize the need for an approach that improves compression effectiveness without sacrificing image quality.[7]

Introduction to RIFD-LZW: An Innovative Method

The RIFD-LZW algorithm integrates the RIFD approach with LZW encoding to form a hybrid solution that advances the performance of existing lossy compression techniques. In this method, RIFD reduces image redundancy by rounding and dividing pixel intensities, while LZW efficiently encodes the resulting data patterns. This combination enables the preservation of high visual quality, with distortions that are generally imperceptible under typical viewing conditions. By leveraging the strengths of both techniques, RIFD-LZW achieves superior compression ratios compared to the standalone RIFD or LZW algorithms.

Paper Contributions and Structure

This paper advances the science of image compression in multiple ways. Initially, it presents the hybrid algorithm RIFD-LZW, which outperforms previous methods in compression performance. Second, it provides a thorough analysis of the algorithm's performance on datasets, showing how well it compresses images in both color and grayscale. The research concludes by highlighting the tiny distortion created by the method and demonstrating how it produces large gains in compression ratio while being unnoticeable to human observers. The remainder of this paper is structured as follows: Section 2 discusses previous research related to the topic. Section 3 elaborates on the RIFD-LZW methodology. Section 4 showcases the experimental findings, while Section 5 wraps up the study and suggests potential future research directions.

Related work

A wide range of image compression techniques have been developed to improve storage efficiency and transmission speed. Lossless methods, such as Huffman coding, Run-Length Encoding (RLE), and Lempel-Ziv-Welch (LZW), ensure perfect reconstruction of the original image without any loss of quality. In contrast, lossy and hybrid techniques such as JPEG and RIFD-Huffman introduce controlled degradation in image quality to achieve higher compression rates. This section reviews both categories of techniques and identifies the limitations they present, particularly in achieving efficient compression without sacrificing image integrity or performance. These limitations form the basis for the development of the proposed RIFD-LZW algorithm, which aims to address these gaps through an improved near-lossless approach. [8,9]

Huffman Coding

One of the first and most used lossless compression methods is Huffman coding. It functions by allocating variable-length codes to symbols according to their occurrence; shorter codes are assigned to symbols that occur more frequently. Huffman coding works well for lossless compression, but its primary drawback lies in its inability to adapt to local variations within the image. When symbol frequencies are rather stable, which is frequently not the case with complex images, this technique performs best. Furthermore, it fails to take spatial redundancy between pixels into account, which results in less-than-ideal compression ratios for large, complex images. Consequently, its application in image compression has been restricted to areas where statistical consistency is required.[8,10,11]

Run Length Encoding (RLE)

Another straightforward but powerful lossless technique is RLE, which works especially well for images with large areas of constant color, like graphics or icons. RLE reduces data size by storing repeated values as a single value and a counter. In certain situations, this can result in a large file size reduction. With higher detail or more complex images, when runs of repeated values are rare, RLE's performance decreases quickly. RLE's main drawback is its poor performance on natural images where pixel values vary a lot.[12] Because of this, it is less applicable in the majority of real-world situations and is better suited for specific image types like binary or synthetic images.[13]

Lempel-Ziv-Welch (LZW)

A popular lossless compression method is LZW, particularly for images in the GIF and Tagged Image File Format (TIFF).[14] In order to accomplish compression, it replaces lengthy data sequences with shorter codes and creates a dictionary of previously encountered sequences. When faced with situations with recurring data patterns, LZW performs better than Huffman and RLE in terms of compression ratios. Though the dictionary grows larger and less effective when there is little repetition in the pixel values, it continues to have trouble with images that contain high-frequency features or noise. The fact that LZW does not automatically take advantage of spatial redundancy in images is another factor that reduces its efficacy. This restriction has led to the frequent use of LZW with other methods, including hybrid approaches or predictive coding, to enhance performance on natural images. Even with these advancements, utilizing LZW alone is still insufficient to provide effective lossless compression.[15,16]

Burrows-Wheeler Transform (BWT)

By making use of its ability to restructure pixel values into more compressible patterns, the BWT, which was initially created for text compression, has been modified for lossless image compression. To increase compression efficiency, BWT has been applied in several works in conjunction with entropy coding strategies such as Move-to-Front (MTF), Huffman coding, and RLE. Since BWT is essentially made for 1D sequences, applying it to 2D image data is difficult since it lacks intrinsic spatial locality. While converting 2D images into linear data streams is a common subject of research, the resulting compression ratios are frequently not as good as they could be when using specialized image compression techniques like JPEG-LS or JPEG 2000. The main area of missing demand is how to efficiently modify BWT to preserve the structural integrity of 2D images while attaining competitive compression performance, especially for color images with a high resolution. To close this gap, more investigation is required; perhaps using hybrid strategies or cutting-edge transformations.[17,18,19]

Top of Form

Joint Photographic Experts Group (JPEG) Family

A highly prevalent standard in use today for lossy image compression is the JPEG family, especially JPEG and JPEG 2000. JPEG is very good at reaching high compression ratios because it combines quantization with the Discrete Cosine Transform (DCT) to minimize image data while maintaining some amount of information. Wavelet transforms are used in JPEG 2000, an upgrade over JPEG that offers both lossless and lossy compression choices and enhanced quality at higher compression rates. However, the main drawback of JPEG is the observable abnormalities such as blocking and ringing effects. that show up at high compression settings. Some of these problems are mitigated by JPEG 2000, although at the expense of more processing complexity. Both approaches have difficulty balancing file size and image quality while achieving near-lossless compression, especially for applications that demand minimal distortion.(20,21,22)

Lossless Image Compression Using the Column Subtraction Technique (LICA-CS)

The LICA-CS is a cutting-edge method that makes use of a column subtraction technique to provide effective lossless compression. The image's matrix is transformed, the values of successive columns are subtracted, and the resulting differences are then encoded. This is how the method operates. Because column subtraction minimizes redundancy and increases data compression, this method works especially well for images where adjacent columns have comparable pixel values. LICA-CS has some significant drawbacks in spite of its potential. It works best on images with smooth transitions or little variation between columns; images with noise or high-frequency details cause it to function much less efficiently. Furthermore, the technique does not take advantage of spatial correlations other than column similarities, which means that it could be improved for compressing images with intricate patterns or textures. Therefore, even though LICA-CS offers a novel method of lossless image compression, its applicability is still limited, requiring additional research and improvement for a wider range of image types.(12)

Rounding the Intensity Followed by Dividing (RIFD)

This method is a relatively new approach that performs well in lossy image compression by reducing the value of intensity levels and then dividing the image into smaller segments. This reduces duplication and increases compressibility; it works best when combined with entropy coding methods such as Huffman or LZW. When RIFD is used to achieve modest compression, it is especially good at reducing visual distortion. However, RIFD's overall compression ratio is limited since it cannot handle the encoding of these shorter segments as effectively as some other approaches can. Hybrid approaches like RIFD-LZW, which combine RIFD's redundancy reduction with more effective encoding algorithms like LZW, have been developed to enhance its performance.(23,24,25)

The Proposed Hybrid Methods Using RIFD and LZW (RIFD-LZW)

Hybrid compression algorithms that combine LZW with preprocessing techniques like RIFD aim to overcome the limitations of each individual method. By using RIFD to reduce spatial and informational redundancy and LZW to perform efficient encoding, these hybrid approaches achieve improved compression ratios while maintaining acceptable visual quality. The RIFD-LZW algorithm, for example, leverages the strengths of both techniques to deliver notable performance gains over standalone methods. The key advantage of such hybrid lossy techniques lies in their ability to balance compression efficiency with perceptual image quality. However, further research is needed to explore optimal configurations and refinements that enhance their applicability across a broader range of image types.

There are many different lossless and lossy compression methods available, but each one has a limit when it comes to achieving a trade-off concerning compression ratio and image quality. Although more sophisticated algorithms have been made possible by the use of traditional methods like Huffman, RLE, and LZW, they are still insufficient for effectively compressing high-detail or natural images. Hybrid approaches, like RIFD-LZW, combine more effective encoding techniques with redundant reduction preprocessing procedures to mitigate some of these drawbacks. To achieve an ideal balance between maximum distortion reduction and compression efficiency, more research and development of these techniques are still required. A start in this direction is the suggested RIFD-LZW algorithm, which provides a promising answer to the problems encountered by current methods.

The Proposed RIFD-LZW Algorithm

Overview of the Proposed Algorithm

The RIFD-LZW algorithm is a lossy image compression technique designed to efficiently handle both color and grayscale images. By combining RIFD with LZW encoding, it forms a hybrid approach that significantly reduces image size while introducing only minimal distortion. This integration enables the algorithm to achieve high compression ratios without substantially compromising visual quality. A detailed flowchart, presented in figure 1, illustrates the step-by-step compression and decompression processes of the RIFD-LZW algorithm, providing a clear and comprehensive understanding of its operational methodology.

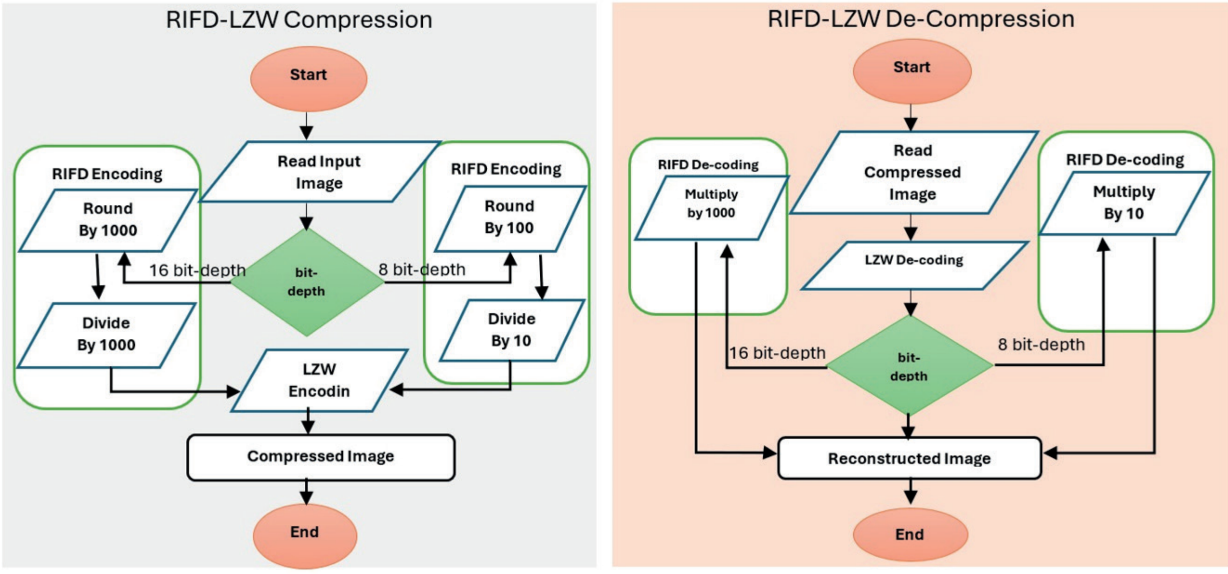

Figure 1. Rifd-lzw image compression & decompression flowchart

First, regulated quantization via intensity rounding is applied by the RIFD process to simplify the image data before compressing the source image. To minimize complexity and enhance the encoding phase effectiveness that follows, the intensities are divided by 10 for the 8-bit depth images or by 1000 for the 16-bit depth images. Repetitive patterns in the altered image are successfully captured and encoded by the LZW algorithm, which then uses a lossless dictionary-based technique to compress the rounded and divided data. With its versatility across several image formats and resolutions, the RIFD-LZW algorithm's adaptability makes it a highly acceptable choice for a diverse set of applications. It can process images of various quality levels, from low-resolution to high-resolution, guaranteeing efficient compression while preserving visual integrity. For situations when high compression efficiency is required without noticeable loss of image quality, the RIFD-LZW algorithm is a potential option because of its low distortion and compatibility with common image formats.

RIFD-LZW Encoding

To attain effective compression ratios while preserving the highest level of image quality preservation, the RIFD-LZW algorithm combines together lossy and lossless image compression techniques that operate in two primary phases. In the first phase, two essential operations are performed by using the RIFD approach. The lone lossy element within the algorithm is the rounding function. RIFD simplifies the image data by rounding each pixel intensity to the closest multiple of 10. This is followed by a factor of 10 values scaling down using the division function to further process the rounded image. This process helps to further facilitate efficient compression in the next phase by reducing the image's numerical range and complexity. The algorithm's second phase uses LZW coding, a well-known lossless compression method. This stage involves encoding the image data which has been prepped by RIFD into a compressed bitstream using LZW. As it processes the input, LZW creates a dictionary of data patterns. Within the modified image data, it locates and recognizes repeated sequences, giving these sequences shorter codes. This dictionary-based method effectively reduces the amount of data by capturing and compressing recurring patterns in the image. Notably, during this procedure, LZW does not result in any further data loss. This guarantees that the data reduction is accomplished without sacrificing the integrity of the image because the resulting compressed bitstream keeps all the information required to precisely recreate the image.

RIFD-LZW Decoding

The following procedures are involved in the RIFD-LZW algorithm's decoding phase, which reconstructs the image from the compressed bitstream:

1. LZW Decompression: the compressed bit stream is loaded into the LZW decompression module to start the process. Here, the encoding process is essentially reversed because the LZW algorithm decodes the bitstream to rebuild the quantized image data.
2. Inverse Scaling: the first thing to do after recovering the image data is to undo the scaling that was done during RIFD compression. To return the pixel intensities to their roughly original range, this entails multiplying the pixel values by 10.

3. Image Reconstruction: the image data is arranged to rebuild the entire image after scaling. In this step, the data will be arranged according to its original structure, and the image format and layout will be precisely restored.

With the use of these procedures, the RIFD-LZW decoding stage can recreate the image with unnoticeable distortion, nearly matching the original input. As a result, the algorithm strikes a balance between effective compression and maintaining visual quality.

The RIFD-LZW algorithm successfully combines lossy and lossless compression methods to reduce data by significant amounts. The first RIFD stage lowers the complexity of the image and prepares it for the next LZW compression. This method guarantees considerable compression ratios with no noticeable distortion and image quality preservation. The RIFD-LZW approach provides a reliable and effective solution for compressing both color and grayscale images, optimizing efficiency while introducing minimal distortion that remains imperceptible to the human eye by achieving a balance between data reduction and visual fidelity.

Experiments

Comprehensive experiments were conducted to assess how well the RIFD-LZW algorithm performs. This section describes the datasets that were used, the standard comparison methods employed, and the conclusions gained after analyzing these datasets.

About the Datasets

The implementation was evaluated using the following datasets and table 1, 2, 3 and 4 provides more information regarding each image resolution and type.

- Kodak: the Kodak Group provides this benchmark dataset, which is widely used in image processing and compression research. It consists of twenty-four colored medium-resolution (768 × 512) images, covering a diverse range of subjects and environments.[26]
- Waterloo: established by the University of Waterloo, this dataset is widely used to evaluate various imaging methods. It consists of three subsets: the color dataset covering eight large images, Grayscale dataset 1 covering twelve medium images, and Grayscale dataset 2 covering twelve small images. This structured variety allows for a comprehensive evaluation across different compression settings.[27]
- EPFL: provided by the École Polytechnique Fédérale de Lausanne (EPFL), this dataset includes ten color, high-resolution images with resolution ranges from (1280 × 1506) to (1280 × 1600), making it ideal for assessing compression performance on complex, high-detail visuals. These high-resolution images are particularly useful for evaluating fine textures, intricate patterns, and color fidelity under different compression techniques.[28]
- HQ-50K: the dataset is a large-scale collection of 50,000 high-quality images designed for benchmarking image compression techniques. It encompasses a diverse range of images with rich texture details and semantic diversity, making it well-suited for evaluating the performance of restoration algorithms across various visual characteristics. The high-resolution nature of the dataset ensures that fine details and subtle variations in color and structure are preserved, allowing for a comprehensive analysis of restoration efficiency and visual fidelity. Additionally, a subset of 12 selected test images is provided, spanning various semantic categories and frequency ranges, facilitating detailed and fine-grained performance comparison and analysis.[29]

Experiments Setup

The algorithm was implemented in MATLAB and tested on a computer system with an Intel Core i7-10510U processor (1,80 GHz, up to 2,30 GHz), 8 GB of RAM, and go on Windows 11.

Experimental Metrics

Compression Size BPP and Saving Percentage

The compressed images size was first determined in Bits-Per-Pixel (BPP). Equation (1) was used to calculate these ratios, where the size of the compressed image, represented as s in bytes, includes the three independently compressed components (RGB). The original image contains n pixels. The compression performance is calculated by dividing the compressed image size by the total number of pixels. A lower BPP value signifies more effective compression.[24,30]

$$BPP = \frac{8 \times s}{n} \quad (1)$$

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The saving percentage is computed using Equation (2), as obtained from[24].

$$\frac{Original\ Image\ Size - Compressed\ Image\ Size}{Original\ Image\ Size} x100 \qquad (2)$$

For the purpose of full-reference objective quality assessment, basic statistical error measurements are essential, such as:

Mean Squared Error (MSE) The Mean Squared Error (MSE), as outlined in equation (3), is one of the most straightforward and widely used techniques for evaluating image quality. In this equation, M and N represent the pixel coordinates (image dimensions), I(i,j) denote the pixel value at position (i,j) in the original image, and K(i,j) corresponds to the pixel value at the same position in the compressed or reconstructed image. The output is a single scalar value that quantifies the average squared difference between the original and reconstructed images, with lower values indicating higher visual similarity.[31]

$$MSE = \frac{1}{M*N} \sum_{i=1}^{M} \sum_{j=1}^{N} [I(i,j) - [K(i,j)]^2] \qquad (3)$$

Peak Signal-to-Noise Ratio (PSNR) As defined in equation (4), it is a widely used metric for assessing the quality of compressed images in full-reference evaluations. Measured in decibels (dB), it is derived from the MSE, where a higher PSNR value signifies better image quality preservation and lower distortion. In this equation, MAX is the maximum possible pixel value of the image (e.g., 255 for 8-bit images), MSE is the Mean Squared Error between the original and the compressed/reconstructed image. A higher PSNR value indicates greater similarity between the original and reconstructed images, minimizing visual information loss.[30,31]

$$PSNR = 10 \text{ x} \log_{10}\left(\frac{MAX^2}{\text{MSE}}\right) \qquad (4)$$

Experimental Results

Extensive evaluations were conducted to assess the performance of the RIFD-LZW algorithm, demonstrating significant improvements in compression efficiency, as quantified by (BPP), and in reconstructed image quality, as measured by (PSNR). Table 1, 2, 3 and 4 presents the resulting data after running the algorithm on different datasets including the EPFL, Kodak, Waterloo, and HQ-50K datasets respectively. The tables showcases the results for RIFD and LZW individually, as well as the hybrid RIFD-LZW algorithm, providing a clear comparison of these methods. This structured presentation facilitates a more straightforward analysis of their performance in the following sections, allowing for a detailed examination of the benefits and trade-offs associated with each approach. The inclusion of multiple benchmark datasets ensures a comprehensive evaluation of the algorithm's effectiveness in enhancing compression efficiency across diverse image types.

Table 1. Comparison of compression efficiency (bpp) and image quality (psnr) between the proposed rifd-lzw and traditional rifd and lzw using the epfl dataset

EPFL Dataset									
#	Image	Type	Dimensions	BPP			PSNR (dB)		
				RIFD	LZW	RIFD-LZW	RIFD	LZW	RIFD-LZW
1	bike_orig	BMP	1280 x 1600	15,00	22,07	8,52	58,41	-	39
2	cafe_orig	BMP	1280 x 1600	15,00	22,38	10,87	59,08	-	39,59
3	p01_orig	BMP	1280 x 1600	15,00	20,84	7,29	58,34	-	38,83
4	p04_orig	BMP	1280 x 1510	15,00	19,81	6,71	57,85	-	38,54
5	p06_orig	BMP	1280 x 1600	15,00	18,47	5,93	58,40	-	38,98
6	p10_orig	BMP	1280 x 1600	15,00	18,34	5,62	58,24	-	38,73
7	p14_orig	BMP	1280 x 1600	15,00	18,95	6,31	58,48	-	38,95
8	p22_orig	BMP	1280 x 1506	15,00	19,61	6,09	57,98	-	38,96
9	p30_orig	BMP	1280 x 1600	15,00	16,25	5,59	59,96	-	40,14
10	woman_orig	BMP	1280 x 1600	15,00	21,71	8,00	58,36	-	38,95

Table 2. Comparison of compression efficiency (bpp) and image quality (psnr) between the proposed rifd-lzw and traditional rifd and lzw using the kodak dataset

Kodak Dataset									
#	Image	Type	Dimensions	BPP			PSNR (dB)		
				RIFD	LZW	RI-FD-LZW	RIFD	LZW	RI-FD-LZW
1	kodim01	PNG	768 x 512	15	24,75	10,37	51,21	-	38,88
2	kodim02	PNG	768 x 512	15	18,27	5,82	51,11	-	38,85
3	kodim03	PNG	768 x 512	15	19,27	5,80	51,10	-	38,90
4	kodim04	PNG	768 x 512	15	21,10	6,71	51,25	-	38,87
5	kodim05	PNG	768 x 512	15	24,91	10,38	51,23	-	38,91
6	kodim06	PNG	768 x 512	15	23,60	9,63	51,47	-	39,13
7	kodim07	PNG	768 x 512	15	20,11	6,31	51,19	-	38,85
8	kodim08	PNG	768 x 512	15	25,30	10,55	51,34	-	39,04
9	kodim09	PNG	768 x 512	15	20,56	6,28	51,09	-	38,90
10	kodim10	PNG	768 x 512	15	20,81	6,48	51,26	-	40,28
11	kodim11	PNG	768 x 512	15	21,92	8,09	50,90	-	38,63
12	kodim12	PNG	768 x 512	15	20,55	6,49	51,36	-	39,02
13	kodim13	PNG	768 x 512	15	26,71	12,03	51,35	-	38,95
14	kodim14	PNG	768 x 512	15	24,56	9,86	51,21	-	38,88
15	kodim15	PNG	768 x 512	15	19,73	6,12	51,36	-	39,01
16	kodim16	PNG	768 x 512	15	22,12	7,66	51,15	-	38,91
17	kodim17	PNG	768 x 512	15	21,23	6,89	51,21	-	38,97
18	kodim18	PNG	768 x 512	15	23,41	9,10	51,17	-	38,90
19	kodim19	PNG	768 x 512	15	22,68	7,87	51,22	-	38,86
20	kodim20	PNG	768 x 512	15	15,75	5,72	52,97	-	40,68
21	kodim21	PNG	768 x 512	15	22,59	8,58	51,19	-	38,93
22	kodim22	PNG	768 x 512	15	22,34	7,66	51,26	-	38,88
23	kodim23	PNG	768 x 512	15	19,28	5,51	51,29	-	38,90
24	kodim24	PNG	768 x 512	15	21,95	8,32	51,40	-	39,10

Table 3. Comparison of compression efficiency (bpp) and image quality (psnr) between the proposed rifd-lzw and traditional rifd and lzw using the waterloo dataset

Waterloo Dataset									
#	Image	Type	Dimensions	BPP			PSNR (dB)		
				RIFD	LZW	RI-FD-LZW	RIFD	LZW	RI-FD-LZW
1	clegg.	TIF	814 x 880	15	14,46	6,83	54,16	-	39,45
2	frymire	TIF	1118 x 1105	15	5,81	4,12	58,81	-	42,02
3	lena3	TIF	512 x 512	15	21,60	7,28	49,42	-	38,81
4	monarch	TIF	768 x 512	15	20,25	6,25	51,02	-	38,82
5	peppers3	TIF	512 x 512	15	20,93	6,98	49,53	-	39,00
6	sail	TIF	768 x 512	15	24,76	10,22	51,19	-	38,91
7	serrano	TIF	629 x 794	15	6,27	4,11	52,54	-	40,36
8	tulips	TIF	768 x 512	15	21,92	7,28	51,13	-	38,96

Table 4. Comparison of compression efficiency (bpp) and image quality (psnr) between the proposed rifd-lzw and traditional rifd and lzw using the hq-50k dataset

#	Image	Type	Dimensions	HQ-50K Dataset BPP RIFD	BPP LZW	BPP RIFD-LZW	PSNR (dB) RIFD	PSNR (dB) LZW	PSNR (dB) RIFD-LZW
1	Natural_View	JPG	2100 x 3500	15,00	16,91	6,14	63,99	-	38,85
2	maple_chocolate	JPG	1334 x 2000	15,00	20,96	8,09	59,50	-	38,83
3	HOFFMAN-2	JPG	1360 x 2040	15,00	22,57	9,69	59,66	-	38,93
4	traintrail_spain	JPG	1366 x 2048	15,00	24,49	9,75	59,81	-	38,93
5	Traditional_sofa	JPG	1333 x 2000	15,00	20,37	7,39	59,48	-	38,94
6	1583	JFIF	1403 x 2000	15,00	25,54	10,35	59,68	-	38,83
7	lion_king	JPG	1920 x 1080	15,00	21,54	8,61	58,49	-	38,89
8	thumb	JPG	1440 x 1920	15,00	14,55	5,14	59,63	-	38,86
9	leopard	JPG	1920 x 1200	15,00	22,79	9,51	59,43	-	39,10
10	holiday_19	JPG	1676 x 2000	15,00	20,64	7,81	60,58	-	38,84
11	Camel_1	JPG	1600 x 1300	15,00	23,22	9,50	58,31	-	38,85
12	bears	JPG	1065 x 1600	15,00	23,80	9,96	57,69	-	38,90

Comparison of Compression Sizes Among RIFD, LZW, and the Proposed Algorithm

The proposed algorithm efficiency was evaluated via comparing its compressed file sizes against two widely used methods, RIFD and LZW. The primary emphasis was on analyzing the compressed image size in relation to the original file size, determined in (BPP). While LZW typically results in larger compressed file sizes, RIFD significantly reduces file size due to its compression approach. By combining elements of both techniques, the proposed RIFD-LZW hybrid algorithm achieved a more efficient compression, reducing file sizes beyond what either RIFD or LZW could achieve individually. To quantify this efficiency, the compression performance of each method was measured in terms of (BPP), calculated using Equation (1). across four benchmark datasets: Waterloo, Kodak, EPFL, and HQ-50K. Table 5 summarizes the average BPP results, with the best values highlighted in bold. Among the evaluated methods, RIFD-LZW demonstrated the highest compression performance, achieving an average BPP of 7,51, effectively minimizing file sizes compared to both RIFD and LZW.

Table 5. Average compression efficiency (bpp) comparison of the proposed rifd-lzw with traditional rifd and lzw

Method	Datasets EPFL	Kodak	Waterloo	HQ-50K	Average
RIFD	15	15	15	15	15
LZW	19,84	21,8	17	21,45	20,02
RIFD-LZW	7,09	7,84	6,63	8,49	7,51

This combination illustrates how LZW and RIFD encoding techniques effectively complement each other to achieve more efficient compression. The proposed RIFD-LZW method significantly enhances compression performance by leveraging the strengths of both approaches. As shown in table 5, the RIFD-LZW method achieves a lower average BPP value of 7,51, compared to 15,00 for RIFD and 20,02 for LZW. Based on Equation (2), this corresponds to an average compression efficiency improvement of 49,93 % over RIFD and 62,49 % over LZW, indicating substantial gains. These results are further visualized in figure 2, which compares the average BPP values across the four datasets for each method. Figure 2. comparison of average (BPP) for the proposed RIFD-LZW algorithm vs. traditional RIFD and LZW techniques

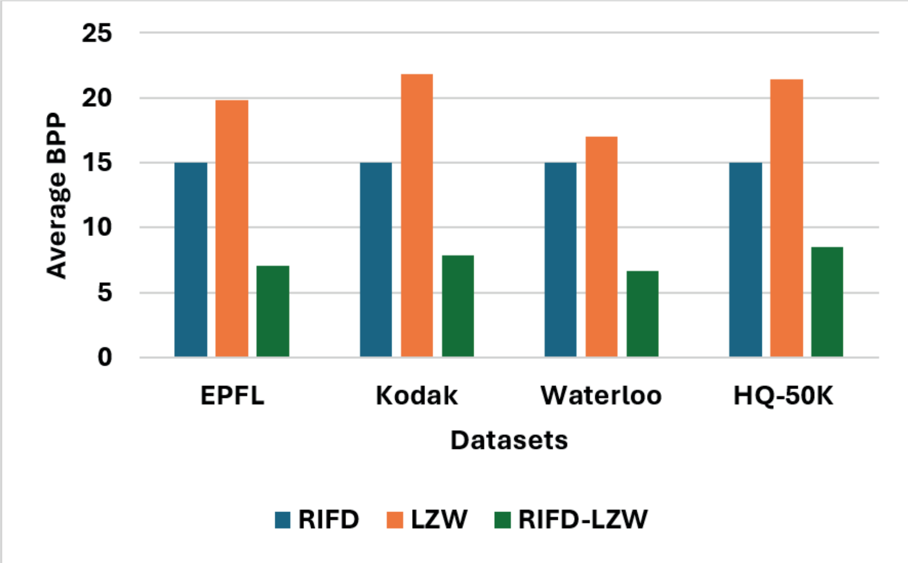

Figure 2. Comparison of average (bpp) for the proposed rifd-lzw algorithm vs. Traditional rifd and lzw techniques

Comparative Analysis of Compression Size: RIFD-LZW vs. Standard Compression Techniques

Table 6. Average compression efficiency (bpp) of the proposed rifd-lzw compared to standard compression algorithms

Standard Methods			Datasets			
No	Compression Type	Method	EPFL	Kodak	Waterloo	Average
A	Lossless	RCT-JPEG2000	10,84	9,51	11,21	10,52
B	Lossless	RCT-JPEG LS	10,47	9,57	8,96	9,67
C	Lossless	RCT-JPEG XR	11,76	10,92	13,32	12,00
D	Lossless	RCT-Huffman	16,9	15,06	16,55	16,17
E	Lossy	RIFD-Huffman	9,35	8,72	9	9,02
F	Lossy	RIFD-LZW	7,9	7,84	6,63	7,51

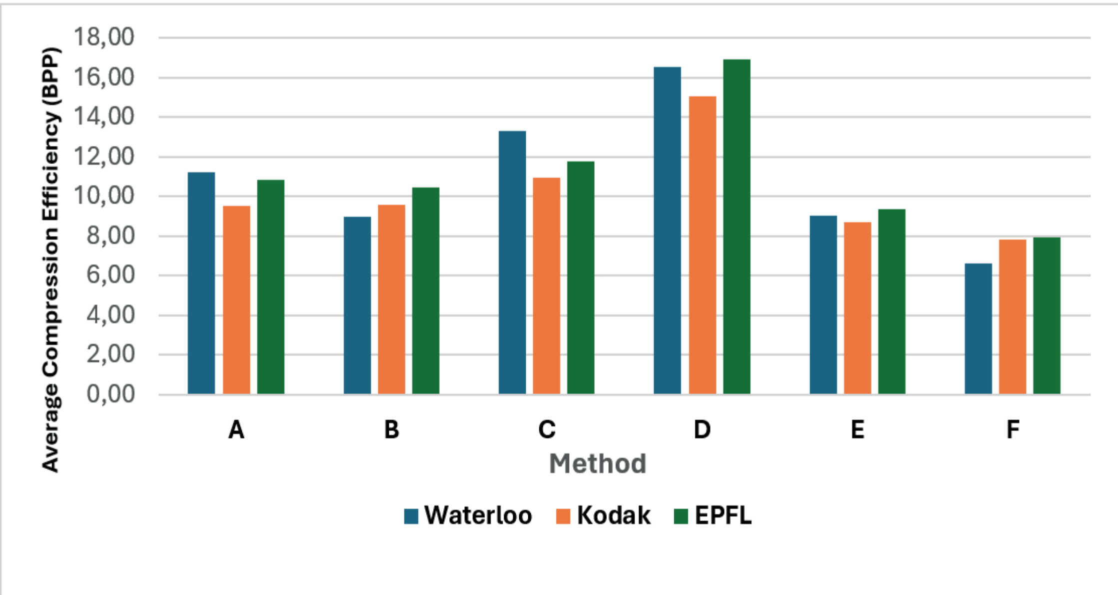

Figure 3. Average compression efficiency (bpp) of the proposed rifd-lzw algorithm compared to standard compression techniques

The effectiveness of the proposed RIFD-LZW method was further evaluated by comparing its performance against several widely recognized lossless and lossy compression standards results obtained from [12], including

RCT combined with Huffman, JPEG2000, JPEG XR, and JPEG-LS, as well as the RIFD-Huffman approach. Compression efficiency, measured in (BPP), was calculated using Equation (1) across three standard color image datasets. The comparative results are summarized in table 6, where the best-performing values are highlighted in bold. The findings reveal that the proposed RIFD-LZW method (Method #F) consistently outperforms most conventional techniques, achieving the lowest average BPP of 7,51, indicating superior compression efficiency. This is followed by Method #E (RIFD-Huffman) with an average BPP of 9,02, and Method #B (RCT-JPEG-LS) with 9,67.

For visual comparison, figure 3 presents a graphical representation of table 6, highlighting the average BPP performance of RIFD-LZW against the other standard methods.

Image quality compared with original schemes

To evaluate the image quality performance of the proposed method, four color datasets including EPFL, Kodak, Waterloo, and HQ-50 were utilized in comparison with RIFD and LZW. The assessment was based on Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), as defined in Equation (3) and Equation (4). The results, summarized in table 7, indicate that the proposed approach achieves exceptional image quality after decompression. The slight distortion observed originates from the RIFD phase. Notably, both the RIFD-LZW and RIFD algorithms produce comparable levels of distortion. Their average MSE values are 7,41, 8,21, 8,10, and 8,37 for the Waterloo, Kodak, EPFL, and HQ-50K datasets, respectively. These findings highlight the effectiveness of the proposed method in achieving high compression ratios while maintaining superior image quality. In contrast, the LZW algorithm, being fully lossless, introduces no distortion.

Table 7. Average mse and psnr for the proposed rifd-lzw compared with original methods applying the four image datasets

Dataset	Mse			Psnr (db)		
	Rifd	Lzw	Rifd-lzw	Rifd	Lzw	Rifd-lzw
Epfl	8,10	0	8,10	39,07	-	39,07
Kodak	8,21	0	8,21	35,97	-	35,97
Waterloo	7,41	0	7,41	39,54	-	39,54
Hq-50k	8,37	0	8,37	38,89	-	38,89

An illustration of the information from table 7 is shown in figure 4. It presents the PSNR values comparison between the original RIFD and the suggested RIFD-LZW method.

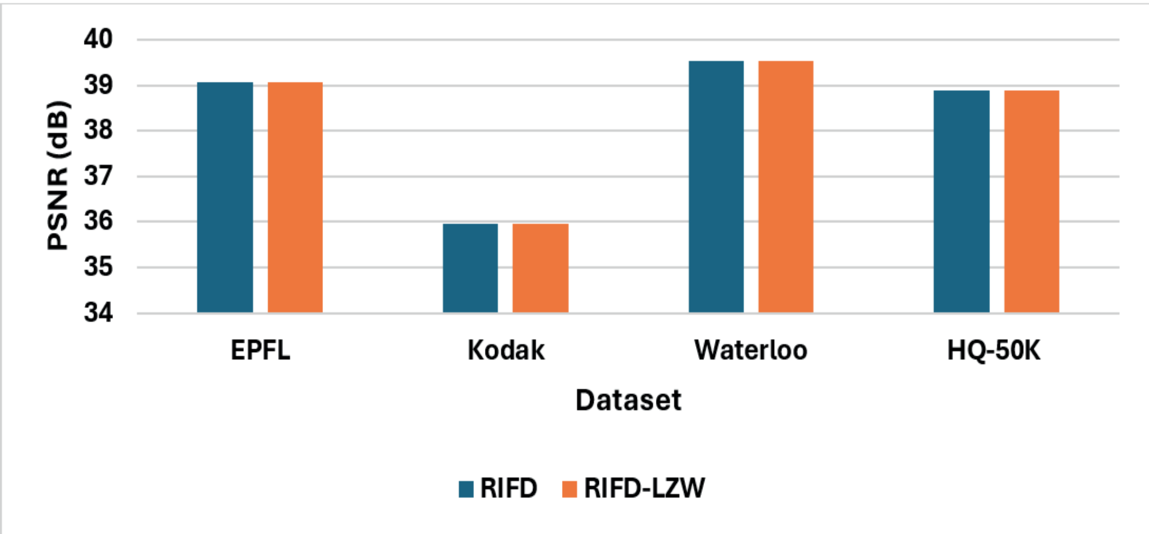

Figure 4. Average (psnr) of the proposed rifd-lzw algorithm in comparison with rifd techniques

Figures 5, 6, 7, 8 and 9 presents sample images before and after reconstruction using the proposed algorithm. The reconstructed images exhibit minimal distortion, which is imperceptible to the human eye.

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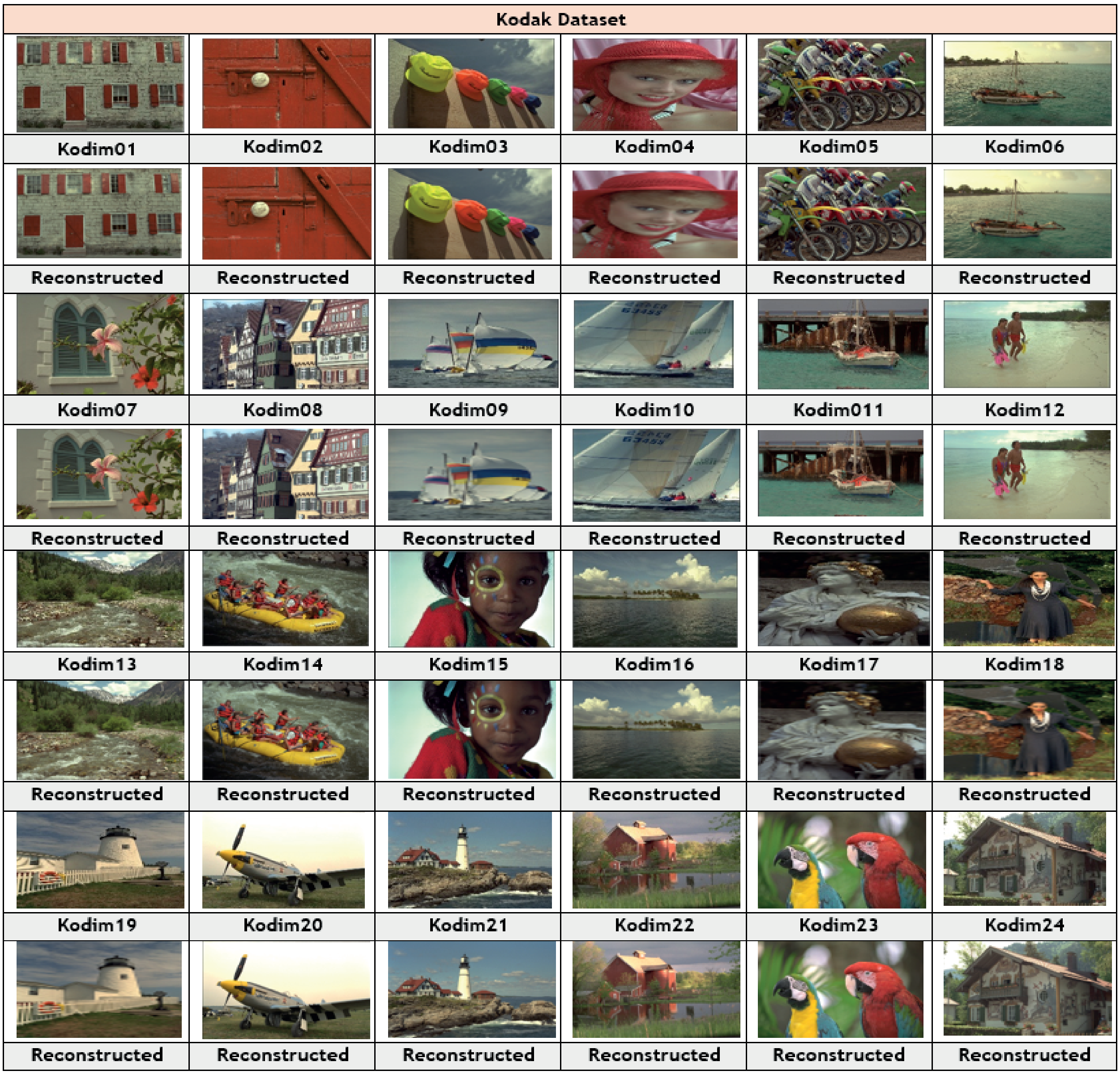

Figure 5. Examples of original and reconstructed images after applying rifd-lzw on the kodak datasets

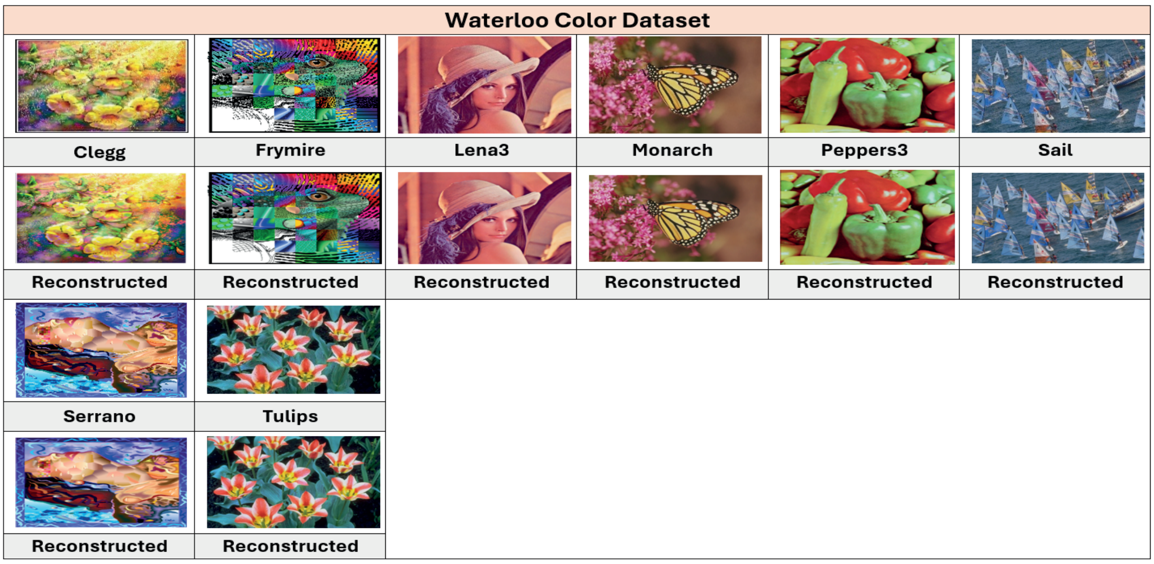

Figure 6. Examples of original and reconstructed images after applying rifd-lzw on the waterloo color datasets

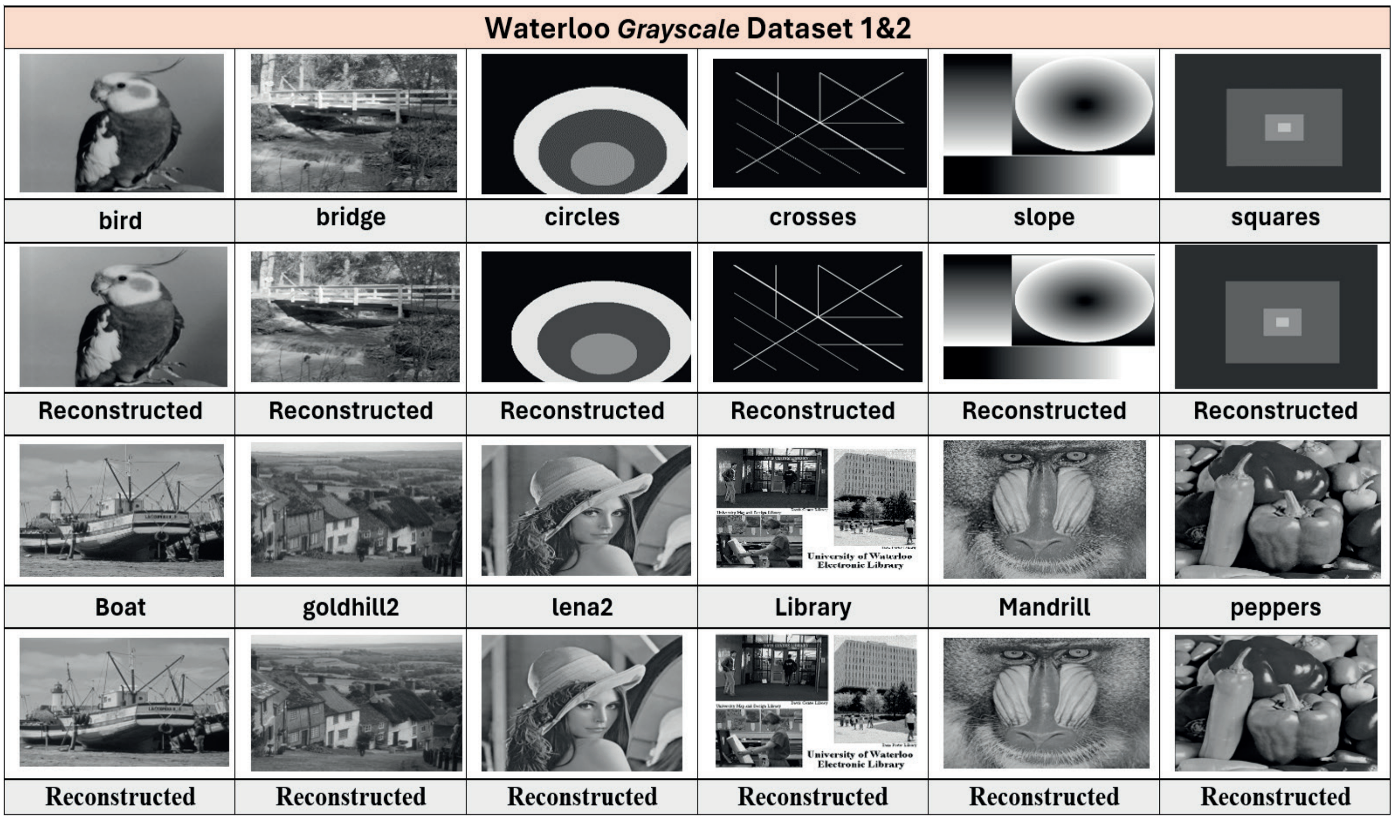

Figure 7. Examples of original and reconstructed images after applying rifd-lzw on the waterloo gray datasets 1 and 2

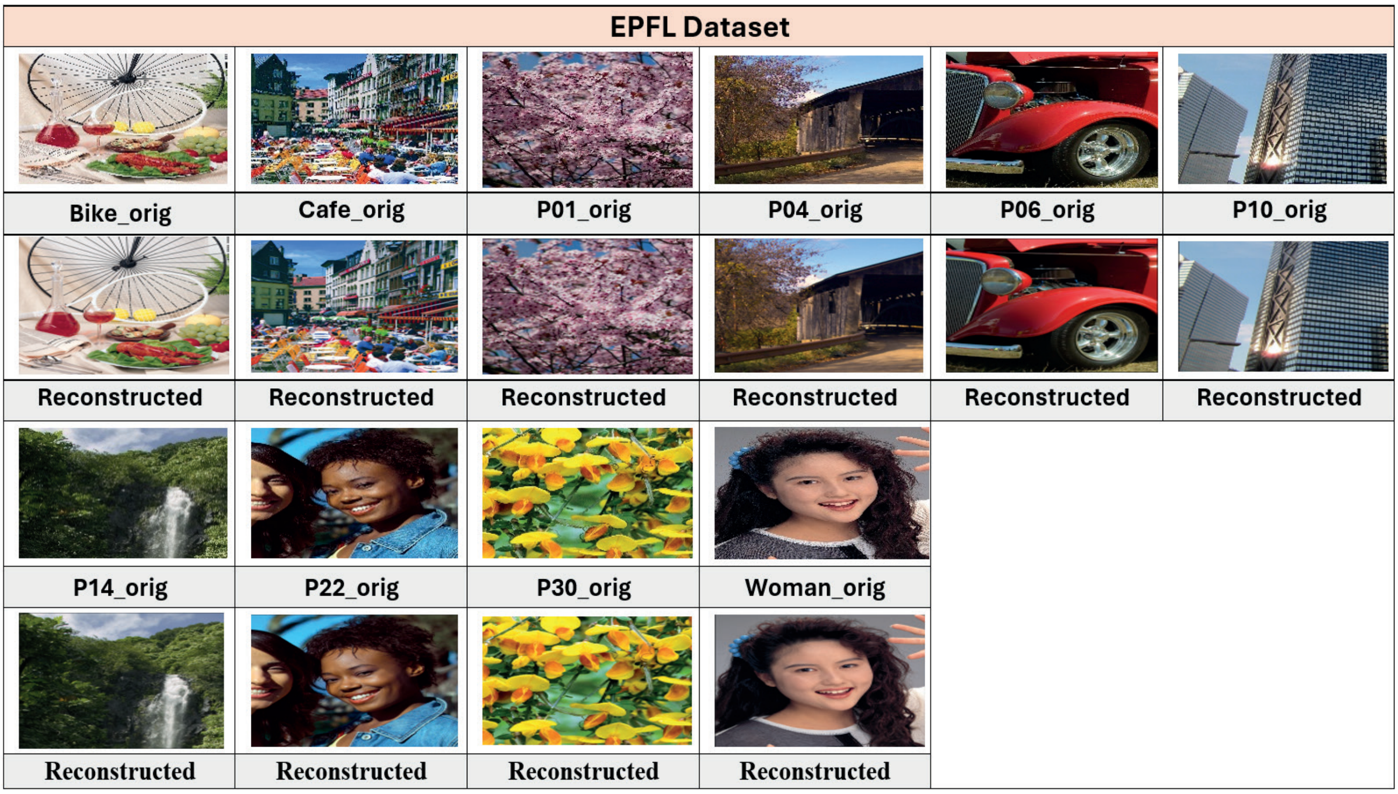

Figure 8. Examples of original and reconstructed images after applying rifd-lzw on epfl datasets

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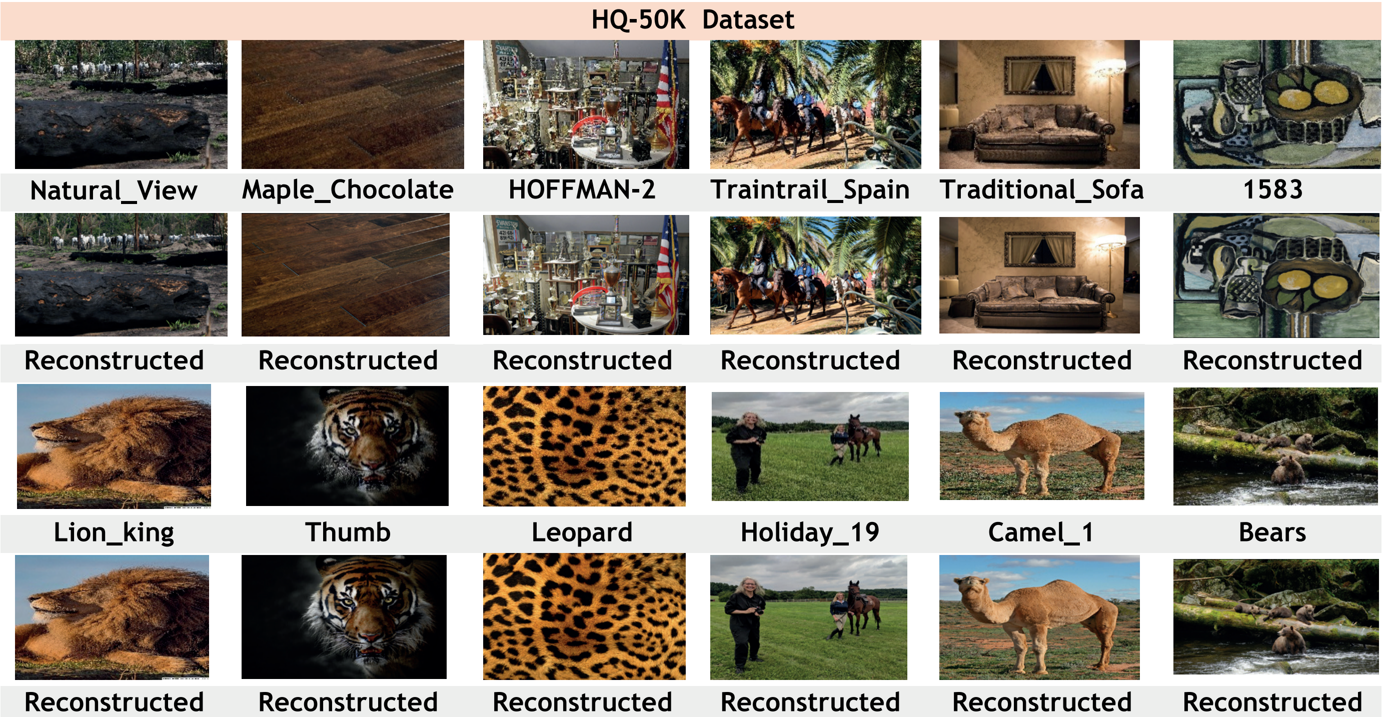

Figure 9. Examples of original and reconstructed images after applying rifd-lzw on hq-50k datasets

Comparison of Compression Size (BPP) for grayscale images

To evaluate the compression efficiency of the proposed RIFD-LZW algorithm, twelve grayscale images in TIF format were selected from the Waterloo dataset (Sets 1 and 2). Compression performance was measured in (BPP) using equation (1). The results, presented in table 8, include a comparison with several established lossless and lossy compression methods, namely JPEG2000 (J2K), Arithmetic Coding, IWT-HF, JPEG-LS (JLS), 7-Zip as well as standalone RIFD and LZW techniques. The findings show that the RIFD-LZW method consistently outperforms all other methods, achieving the lowest average BPP of 1,92, compared to 4,74 for LZW and 5,00 for RIFD. This represents a 59,51 % improvement over RIFD and a 59,49 % improvement over LZW, confirming the effectiveness of integrating RIFD preprocessing with LZW encoding. Moreover, it surpasses traditional compression standards such as JPEG-LS (3,36 BPP) and JPEG2000 (3,51 BPP), highlighting the superior performance of the proposed approach in compressing grayscale images.

Figure 10 provides a visual representation of the average compression performance (in BPP) for each method, based on the image set listed in table 8. The results clearly illustrate the advantage of the RIFD-LZW hybrid method over both standard and individual compression algorithms.

Table 8. Average (BPP) of the proposed RIFD-LZW algorithm compared with standard compression techniques using 12 selected waterloo images.

Image	J2K	Arithmetic	IWT-HF	JLS	7-Zip	RIFD	LZW	RIFD-LZW
bird	3,13	6,77	2,86	3,47	4,23	5	5,8	1,95
bridge	5,90	7,67	4,90	5,79	6,32	5	9,7	4,26
circles	1,26	1,78	1,33	0,15	0,11	5	0,21	0,21
crosses	1,43	0,19	2,02	0,39	0,18	5	0,22	0,23
slope	1,06	7,52	1,64	1,57	1,69	5	3,7	1,31
squares	0,25	1,08	0,69	0,08	0,05	5	0,13	0,14
boat	4,10	7,12	3,51	4,25	5,29	5	7,08	2,39
goldhill2	4,65	7,48	3,80	4,71	5,60	5	7,72	2,84
lena2	4,02	7,45	3,25	4,24	5,52	5	7,06	2,29
library	5,83	5,84	5,16	5,10	4,25	5	5,8	3,24
mandrill	6,02	7,36	5,04	6,04	6,38	5	9,3	3,97
peppers	4,40	7,57	3,51	4,49	5,54	5	0,21	0,23
Average	3,51	5,65	3,15	3,36	3,77	5	4,74	1,92

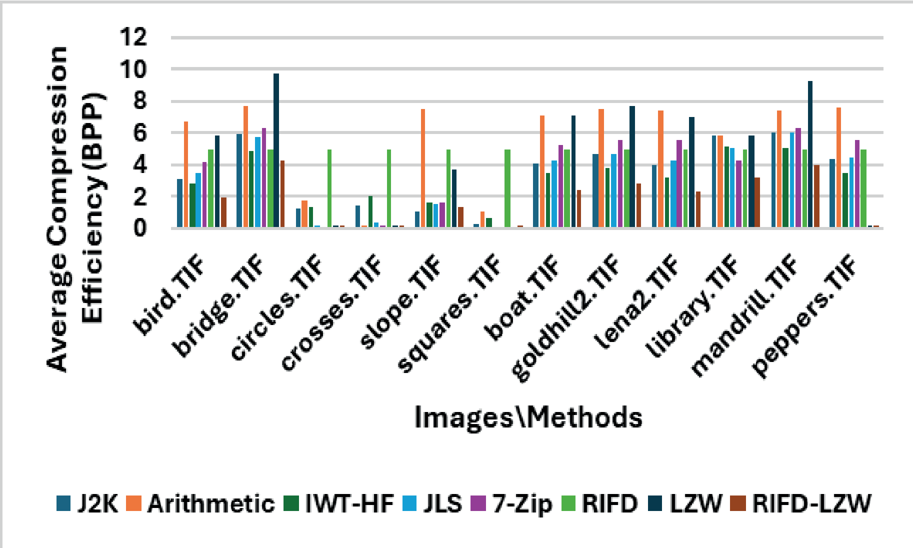

Figure 10. Average (bpp) of the proposed rifd-lzw algorithm in comparison with standard compression techniques

CONCLUSIONS

This study introduced RIFD-LZW, a new hybrid image compression algorithm that effectively integrates the Rounding the Intensity and Dividing (RIFD) technique with Lempel-Ziv-Welch (LZW) encoding. Designed for lossy compression, the method achieves a superior balance between compression efficiency and image quality across both color and grayscale datasets. By first reducing image redundancy through RIFD and then applying the dictionary-based LZW compression, the proposed approach successfully combines the strengths of lossy and lossless techniques.

Experimental results on benchmark datasets including EPFL, Kodak, Waterloo, and HQ-50K demonstrated that RIFD-LZW consistently outperforms traditional methods such as standalone RIFD, LZW, JPEG2000, JPEG-LS, and RIFD-Huffman. It achieves significantly lower bits per pixel (BPP) values while maintaining high peak signal-to-noise ratio (PSNR), indicating minimal distortion. In grayscale image tests using the Waterloo dataset, the algorithm achieved an average BPP of 1,92, surpassing RIFD (5,00) and LZW (4,74), yielding over 59 % improvement in compression efficiency. Additionally, on color datasets, RIFD-LZW achieved a file size reduction of 73,03 % compared to RIFD-Huffman, as evidenced by performance on the Kodak dataset.

Furthermore, the visual fidelity of reconstructed images verified through PSNR confirms that the minimal loss introduced during compression does not compromise perceptual quality. These findings establish RIFD-LZW as a highly promising solution for applications requiring efficient, lossy image compression, particularly where storage or transmission efficiency must be maximized without noticeable degradation in quality.

Looking forward, future work may focus on optimizing the algorithm for real-time or large-scale applications by enhancing its processing speed and adapting it to hardware-accelerated environments. The proposed RIFD-LZW method lays a robust foundation for further advancements in intelligent and adaptive image compression strategies.

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Availability of data and material

The image datasets utilized in this study are publicly accessible and can be retrieved from the links cited in the references section. Any additional data generated or analyzed during this research can be obtained from the corresponding author upon reasonable request

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT in order to improve readability and language. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Formal Analysis: Mahmoud AL Qerom.

Research: Mahmoud AL Qerom.
Methodology: Mahmoud AL Qerom.
Project Management: Mahmoud AL Qerom.
Resources: Mahmoud AL Qerom.
Software: Mahmoud AL Qerom.
Supervision: Mahmoud AL Qerom.
Validation: Mahmoud AL Qerom.
Display: Mahmoud AL Qerom.
Drafting - Original Draft: Mahmoud AL Qerom.
Writing - Proofreading and Editing: Mahmoud AL Qerom.