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Research Article

Diverse Techniques on Digital Image Compression Techniques: A Meta Analysis on Medical Images

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ABSTRACT

This paper examines a diverse array of image compression methods. This paper presents a review of existing research papers that are based on an examination of the diverse image compression methods. This paper investigates a diverse array of existing image compression techniques. The compression of binary unprocessed data is significantly different from that of an image. To resolve these issues, employ a diverse array of image compression techniques. The question of how to compress an image and which techniques are employed may now arise. The two primary methods introduced for this purpose are lossless and lossy image compression techniques. Presently, the fundamental procedure is supplemented by supplementary methodologies. In specific regions, neural network and wavelet-based algorithms are employed to compress images.

Keywords: Image compression, lossy lossless compression, deep learning, medical image, and wavelet.

INTRODUCTION

Data Compression is a prime need for current digital system operations and data exchange. As the volume of data is rapidly increasing new compression techniques were proposed for optimal compression. The developed approaches are however limited with the resource constraint in remote devices. Through reducing the size of data files or streams, data compression techniques play an important part in improving efficiencies in all phases of storing, sending and handling. Lossless compression methods seek to preserve all original information, and use different encoding strategies for achieving efficient media loss. Examples include Run-Length Encoding (RLE), Huffman Coding and Lempel-Ziv Welch (LZW) [1].

In multimedia applications, where information loss is acceptable at a certain level, Discrete Cosine Transform and Wavelet Transform are often used as lossy compression techniques. With these methods, data can be converted into frequency components or groups of similar vectors and greatly reduced in size. Using dictionary structures and probability models, methods such as Lempel-Ziv (dictionary-based compression), entropy coding etc. all enhance efficiency of compression. Standards for multimedia compression like JPEG, MPEG and MP3 are designed according to specific image, video or audio data. DCT, spatial-temporal compression and perceptual coding algorithms are involved as well. Many compression methods rely on a variety of quantization techniques (uniform and non-uniform), which allows data to be represented more economically [2, 3]. Whether it is run-length encoding or any other compression method, the choice involves weighing up tradeoffs between various parameters, making choices according to exactly what an application needs.

Fundamental to optimizing digital operations, data compression techniques vary in their impact on access time, device cost factor and computational speed. Because they have relatively simple algorithms, lossless compression methods such as Huffman Coding and Run-Length Encoding usually require little time to carry out. As a result, these work best in applications where rapid retrieval is important. But their simplicity often means low compression ratios. Yet lossy compression techniques such as Discrete Cosine Transform and Wavelet transform can achieve even higher ratios, but the more complex algorithms they employ may require longer access times. As for device cost, lossless methods are generally cheaper [4]. So they also tend to be the preferred choice for resource-constrained devices. However, for lossless techniques the computational time can be rather long-and becomes even longer when using large datasets.

Lossy compression is capable of reducing data by a higher degree, and demands more sophisticated hardware which will affect device costs. With the increasing volumes of information today, data compression is a basic necessity for contemporary digital systems and interchange [5]. Traditional data compression methods are aimed at improving the accuracy and quality of exchanged information. They suffer from several problems, however, such as high power consumption and complicated architecture; they thus cannot be adopted by low-power devices. This paper attempts to resolve these deficiencies and improve upon existing methods of reducing power consumption as well as minimalizing area coverage for seamless integration with remote devices [6].

- Data Compression Techniques: It then dives into a thorough examination of different data compression techniques, ranging from classic methods to modern approaches. Paying special attention are lossless and lossy compression techniques, spatial and frequency domain models, as well as transformational methods like the discrete wavelet transformation (DWT). These techniques are analyzed in terms of their theoretical foundations and practical implications to provide a springboard for suggested improvements.
- Technical Status of Data Compression: The following subsection provides an introduction to the current state of techniques for data compression. Such models tend to be complex and resource-intensive, which underlines the need for refinement. Significant methods and algorithms are introduced, highlighting their advantages and limitations. The incorporation of the latest developments in hardware-efficient architectures and FPGA implementations reveals that data compression technologies can also evolve.
- Applications and Real-world Implications: Although data compression is found in such varied fields of application as handheld devices -- including mobile phones-- to hightech areas like medical applications, satellite image coding and military systems. The section explores the multifaceted practical applications of data compression. It stresses that data compression is absolutely essential for efficient transfer and storage or digital information. This exchange also involves the problems encountered in real-time applications because of limited resources [7].

Medical Image Compression

The medical image compression comes under the network access category with wider scope to investigate. It is necessary to transfer medical data from one place to another without any loss or delay. But transferring such huge volume of data through the network demands huge chunk of network resource like bandwidth which is always on-demand. So an effective way to transmit data without spending too much of bandwidth is through compressing medical images and then transmitting through the network [8]. The existing compression schemes like JPEG (Joint Pictures Expert Group) cannot be applied for medical data as they are highly sensitive to data loss or modifications. So compression schemes exclusively for medical data must be developed, which is the major domain of this research approach.

The standard image processing techniques cannot be applied to the medical images because they differ considerably from that of common images [9]. While the common images including natural or other profile pictures are captured from any digital or DSLR (Digital Single-Lens Reflex) cameras, the medical images are captured through more advanced and sophisticated medical image capturing devices. Usually most of the medical images captured are of graytoned and very rarely include colored images because the color images lose essential clinical elements for diagnosis. Even if it needs to be colored, it is represented using special format that could represent the clinical features more clearly.

The normal algorithms that were previously employed for image compression cannot be applied directly to medical image compression, because such algorithms when applied to medical images will result in damage or loss in significant medical data [10]. Also, the fact is that the conventional compression algorithms are of no match to handle the large volume of medical data especially compressing without resulting in losing any clinically significant data. Normally common images are light-weight when compared to medical images which are heavy-weight and need more sound and robust hardware and software for storage and retrieval of medical data from hospital servers. Literature studies have shown that the conventional compression scheme does not provide considerable reduction in the size of medical images and reduction in bit rate for transmission through network. For the past decade many works on developing proper compression mechanism for medical images that could compress the medical image without any quality loss and could achieve better bitrates are underway [11].

Analysis on Literature

He et al. (2022) [12] discuss the remarkable performance of learned image compression techniques, which have recently surpassed the best manually designed lossy image coders and show potential for large-scale adoption. The authors emphasize the importance of examining the architecture design of learned image compression concerning both performance and speed for practical application. They propose uneven channel-conditional adaptive coding, inspired by energy compaction in learned image compression. By integrating this uneven grouping model with existing context models, they develop a spatial-channel contextual adaptive model that enhances coding performance without sacrificing speed. Additionally, He et al. introduce an efficient model, ELIC, which achieves state-of-the-art speed and compression performance. ELIC supports extremely fast preview and progressive decoding, making learning-based image compression more viable for future applications.

Zou et al. (2022) [13] highlight that learned image compression methods have shown superior rate-distortion performance compared to classical standards, with most models based on Convolutional Neural Networks (CNNs). However, the authors note that CNNs struggle with capturing local redundancy and nonrepetitive textures, which affects reconstruction quality. To address this issue, Zou et al. combine local-aware attention mechanisms with global feature learning, inspired by Vision Transformer (ViT) and Swin Transformer. They introduce a flexible window-based local attention block that enhances both CNN and Transformer models. Moreover, Zou et al. propose a novel Symmetrical Transformer (STF) framework with transformer blocks in the encoder and decoder. Extensive experiments demonstrate the effectiveness and superiority of their method over state-of-the-art techniques.

Yang et al. (2023) [14] present an end-to-end optimized lossy image compression framework using diffusion generative models. Unlike VAE-based neural compression, which employs a deterministic neural network decoder, their approach utilizes a conditional diffusion model for decoding. Yang et al. introduce a "content" latent variable to condition the reverse diffusion process and use "texture" variables synthesized at decoding time. Their framework's performance can be tuned to specific perceptual metrics. Extensive experiments show that their approach achieves superior FID scores compared to GAN-based models and competitive performance with VAE-based models in distortion metrics. Training the diffusion with X-parameterization allows high-quality reconstructions in few decoding steps, enhancing practicality.

Mall et al. (2022) [15] review the significant advances in medical image processing enabled by Artificial Intelligence (AI) solutions, particularly deep neural networks. They focus on the development of automated systems to assist medical practitioners in diagnosing diseases such as brain tumors, bone cancer, breast cancer, and bone fractures. This comprehensive review by Mall et al. highlights recent advancements in medical imaging using deep neural networks and provides an overview of the literature, available data sources, and future research directions.

Zalik et al. (2021) [16] have employed a novel approach for sequential coding. A Zero-Run Transform has been introduced in the compression framework for chain codes compression. The sequence obtained after transformation is then compressed using Golomb coding, Binary adaptive sequential coding and then with sequential coding with return to bias approach. In the final stage, a comparative analysis has been employed using state of the art approaches namely, chain code 8 and chain code 4. This work has achieved a compression performance similar to that of chain code 8.The compression efficiency attained by the proposed method is superior when analyzed to the existing methods but this work has not considered hex orientations.

Urvashi et al. (2021) [17] have employed medical image compression for CT and MRI imaging modalities. RIGED lossless prediction technique is employed for finding the correlations which exist between the neighboring pixels. Intra and inter modes for prediction is performed for eliminating redundancies between 2D and 3D images. GED predictor is implemented by the authors for removing inter pixel redundancies efficiently.MED predictor and GAP predictor approaches are combined in the name of GED for attaining simplicity and efficiency. Residual or error image is obtained after subtracting the input image with the image after prediction. Then the residual part of the image is divided into blocks of size 8×8 for identifying homogeneous regions. The block size is chosen based on the analysis of various block sizes. The compression results obtained is 3.70 for 8 bit medical samples and 3.11 for 16 bit medical image samples.

Kumar et al. (2021) [18] have presented a lossless image encoding approach for medical images. The input image is sub-divided into blocks of size 4×4. The pixels in the input image are scanned based on left to right fashion and polynomial approximation is performed on each 4×4 sub-blocks. Preprocessing is employed for performing normalization and the technique used for that is min-max. To minimize the storage size of the image, Llyods quantization has been performed. Legendre polynomial is presented in which legendre moments are generated and the order of polynomial used is 6. Orthogonal moments are produced using Gaussian Hermite approach and arithmetic encoding which is an entropy encoding technique is implemented as a final step for performing compression. This technique is analyzed with real time CT abdomen images and the compression results achieved is better when evaluated with existing polynomial methods.

Guo et al. (2021) [19] have presented an encoding method based on learning methodology. Quantization has been performed to reduce the gray level transformations by transforming the input image into latent representations. A channel-adaptive codebook has been used to speed up the arithmetic encoding process after quantization. From the latent map rate generated, the channels are distinguished into three types of channels. Each channel which has varying frequency characteristics are compared with neural based frequency filtering approaches. Finally, arithmetic encoding has been implemented to accelerate the encoding process after quantization.

Yousif et al. (2021) [20] have presented an approach for image compression using integer execution entropy, encoding and transform based coding. This approach has been tested and compared with the existing approaches using color images. Firstly, Discrete Cosine Transform (DCT) method has been applied to the chrominance and luminance color components i.e. YCbCr. Secondly, a standard quantization table is used to perform quantization on the YCbCrcolor components. Zigzag scanning order is performed on the coefficients obtained after quantization process. Lastly, the image is encoded using an entropy encoder namely, Arithmetic encoder for achieving best compression results.

Geetha et al. (2021) [21] have implemented a technique namely LindeBuzo-Gray (LBG) which is a vector quantization approach used for reducing the codebook size. A bio-inspired technique is implemented for deriving a solution to the optimization problem. Lion Optimization Approach (LOA) is coordinated with Lempel Ziv Markov Technique (LZMA) in order to provide an efficient codebook. An optimal codebook is generated using line optimization algorithm, and size reduction is performed using LZMA technique. Compression Ratio and Peak Signal Noise Ratio reported in this work are 0.3425375 and 52.62459 respectively.

Sharma et al. (2020) [22] have implemented 3-D predictor for volumetric medical images of different resolutions belonging to various modalities. In this work, the residual or error image obtained after prediction is sub-divided into 8×8 blocks for identifying the spatial redundancies. Arithmetic coding is performed on the blocks for classifying the error. A novel Inter Slice Correlation Switched Predictor (ICSP) is proposed with a Block based Adaptive Arithmetic Encoding (BAAE) for compressing the 3D bit depth medical data. A switching predictor is proposed for choosing a threshold between the correlating pixels. Resolution Independent Gradient Edge Detector (RIGED) is employed for performing intra prediction. The compression ratio of 3.70 and 3.11 is achieved for 8 bit depth images and16 bit depth images respectively.

Xu et al. (2020) [23] have proposed a novel approach for achieving efficient compression. A hybrid approach is employed by combining vector quantization with pixel prediction. Firstly, the input image is partitioned into various blocks which are non-overlapping in nature. This approach is varied from traditional vector quantization method during block division. Based on the results of pixel prediction, block division has been performed in two ways either with vector quantization or with pixel prediction. An addition bit is employed on the blocks for determining whether to perform with vector quantization or with pixel prediction. Only one bit is considered during pixel prediction. From the experimental analysis, it is obvious that the proposed work has achieved a better compression ratio (CR) with a permissible image quality.

Paramveer et al. (2020) [24] have implemented segmentation based encoding for compressing brain MRI image samples. They have employed a two stage process for performing efficient encoding. During the first phase, a clustering technique namely Fuzzy C-Means is employed for extracting the foreground part of the image. During the second phase, SPHIT technique is employed for encoding the foreground and background regions. Fuzzy c-Means technique is exhibited as an initial step before compression for providing a better performance on noiseless images. FCM method is incorporated with other techniques in order to remove the occlusions.

Uma Maheswari et al. (2020) [25] have implemented a lossless tetrolet wavelet transform for image compression. The input image is sub-divided into blocks of size 4×4. A one dimensional shape of four tiles with different components of various unit squares are formed by joining the edges named as tetrominoes. For the input image, the sparse representation of the tetrolet transform is identified. The tetrolet low-pass and high-pass coefficients obtained for each block is transformed into 2×2 blocks. Different wavelet approaches are compared with tetrolet transform. From the results, it is concluded that this work has accomplished a better performance with superior quality images.

Manimekalai et al. (2019) [26] have proposed a technique for the major demand to achieve high Compression Ratio (CR) with better image quality. RegionOf Interest (ROI) approaches are essential to meet the demand. An image is sub categorized as Less Significant (LS) and Most Significant (MS) areas. The MS portion has played a prominent role in diagnosing the disease. The authors have employed Freeman Chain Code 8 (C8) technique using edge based encoding to achieve high compression ratio. N-ROI portion is compacted by Enhanced Zero Tree Wavelet (EZW).COMPRESSION RATIO (CR) achieved by the authors is 85% and Peak Signal to Noise Ratio (PSNR) achieved is 45%. C8 utilized three bits for encoding a symbol. Also this method can represent edges only for 8 directions.

Zalik et al. (2019) [27] have proposed a lossless chain code representation based encoding approach namely interpolative coding. In this work, a hybrid approach is implemented i.e. Golomb coding has been used with the interpolative coding to attain an efficient compression. A prediction of the coded value is done at first, and then an error is calculated between the actual and the predicted values. The coded value is predicted initially. After that, error value is computed with the original pixel and the predicted value. The entire encoding approach is enhanced by compression framework comprising of Burrows Wheeler, Move-To-Front transform and the interpolative coding and thereby enhanced by FELICS and novel coding. The recursive character of interpolative coding, make large range values to be encoded less frequently than the values in the shorter range.

Sharma et al. (2019) [28] have presented Gradient Edge Detector (GED), a predictive coding technique based on threshold value. This work has been implemented on 8 bit and 16 bit depth volumetric medical images. Neighboring pixels from the causal template are scanned in a raster manner during prediction. Error image or residual image is obtained by computing difference between original image and predicted image values. The error image attained has lower entropy which is then encoded using entropy encoder. Resolution Independent Gradient Edge Predictor (RIGED)is presented to implement 8- and 16-bit depth medical images. This work has achieved an entropy improvement of 30.39% over state-of-the-art Median Edge Detectors (MED) and 0.92% over Gradient Adjusted Predictor (GAP) for various resolution medical images.

Kasban et al. (2019) [29] have employed an image compression approach for partitioning the image into foreground and background regions. As a first step, foreground portion is isolated from background using an automatic threshold value based on the histogram variance image. General Lloyd algorithm which is a vector quantization based lossy compression approach is implemented for generating the codebook. The structuring element used during this process is grouped into background pixel group based on the size. As a next step, the foreground image portion is compressed using Huffman encoding. Radiographic medical samples are used for experimentation purpose. From the results, it is clear that that the compression results achieved is superior while segmenting into foreground and background rather than compressing the entire image.

Dumas et al. (2019) [30] have designed Prediction Neural Networks Set (PNNS), which focused both on fully-connected network and convolutional neural networks architectures. Selecting a best neural network plays a dominant role in image compression in order to perform a better reconstruction. Fully-connected neural networks showed superior performance for blocks of small sizes and also convolutional neural networks facilitated good predictions for complex textures which are of large size blocks. A complete representation is essential in a fully-connected neural network to perform prediction of high quality. Hence, the availability of number of neurons is larger than the context size in every fully-connected layer. Similarly, convolutional neural network feature map size is very large in each layer which has incurred a huge computational cost.

Chaari et al. (2019) [31] have introduced wavelet transforms for image compression, image restoration or processing texture areas. The coefficients obtained from the grouplet transform have been combined to identify geometric regularities. The results attained for this work has exhibited better image compression, denoising or image restoration.

Abdul hameed et al. (2018) [32]. In their work the main focus was to reduce the amount of space required to store and transmit the medical image for compression and transmission. Because of the redundancy issues they opted for contourlet transform for decomposing the images. Their model employed multi-directional decomposition together with dual-iteration filter banks provided by Laplacian Pyramid and Directional filter banks has provide a decomposition model that represented the medical image in different scales and directions. This multi-scale and multi-directional representation of images had provided an opportunity to protect the essential; information of the image and the same time gives an opportunity to eliminate the unnecessary information. Their model outperformed other wavelet based transform models in terms of PSNR and compression ratio.

Ma et al. 2018 [33], The authors in their work presented a novel approach to provide a compressed scanning scheme for 3D CMR (Cardio Vascular Magnetic Resonance). They have chosen shearlets for its optimal performance in compressing natural images and its efficiency against other wavelet models. They employed 3D Radical Phase Encoding (RPE) and iterative weighing scheme for image acquiring and reconstruction process respectively. They ensured better reconstruction rate with very lesser relative errors and higher structural similarity index.

Thayammal et al. [2017] [34] proposed a compression model to reduce the number of bits during image transmission and storage. They also focused on maintaining the image quality after the image reconstruction. They emphasized the importance of edges in an image and its need in maintaining the image quality. They compared the performance of the model with JPEG 98 and 2000 versions and proved that the level of artifacts resulted after reconstruction is much lesser in the proposed model at lower bitrate.

Haydar et al. 2017 [35] proposed a model to compress a new modality of image 3D OCT (Optical Coherence Tomography), a technique that provides non-destructive and contactless cross-sectional medical images. The authors presented a compression model for OCT images by decomposing the image in to sparsely approximated coefficients using a generating function. They reconstructed the original image by adding the shearlet filter convolutions with its corresponding coefficients. They proved that the rate of compression of 3d OCT images is directly proportional to the number of shearlet coefficients used to reconstruct the image

Dogra et al. (2016) [36] had in their work presented six different medical image compression approaches which include Ripplets, Directional DCT and other combinations. in their work they expressed that decomposing the image first by DDCT and followed with Ripplets provides better representation of the image objects and other essential textures. They restricted their encoding scheme just with DDCT and Ripplet and did not use any other encoding schemes for compression like EZW or SPIHT.

Sujitha Juliet et al. [2016] [37] proposed a novel ripplet and SPIHT based compression model that represents the singularities among the curves. The SPIHT provides better encoding and higher compression ratio. The resultant model compresses images in high quality and at multiple scales and directions there by achieving better compression ratio.

Aneja et al. 2016, [38] In their approach employed a histogram based thresholding to segment the input image into multiple regions including ROI, non-ROI and background regions. The idea is to focus only regions of interest and omit the rest. They applied shearlet transform to ROI and non-ROI regions to generate coefficients and compress the regions using Huffman encoding and SPIHT encoding for ROI and non-ROI respectively. The rest of the regions are omitted by converting it to zero. They provided a desired quality based image reconstruction facility. Their scheme had provided better PSNR and better compression ratio.

Karami 2015 [39] proposed a hybrid shearlet transform model for a new modality of image called hyper spectral images (HSI), such images are represented three dimensionally with spatial domain sharing two dimension and one dimension in spectral domain. The authors opted for shearlets because of its nature to represent the edges and other geometric features of the image efficiently. They encoded the image using

3D Set Partitioned Embedded Block and proved their method performance better in terms of signal to noise ratio than other models.

Dhaarani et al. (2014)&P.Suganya et al., (2023) [40-41]; employed ripplet transform to represent the images at multiple angles and scales and they also employed Huffman encoding to compress the image. They attempted this effort to achieve better compression ratio and reduce the mean square error and they proved by providing the experimental results which favoured the proposed model for better compression ratio and peak signal to noise ratio against other models.

Research Directions

Based on the comprehensive analysis in the above research works on image compression, several promising research directions can be identified:

1. Enhancing Computational Efficiency:
- Energy-Efficient Models: Develop models that reduce computational overhead and energy consumption, suitable for deployment on edge devices and mobile platforms.
- Hardware Acceleration: Explore the use of specialized hardware, such as FPGAs and GPUs, to accelerate learning-based image compression techniques.

2. Integration of Advanced Neural Networks:
- Transformer-Based Architectures: Further investigate the potential of transformer models, including variants like Vision Transformers (ViTs) and Swin Transformers, for image compression tasks.
- Hybrid Architectures: Combine Convolutional Neural Networks (CNNs) with other neural network architectures, such as Generative Adversarial Networks (GANs) and Diffusion Models, to enhance compression performance.

3. Optimizing Perceptual Quality:
- Perceptual Metrics: Develop compression algorithms that optimize for perceptual quality metrics, such as Structural Similarity Index (SSIM) and Fréchet Inception Distance (FID), to ensure high-quality reconstructions.
- Content-Aware Compression: Implement adaptive techniques that prioritize regions of interest (ROI) in images, improving the quality of critical areas while maintaining overall compression efficiency.

4. Lossless and Near-Lossless Compression:
- Medical Imaging: Focus on lossless or near-lossless compression methods tailored for medical imaging applications, ensuring no critical diagnostic information is lost.
- Multispectral and Hyperspectral Imaging: Explore compression techniques for multispectral and hyperspectral images, which are increasingly important in remote sensing and medical diagnostics.

5. Contextual and Semantic Compression:
- Context Modeling: Enhance context modeling techniques to improve the efficiency of entropy encoding methods, such as arithmetic coding and context-adaptive binary arithmetic coding (CABAC).
- Semantic Compression: Develop methods that leverage semantic information from images to achieve higher compression ratios without significant loss of essential details.

6. Progressive and Scalable Compression:
- Progressive Encoding: Research progressive encoding techniques that allow for gradual image quality improvement as more data is received, beneficial for streaming applications.
- Scalability: Ensure that compression algorithms are scalable and can be adjusted dynamically based on bandwidth and storage constraints.

7. Integration with Emerging Technologies:
- Quantum Computing: Investigate the potential of quantum computing for developing novel compression algorithms that could outperform classical approaches.
- Blockchain and Privacy: Explore the use of blockchain for secure and efficient image compression, ensuring data integrity and privacy during transmission and storage.

8. Benchmarking and Standardization:
- Standardized Datasets: Develop and utilize standardized datasets and benchmarks to evaluate the performance of image compression algorithms across diverse scenarios.
- Interoperability: Ensure that new compression techniques are compatible with existing standards and can be seamlessly integrated into current systems and workflows.

By pursuing these research directions, advancements in image compression can significantly impact various fields, including medical imaging, remote sensing, and multimedia applications, ultimately leading to more efficient storage and transmission of high-quality visual information.

CONCLUSION

This meta-analysis provides an extensive review of diverse image compression techniques, encompassing both classical and contemporary approaches. It highlights the evolution from traditional methods like Huffman Coding and Run-Length Encoding to advanced techniques involving neural networks and wavelet transforms. The review reveals a significant trend towards learning-based compression, with Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and Generative Adversarial Networks (GANs) demonstrating superior performance in various contexts, including medical imaging. The study underscores the necessity for energy-efficient and hardware-accelerated models to meet the growing demand for real-time applications and resource-constrained environments. Future research should focus on integrating hybrid neural network architectures and optimizing computational efficiency to achieve higher compression ratios and better image quality without compromising speed and resource usage. The insights from this meta-analysis serve as a foundation for advancing the field of image compression, paving the way for innovative solutions that can handle the increasing volume and complexity of digital data.

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