A Survey of Image and Video Compression Techniques in Microscopy and Data Reduction

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Abstract

This survey paper provides a comprehensive overview of image and video compression techniques, with a focus on applications in microscopy, medical imaging, and data reduction. The study highlights the importance of compression technologies in managing the increasing volume of digital data across various domains, such as multimedia and scientific research. It explores both traditional methods like JPEG and H.264, which optimize storage and bandwidth, and more advanced techniques involving wavelet-based and neural network-driven innovations. The paper emphasizes the dichotomy between lossy and lossless compression methods, discussing their respective advantages and limitations in terms of file size reduction and quality preservation. In microscopy, the need for efficient management of high-resolution images is crucial, necessitating advanced compression techniques that maintain essential data integrity. The survey also examines the role of data reduction in enhancing processing efficiency and storage management, particularly in data-intensive domains. The integration of machine learning into compression frameworks has shown promise in optimizing compression efficiency and quality preservation, with methods such as the I2Icodec framework and cResNet architecture demonstrating significant advancements. The ongoing research and development in hybrid and adaptive compression techniques reflect a shift towards more efficient and flexible solutions for managing digital visual data. As the field continues to evolve, the integration of AI and machine learning is expected to play a pivotal role in shaping the future of image and video compression technologies, addressing the challenges of modern data-intensive applications.

1 Introduction

1.1 Significance of Image and Video Compression

Image and video compression is essential for managing the increasing volume of digital data across various fields, including multimedia, medical imaging, and scientific research. The evolution of digital image compression since the 1960s has aimed to optimize storage and bandwidth [1]. In modern applications, efficient compression of multi-dimensional images is crucial for storing and transferring large high-resolution datasets, particularly in microscopy and bioimaging, where advanced techniques generate substantial imaging data, challenging existing data management frameworks [2, 3].

Lossless image compression is vital in applications requiring the preservation of original data, emphasizing the need to reduce storage and transmission costs without compromising integrity [4]. Conversely, lossy compression techniques, which permit some data loss for enhanced file size reduction, are integral to visual analysis applications involving classification and semantic interpretation [5]. The development of advanced compression algorithms is necessary to overcome the limitations of traditional standards like JPEG, which can lead to errors in reconstructed images [6]. Furthermore, existing methods struggle with large quantities of similar images, such as facial images, at high compression ratios, highlighting the need for innovative approaches [7, 8].

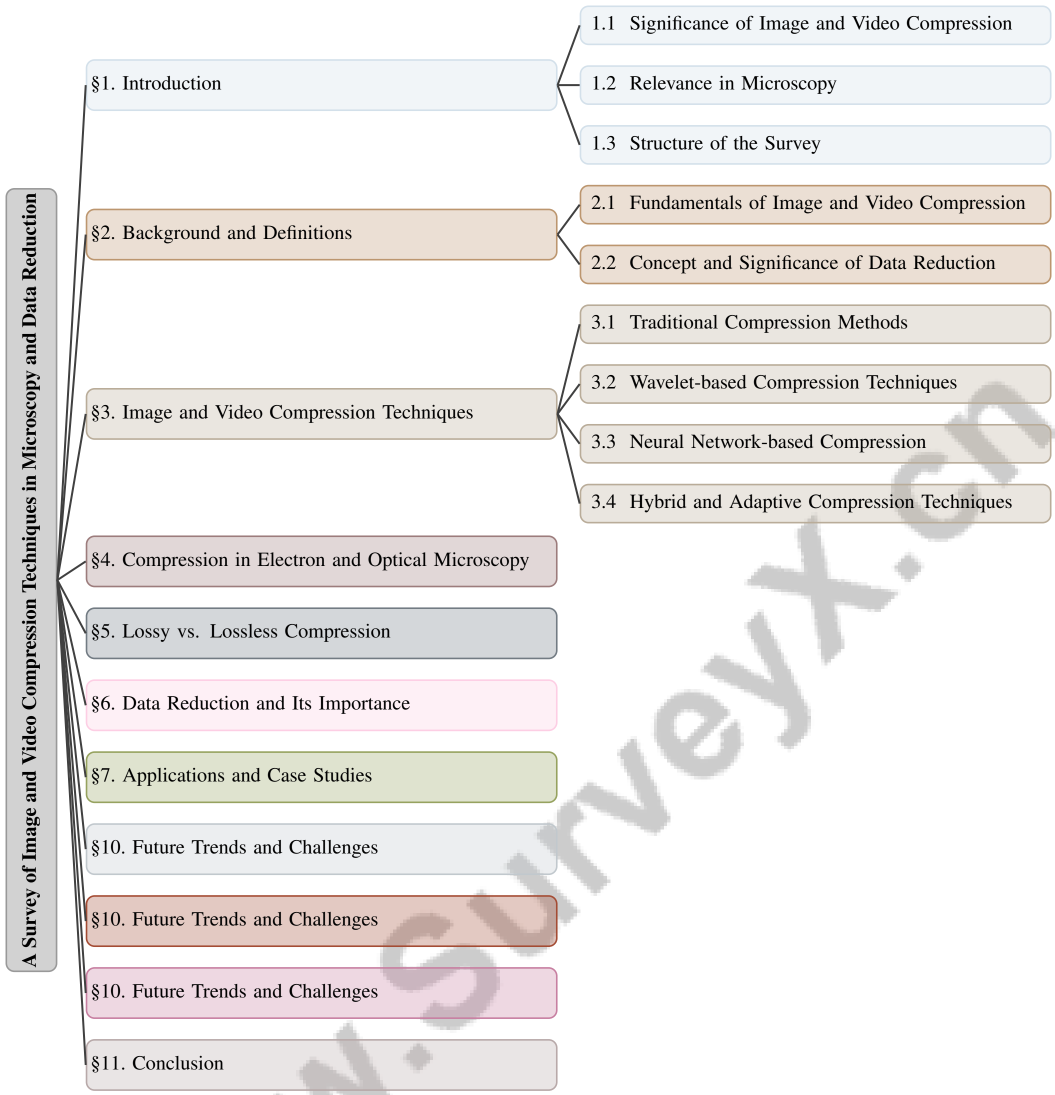

Figure 1: chapter structure

In medical imaging, compression not only optimizes storage and transmission but also enhances diagnostic processes [9] and manages the high storage demands of formats like DICOM [10]. The integration of compression techniques with image-to-image translation frameworks further underscores the importance of encoding efficiency in distributed data management systems [11]. As digital content proliferates, advancing compression technologies remains critical for streamlining data management across applications and ensuring efficient processing without the overhead of decoding images [12]. The optimization of compression in the context of display device degradation also highlights the necessity of maintaining end-to-end quality in image and video compression [13].

1.2 Relevance in Microscopy

In microscopy, image and video compression is crucial due to the large datasets generated by high-resolution imaging techniques. Efficient compression is necessary for managing gigapixel images, which are common in fields like Computational Pathology and electron microscopy, requiring robust solutions for storage, sharing, and analysis [14]. The challenge of achieving high-quality visual data compression while facilitating effective machine perception tasks highlights the need for advanced techniques in microscopy [15].

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The management of large datasets in medical imaging, particularly high-bit-depth images, relies heavily on effective compression strategies [10]. Traditional lossless methods are increasingly inadequate for the current data explosion, prompting the exploration of lossy techniques that offer greater file size reductions without sacrificing data integrity. Existing inefficiencies in compression methods, such as inadequate compaction of spatial and temporal energy, further emphasize the necessity for innovative solutions [16].

While lossy compression can reduce file sizes, it risks introducing artifacts detrimental to the precision required in microscopy [17]. Traditional methods like JPEG and H.264 often prioritize pixel fidelity over perceptual quality, resulting in suboptimal performance at low bitrates, which poses a significant challenge in managing large microscopy datasets. This inefficiency underscores the need for novel approaches capable of adapting to varying requirements and optimizing perceptual redundancy.

Integrating machine learning techniques into compression frameworks can enhance decision-making processes and patient outcomes in healthcare systems reliant on microscopy data [18]. For example, deploying lossy compression methods that balance file size reduction with image quality is crucial for supporting machine vision analytics, thereby improving the utility of compressed visual data in microscopy. Additionally, the relevance of compression is highlighted by the need for methods optimizing deep learning-based segmentation accuracy in 3D medical images [19].

The challenges of large image resolutions and file sizes in Direct Immunofluorescence (DIF) Whole Slide Images (WSIs) used in renal analysis necessitate advanced compression techniques to ensure efficient data handling and mitigate data scarcity issues [20]. Effectively compressing large digital images without significant quality loss remains a critical challenge, particularly in medical imaging, where accuracy is paramount. Consequently, developing sophisticated algorithms tailored to microscopy's unique demands is essential for managing the extensive datasets generated in this field.

Understanding the effects of image compression on recognition models is vital for deploying these models in real-world applications where bandwidth and storage are limited [21]. Techniques like PatchSVD have been developed to address inefficiencies in existing methods, particularly in preserving quality while achieving high compression ratios for images with sharp intensity changes [22]. Compression is especially critical for managing large datasets in microscopy, particularly high bit-depth volumetric medical images [23]. The need for improvement is driven by the proliferation of high-resolution images and novel formats, necessitating optimal solutions for diverse image content [24].

1.3 Structure of the Survey

This survey is structured to comprehensively explore image and video compression techniques, particularly in microscopy and data reduction. It begins with an introduction that establishes the significance of compression in managing digital data across various domains. The subsequent background and definitions section provides an overview of key concepts related to image and video compression, electron and optical microscopy, and the distinction between lossy and lossless methods.

The core of the survey focuses on an in-depth discussion of compression techniques, covering traditional methods such as JPEG and H.264, wavelet-based approaches, neural network-driven innovations, and hybrid techniques that integrate multiple methods for enhanced efficiency. The analysis emphasizes the significance of compression in electron and optical microscopy, particularly in managing high-resolution images while addressing the challenges of compressing microscopy data. This includes balancing data size reduction with preserving essential information, as traditional lossy methods can introduce artifacts that compromise the reliability of automated analysis in clinical settings. Recent advancements, including lossless algorithms and deep learning-based techniques, show promise in minimizing data loss and maintaining prediction accuracy, thus enhancing data management and transmission efficiency in microscopy applications [3, 25, 17].

The survey further compares lossy and lossless compression, highlighting the trade-offs between file size reduction and quality preservation. It thoroughly examines the significance of data reduction in enhancing processing efficiency and optimizing storage management, showcasing techniques such as downsampling, compression, and strategic training data usage. These methods aim to simplify datasets while preserving critical information, as evidenced by findings that balance detection accuracy and file size in renal image analysis, the innovative Reduced Bit Median Quantization technique for

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image compression, and the benefits of generating distinct compressed representations to improve signal reconstruction quality [26, 20, 25, 27, 28].

Practical implementations of various compression techniques are illustrated through applications and case studies in fields such as medical imaging, where innovative methods like JPEG2000 and fast algorithms are crucial for high-quality image viewing; scientific research, benefiting from comparative analyses of lossy image compression algorithms like Discrete Cosine Transform (DCT) and Wavelet Transform for efficient data handling; and digital media, where frameworks like Kuchen enhance existing codecs to optimize data transmission and storage efficiency [29, 30, 31, 28, 32]. The survey concludes with a discussion on future trends and challenges, emphasizing the integration of AI and machine learning in compression technologies and identifying potential areas for further research and development.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Fundamentals of Image and Video Compression

Image and video compression techniques, essential for reducing file sizes while maintaining quality, are divided into lossy and lossless methods. Lossy compression allows some data loss for significant size reduction, crucial in precision-demanding fields like medical imaging [33]. Conversely, lossless compression retains all data for exact reconstruction, achieving less pronounced size reductions [34]. Traditional methods like JPEG use the Discrete Cosine Transform (DCT) to convert spatial data into frequency domain coefficients, reducing redundancy [35]. However, these methods often fall short in applications with high storage demands, such as histopathological Whole Slide Images (WSI) in deep learning contexts [32]. Innovations like Quantum JPEG Compression (QJC) advance compression by encoding JPEG coefficients in qubits [36].

Conventional compression methods often underperform in machine learning tasks, particularly in machine vision systems, where object detection and classification suffer [37, 38]. To address these challenges, end-to-end optimized image compression methods have been developed, specifically for machine learning and vision applications [32]. Hybrid approaches, such as clustering-based quantization, enhance compression by selecting optimal data for inpainting in partial differential equation-based scenarios [39]. Techniques like Block Modulating Video Compression (BMVC) use binary random coding patterns to efficiently modulate high-resolution images into smaller blocks [40].

The theoretical foundations of compression are rooted in Shannon's information theory and Kolmogorov's entropy, which quantify information storage in noisy fringe patterns, providing a framework for understanding compression capabilities and limitations [36]. Recent benchmarks compare learning-based image compression models with traditional codecs like JPEG2000 and BPG, focusing on visual quality and processing times [41]. Such evaluations are crucial for advancing compression technologies to meet modern application demands, particularly in machine vision, where maintaining feature representation quality is critical [21].

The fundamentals of image and video compression involve a complex interplay of techniques balancing file size reduction with quality preservation, tailored to diverse application needs. As digital data volumes surge in sectors like medicine and remote sensing, advancing both lossless and lossy techniques is imperative. Research focuses on innovative methods such as predictive coding and context modeling to enhance compression ratios, with standards like JPEG XL showing potential for specific image types [42, 25].

2.2 Concept and Significance of Data Reduction

Data reduction is crucial for managing large datasets, simplifying data while preserving essential features. This process enhances processing efficiency and optimizes storage, particularly in high-dimensional domains like genomics and image processing. The primary aim is to achieve high compression ratios without significant quality loss, a challenge exacerbated by the time complexity of compression and decompression [25]. Adapting processing approaches based on real-time data characteristics improves throughput and reduces latency, enhancing data handling efficiency [43]. However, computational intensity in selecting optimal point locations and storing data in floating-point precision remains challenging [44]. Compressibility of a color image depends on its spatial

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structure, intensity variations, and color differences, with the binary version capturing fundamental spatial characteristics [4].

Data reduction's effectiveness is limited by the lack of a universal binarization scheme optimal for all probability distributions, necessitating tailored compression methods for specific applications [45]. Lossy compression can degrade images, leading to semantic information loss and covariate shifts, complicating model training and testing when data quality differs [46]. In high-dimensional data classification, the curse of dimensionality poses challenges, as traditional methods struggle to generalize effectively. This necessitates advanced techniques to manage and reduce dimensionality without sacrificing accuracy [47]. Performance degradation from lossy image compression underscores the need for efficient data storage and transmission solutions [48].

Benchmarking efforts aim to preserve image quality while minimizing data size through lossy compression methods [30]. These initiatives are crucial for advancing data reduction, ensuring compression techniques remain effective and computationally efficient for real-time applications [49].

3 Image and Video Compression Techniques

Category	Feature	Method
Traditional Compression Methods	Efficiency Improvement	JIQN[50], OPC[13]
Wavelet-based Compression Techniques	Wavelet Decomposition	DHWT[51]
Neural Network-based Compression	Quality-Preserving Methods Adaptive Compression Techniques Integrated Inference Approaches Hybrid Compression Strategies	FLLIC[36] CHM[52] cResNet[12] LHVCF[53]
Hybrid and Adaptive Compression Techniques	Data Grouping Strategies Hierarchical and Structural Methods Randomized Techniques Machine Learning Enhancements	CBQ[44] VVC[54] BMVC[40] DR[46], CAE[33]

Table 1: This table provides a comprehensive overview of various image and video compression techniques categorized into traditional, wavelet-based, neural network-based, and hybrid/adaptive methods. It highlights the key features and specific methods associated with each category, illustrating the evolution and diversity of approaches in the field of compression technology.

The progression of image and video compression techniques has transitioned from traditional methods to advanced strategies that address the growing need for efficiency and quality. Table 1 presents a detailed classification of image and video compression techniques, showcasing the progression from traditional methods to advanced neural network-based and hybrid strategies. Additionally, Table 3 provides a comprehensive comparison of traditional, wavelet-based, and neural network-based image and video compression techniques, illustrating the advancements in compression efficiency and quality preservation. This section examines the foundational impact of traditional compression methods like JPEG, JPEG2000, and H.264, which have been instrumental in digital data management. Despite their effectiveness, these methods often involve trade-offs between compression rates and image quality, necessitating a comprehensive understanding before advancing to more innovative techniques.

3.1 Traditional Compression Methods

Traditional compression methods, including JPEG, JPEG2000, and H.264, have been crucial in managing the rapid growth of digital data by effectively reducing file sizes while maintaining acceptable quality. As illustrated in Figure 2, these methods can be categorized to highlight key techniques and innovations, including emerging approaches such as Optimized Pre-Compensating Compression and End-to-End Joint Learning. However, machine learning-based video compression algorithms are now surpassing these legacy codecs by optimizing data encoding and minimizing redundancies in video frames. Research into lossless techniques, such as JPEG XL, highlights the ongoing need for innovation to meet the increasing demands of digital information across various fields [55, 42, 56, 30]. These traditional methods typically use Discrete Cosine Transform (DCT) and Singular Value Decomposition (SVD) to achieve high compression ratios, sometimes at the expense of image quality.

JPEG, a widely used lossy compression standard, utilizes DCT to transform spatial data into frequency domain coefficients, reducing spatial redundancies by quantizing less perceptible frequency components. This allows significant compression, though the balance between compression rate and image quality remains challenging, as higher compression ratios can lead to detail loss and artifacts [13].

JPEG2000 enhances the original JPEG standard by employing wavelet transform techniques, achieving higher compression ratios and better image quality at low bit rates. Its advantages, including compression efficiency and scalability, facilitate progressive transmission and region-of-interest coding, albeit requiring more computational resources [30].

H.264 is renowned for its exceptional compression efficiency and adaptability, supporting applications like real-time streaming and high-definition video storage. Recent advancements, such as multi-resolution tier multi-bitrate encoding, have improved computational efficiency while maintaining coding quality. H.264 employs motion compensation and intra-frame prediction to reduce temporal and spatial redundancies [57, 38].

Innovations like Optimized Pre-Compensating Compression (OPC) enhance standard methods by incorporating pre-processing steps that improve the quality-rate trade-off [13]. Advanced techniques, such as end-to-end joint learning schemes, further refine this balance, reflecting the evolving landscape of traditional compression techniques [50].

SVD-based methods enhance image compression by providing a compact representation of original data, improving Peak Signal-to-Noise Ratio (PSNR) while managing bits per pixel (bpp). The ongoing development of innovative approaches, such as OPC, demonstrates the potential for high compression efficiency without sacrificing image quality.

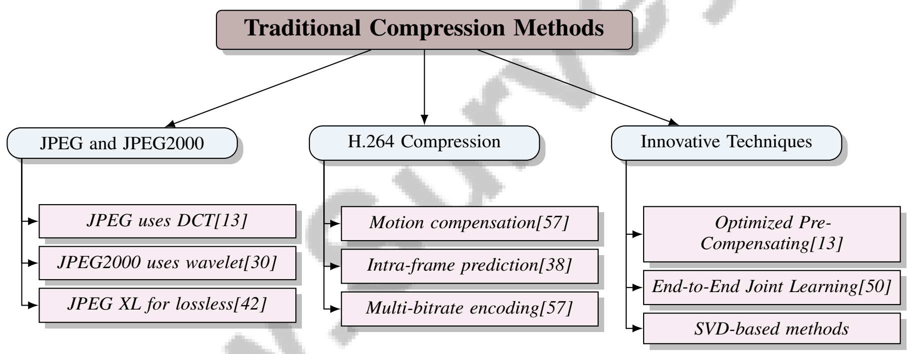

Figure 2: This figure illustrates the categorization of traditional compression methods, highlighting key techniques and innovations in JPEG, JPEG2000, and H.264, alongside emerging approaches like Optimized Pre-Compensating Compression and End-to-End Joint Learning.

3.2 Wavelet-based Compression Techniques

Wavelet-based compression techniques represent a significant advancement in image and video compression, offering superior performance in compression efficiency and quality preservation compared to traditional methods like DCT and Vector Quantization (VQ). These techniques leverage wavelets' multiresolution properties to minimize blocking artifacts and achieve higher energy compaction, resulting in high-quality reconstructed images. Analyses show that wavelet methods, including Embedded Zerotree Wavelet (EZW) and Set Partitioning in Hierarchical Trees (SPIHT) coding, enhance image fidelity and optimize storage and transmission efficiency, making them valuable for applications requiring high compression ratios and clarity [58, 59, 60, 30, 61].

The SPIHT algorithm efficiently encodes image data by exploiting spatial correlations within the wavelet-transformed domain using a hierarchical tree structure, enabling progressive transmission and scalable compression. Set Partitioning in Hierarchical Trees (SPECK), similar to SPIHT, compresses image data by partitioning it into smaller blocks, enhancing compression efficiency and error resilience [62].

Recent advancements, such as Discrete Hybrid Wavelet Transform (DHWT), improve compression ratios while maintaining better image quality in noisy conditions [51]. Additionally, the development of a 3-D affine wavelet-like transform marks a significant step in optimizing compression efficiency for complex datasets.

Shape optimization techniques have been explored to determine optimal pixel sets for image reconstruction through PDE-based approaches, minimizing data fitting errors in the L2-norm between original images and their reconstructions. These methods enhance image quality and denoising effects, with specific PDEs, such as edge-enhancing diffusion, showing promise in reconstructing image structures. Hybrid codecs that strategically select regions for inpainting rather than individual pixels have been developed, outperforming traditional JPEG compression [63, 64].

Wavelet-based techniques continue to evolve, offering robust solutions for image data compression, particularly in noise-resilient scenarios. The ongoing development of innovative techniques, such as the 3-D affine wavelet-like transform, highlights advancements in volumetric image compression, essential for efficiently transmitting and storing images in biological research and clinical practice. This approach addresses traditional methods' limitations, enhancing performance across various datasets and demonstrating superior results compared to existing methods like HEVC [18, 65, 66].

3.3 Neural Network-based Compression

Advancements in neural network-based compression, particularly through deep convolutional neural networks (CNNs), have significantly enhanced image and video compression efficiency and quality. These developments address the challenge of compressing vast amounts of visual data generated by modern acquisition devices, surpassing traditional hybrid coding frameworks. A systematic review highlights innovative approaches leveraging deep learning to optimize rate-distortion performance, balancing file size reduction with image quality preservation [67, 8]. CNNs are particularly effective in capturing intricate visual patterns, improving compression ratios while maintaining high fidelity [33].

Learned image compression methods focus on optimizing encoding and decoding processes by learning complex patterns from visual data. The I2Icodec framework integrates image-to-image translation with compression, allowing efficient visual data processing without separate codecs [11]. Lightweight hybrid video compression methods incorporating binary random coding patterns exemplify the ongoing evolution of neural network-based techniques [53].

Functionally lossless image compression methods, such as Quantum JPEG Compression (QJC), introduce a novel approach by storing quantized JPEG coefficients in qubits, reducing data redundancy while maintaining high-quality visual representations [36]. Machine learning algorithms enhance data management efficiency, exemplified by the cResNet architecture, which operates directly on compressed image representations, optimizing processing efficiency [12]. These methods focus on preserving important visual features to improve machine vision analytics tasks, such as object detection and classification [52].

The exploration of functionally lossless methods, such as Fully Lossless Image Compression (FLIC), demonstrates the potential for high compression efficiency. As digital content volume expands, integrating neural networks into image and video compression processes is vital. Advanced algorithms, particularly CNNs, offer innovative solutions to enhance compression efficiency, significantly outpacing traditional coding methods. Recent studies highlight their capability to optimize compression for various tasks, addressing challenges posed by rapidly growing visual data, paving the way for next-generation standards that balance data reduction with visual quality [67, 68, 33, 69, 70].

3.4 Hybrid and Adaptive Compression Techniques

Hybrid and adaptive compression techniques represent a significant evolution in image and video compression, leveraging multiple methods to enhance efficiency and quality. Table 2 provides a comprehensive overview of different hybrid and adaptive compression techniques, detailing their integration methods, adaptability, and ability to preserve quality, thereby underscoring their relevance in modern image and video compression applications. These techniques combine traditional methodologies, such as DCT and Wavelet Transform, with advanced processing frameworks to overcome conventional standards' limitations. This integration addresses high compression ratios while preserving image quality, as evidenced by improved metrics like compression efficiency and scalability [30, 29, 32, 42].

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Method Name	Method Integration	Adaptivity	Quality Preservation
VVC[54]	Traditional Compression Techniques	-	Maintain Image Quality
DR[46]	Dataset Restoration Approach	Not Explicitly Mentioned	Semantic Integrity
CAE[33]	Adaptive Arithmetic Coding	Adaptive Arithmetic Coding	High-density Compression
BMVC[40]	Binary Random Coding	Real-time Encoding	High-dimensional Data
CBQ[44]	Clustering Strategies Integration	Optimize Quantisation Parameters	Reconstruction Fidelity Optimization

Table 2: Table illustrating various hybrid and adaptive compression methods, highlighting their integration techniques, adaptivity, and quality preservation capabilities. Each method demonstrates unique approaches to enhancing compression efficiency and maintaining image quality, reflecting the ongoing advancements in compression technologies.

Hybrid compression approaches integrate classical methods with modern innovations to enhance performance. [61] categorize existing research into various hybrid techniques that optimize compression efficiency by exploiting different methods. For example, combining classical methods with clustering-based quantization optimizes data selection for inpainting, enhancing compression ratios while maintaining high image quality [63, 39].

DCT-based compression methods that combine binary random coding patterns with novel quantization techniques, such as the V-variable image compression method, show promise in achieving higher compression ratios without sacrificing visual quality [54]. Parametric distributions in dithering approaches further minimize quantization errors [46].

Machine learning integration into compression frameworks has led to adaptive techniques capable of optimizing parameters in real-time based on input data characteristics [33]. These advancements reflect the ongoing evolution of compression technologies, driven by the need for more efficient and flexible solutions to manage increasing digital data volumes [61].

Innovative approaches, such as the I2Icodec framework, highlight hybrid methods' potential to enhance visual data processing without separate codecs [33]. The use of binary random coding patterns in Block Modulating Video Compression (BMVC) exemplifies hybrid methods that achieve high compression ratios while maintaining quality [40].

Advanced algorithms utilizing clustering-based quantization and PDE-based image compression underscore ongoing efforts to improve compression efficiency and quality preservation [44]. By combining multiple methods, hybrid and adaptive compression techniques offer a promising path forward in addressing modern image and video compression challenges, ensuring efficient data storage and transmission without compromising quality.

The development of hybrid and adaptive compression techniques remains a dynamic research area, driven by the need to address traditional methods' limitations and meet increasingly complex and high-resolution datasets' demands. As image and video compression evolves, integrating diverse methodologies, particularly machine learning techniques, is anticipated to significantly influence developing more efficient and effective compression technologies. Recent advancements, such as Video Coding for Machines (VCM), highlight the potential of collaborative compression strategies for various artificial intelligence applications [71, 72, 68, 73, 56].

Feature	Traditional Compression Methods	Wavelet-based Compression Techniques	Neural Network-based Compression
Compression Efficiency	Moderate Efficiency	High Efficiency	Very High Efficiency
Quality Preservation	Trade-offs Exist	High Quality	High Fidelity
Method Integration	Dct, Svd	Wavelet Transform	Cnn-based

Table 3: Comparison of image and video compression techniques, highlighting the efficiency, quality preservation, and integration methods of traditional, wavelet-based, and neural network-based approaches. Traditional methods like DCT and SVD offer moderate efficiency with trade-offs in quality, while wavelet-based techniques achieve higher efficiency and quality. Neural network-based methods demonstrate very high efficiency and fidelity, utilizing CNN-based integration for optimal compression performance.

4 Compression in Electron and Optical Microscopy

Effective management of high-resolution microscopy images is critical, necessitating sophisticated data compression techniques that retain essential details for accurate analysis. This section examines various methodologies for optimizing high-resolution image management, focusing on advancements addressing microscopy's unique challenges. By exploring traditional and contemporary strategies, we elucidate the mechanisms underpinning effective image compression and their applications in high-resolution microscopy contexts.

4.1 Techniques for High-Resolution Image Management

Managing high-resolution microscopy images demands advanced compression techniques capable of handling substantial data volumes while preserving intricate details. Traditional methods like JPEG and JPEG2000 utilize DCT and wavelet-based techniques to minimize data redundancy and achieve significant compression ratios. JPEG, a widely used lossy format, reduces file sizes through color space conversion, downsampling, DCT, quantization, and entropy encoding, maintaining perceptual quality. DCT is noted for its compression efficiency and image fidelity, evidenced by high PSNR and SSIM scores, making it suitable for applications where image quality is paramount [35, 30, 74, 75]. However, these methods often struggle with high-resolution microscopy and histopathological imaging, where image quality is critical.

Wavelet-based compression techniques offer superior performance in compression efficiency and quality preservation. Algorithms like SPIHT exploit spatial correlations within the wavelet-transformed domain, enabling scalable compression and progressive transmission [62]. These methods effectively utilize spatial and frequency domain correlations, enhancing both compression efficiency and error resilience. The development of a 3-D affine wavelet-like transform, specifically trained to adapt to local characteristics of volumetric images, marks a notable step forward in optimizing compression for complex datasets.

Neural network-based compression techniques further revolutionize high-resolution image management. CNNs capture complex visual patterns, significantly improving compression ratios while maintaining high visual fidelity [33]. Learned image compression methods focus on optimizing rate-distortion performance, balancing file size reduction with image quality preservation [8].

Machine learning algorithms enhance data management efficiency in compression frameworks. For instance, the cResNet architecture operates directly on compressed image representations, optimizing processing efficiency by eliminating the need for decoding [12]. These methods prioritize the preservation of important visual features, improving machine vision analytics tasks and enhancing the utility of compressed visual representations in microscopy.

Hybrid and adaptive compression techniques leverage the strengths of multiple methods to achieve enhanced efficiency and quality. Integrating JPEG with PDE-based techniques employs clustering-based quantization to optimize data selection for inpainting, addressing inefficiencies in traditional methods while maintaining high image quality [39]. This dynamic adaptation of compression parameters based on content ensures optimal performance across diverse applications [33].

Ongoing developments, such as lightweight hybrid video compression methods incorporating binary random coding patterns, exemplify the evolution of hybrid and adaptive techniques [53]. Multi-layer representation schemes enhance performance in facial image compression, relevant for high-resolution image management in microscopy [7]. Additionally, methods encoding binary images using learned dictionaries of various patch sizes achieve efficient lossless compression applicable in high-resolution microscopy [4].

Techniques such as the VVMIC framework, designed for compressing volumetric medical images while preserving human-oriented reconstruction and machine-oriented segmentation tasks, illustrate the potential of advanced compression methods in managing high-resolution microscopy images. Furthermore, methods like CARP, which infer optimal pixel permutations through Bayesian modeling and recursive partitioning, enable efficient multi-dimensional image compression [2].

Integrating advanced image compression techniques, especially those leveraging deep learning, is crucial for efficiently storing and transmitting high-resolution microscopy images while maintaining quality. As modern bioimaging technologies produce vast data volumes, these innovative methods significantly reduce data size and enhance downstream applications, such as supervised learning models for automated analysis. AI-based compression methods outperform traditional techniques, achieving superior compression ratios with minimal impact on image fidelity and predictive accuracy, reflecting the ongoing evolution of compression technologies [26, 3, 30, 17, 76].

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As illustrated in Figure 3, the hierarchical categorization of techniques for high-resolution image management highlights traditional, advanced, and innovative approaches, providing a comprehensive overview of the landscape in this rapidly evolving field.

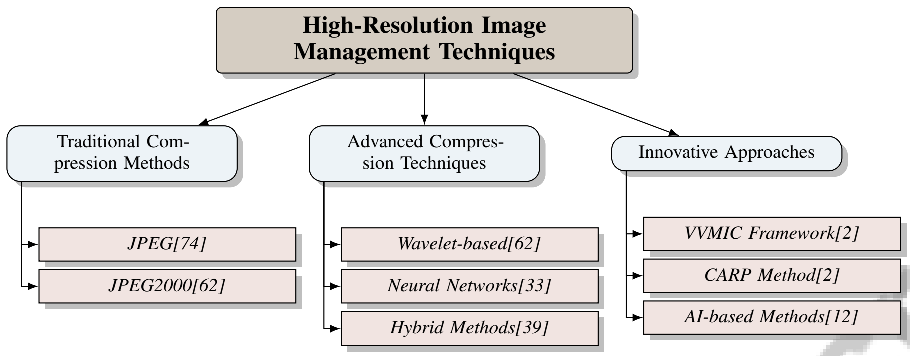

Figure 3: This figure illustrates the hierarchical categorization of techniques for high-resolution image management, highlighting traditional, advanced, and innovative approaches.

4.2 Challenges in High-Resolution Image Compression

High-resolution image compression, particularly in microscopy, faces challenges due to the need to preserve intricate details essential for accurate analysis while achieving substantial data reduction. Traditional codecs like JPEG and JPEG2000, relying on linear transforms such as DCT and wavelet-based techniques, often struggle to meet the specific requirements of high-resolution microscopy and histopathological imaging. These methods can introduce artifacts, particularly at lower bitrates, degrading visual quality and posing significant issues in precision-dependent fields [30, 18, 74].

A critical challenge in compressing microscopy data is the tendency of existing lossy methods to distort or eliminate statistically significant image features. This is particularly problematic in medicine and remote sensing, where maintaining image integrity is crucial for accurate analysis and diagnosis [77]. The irreversible loss of important semantic information during lossy compression can lead to covariate shifts, complicating the accurate interpretation of compressed data [78].

The high computational cost associated with many advanced compression methods, especially those involving large neural networks, presents another significant challenge. These methods often require substantial computational resources and extended processing times, hindering their application in real-time scenarios where efficiency is paramount. Additionally, the lack of a unified experimental framework and variability in codec implementations can affect the generalizability of results, complicating the evaluation of compression techniques [79].

Balancing compression efficiency and quality preservation remains a persistent challenge. While transform-based methods like DCT effectively compress high-frequency textures, they often struggle with smooth regions, creating performance gaps that impact overall image quality [63]. The inability of existing methods to optimize performance based on real-time data characteristics results in suboptimal visual quality.

Existing benchmarks primarily focus on traditional compression methods, often failing to provide adequate compression ratios and quality, limiting applicability in modern bioimaging contexts [3]. The core obstacle in volumetric medical image compression is that existing methods either optimize for human perception or machine vision, leading to inefficiencies in storage and analysis [80]. Moreover, metrics like PSNR and SSIM do not accurately reflect the perceived quality of SVD-compressed images, resulting in misleading evaluations [1].

5 Lossy vs. Lossless Compression

5.1 Trade-offs in Compression Efficiency and Quality

Selecting between lossy and lossless compression methods requires evaluating application-specific needs, balancing file size reduction with data integrity. Lossless formats like JPEG XL and FLIF manage large image datasets without quality loss, whereas lossy methods, such as the Discrete Cosine Transform (DCT), prioritize reduced file sizes, allowing some data loss [81, 30, 42]. Lossy compression, particularly DCT, is beneficial for applications like streaming services where transfer efficiency is crucial, despite some quality degradation. Conversely, fields requiring high precision, such as medical imaging, benefit from lossless methods that ensure perfect data reconstruction [4]. The IAMBTC method exemplifies this by achieving high Peak Signal-to-Noise Ratio (PSNR) values with low bits per pixel (bpp), offering efficient compression [82].

Lossless compression struggles to achieve significant file size reductions, unlike lossy techniques, which is a drawback in storage-constrained scenarios. Hybrid methods combining lossy and lossless techniques, like JPEG with Partial Differential Equation (PDE)-based methods, have shown potential in achieving high compression ratios without compromising quality [7, 63, 39]. These approaches optimize data selection for inpainting, addressing traditional inefficiencies.

Neural network-based techniques have advanced hybrid and adaptive methods, leveraging deep learning, especially convolutional neural networks (CNNs), to improve coding performance and enhance compression ratios [67, 68, 83, 61, 84]. These innovations integrate semantic and visual information, optimizing frameworks for next-generation coding standards.

Advanced methods like CARP adapt the compression process to image features, maintaining critical details while achieving high compression rates [2]. Functionally lossless approaches, such as Quantum JPEG Compression (QJC), reduce data redundancy while ensuring high-quality visual outputs [36].

In video compression, research highlights trade-offs between fast decoding times, lower model complexity, and high-quality output [53, 16]. Balancing compression efficiency with quality preservation remains crucial to meet contemporary application demands.

In recent years, the importance of effective data management has become increasingly evident, particularly as the volume and complexity of data continue to grow. A comprehensive understanding of data reduction techniques is essential for optimizing data handling processes. As illustrated in Figure 5, this figure illustrates the hierarchical classification of image compression methods, highlighting key lossy, lossless, and advanced techniques. It emphasizes the integration of traditional and modern approaches, including neural networks and hybrid methods, to optimize compression efficiency and quality. This visual representation not only enhances our understanding of the various methodologies but also underscores the dynamic nature of the field as it adapts to emerging data challenges.

6 Data Reduction and Its Importance

6.1 Data Reduction Techniques

Data reduction techniques are essential for simplifying datasets while retaining critical information, thereby enhancing processing efficiency and optimizing storage in data-intensive fields. These strategies are crucial for achieving high compression ratios with minimal quality loss, especially given the increasing volume and complexity of digital data [25].

As illustrated in Figure 6, the hierarchical categorization of data reduction techniques highlights clustering-based methods, adaptive methods, and future directions. Each category encompasses specific techniques and frameworks that significantly contribute to enhancing data reduction efficiency and performance.

Clustering-based quantization methods form a foundational approach in data reduction, optimizing data selection for inpainting while preserving spatial and temporal energy. By identifying optimal pixel sets for reconstruction, these methods significantly reduce data size without compromising essential image features [39]. PDE-based image compression augments wavelet techniques by accurately capturing key image features and minimizing redundancy. Shape optimization techniques dynamically prioritize relevant pixels for reconstruction, enhancing compression efficiency and image quality. Iterative algorithms adaptively modify pixel data during inpainting, employing advanced mathematical models such as time-dependent PDEs and -convergence methods, improving image restoration accuracy in noisy conditions [64, 18, 85, 30].

Recent advancements focus on adaptive methods that optimize compression parameters in real-time according to input data characteristics. The I2Icodec framework exemplifies this by merging image-to-

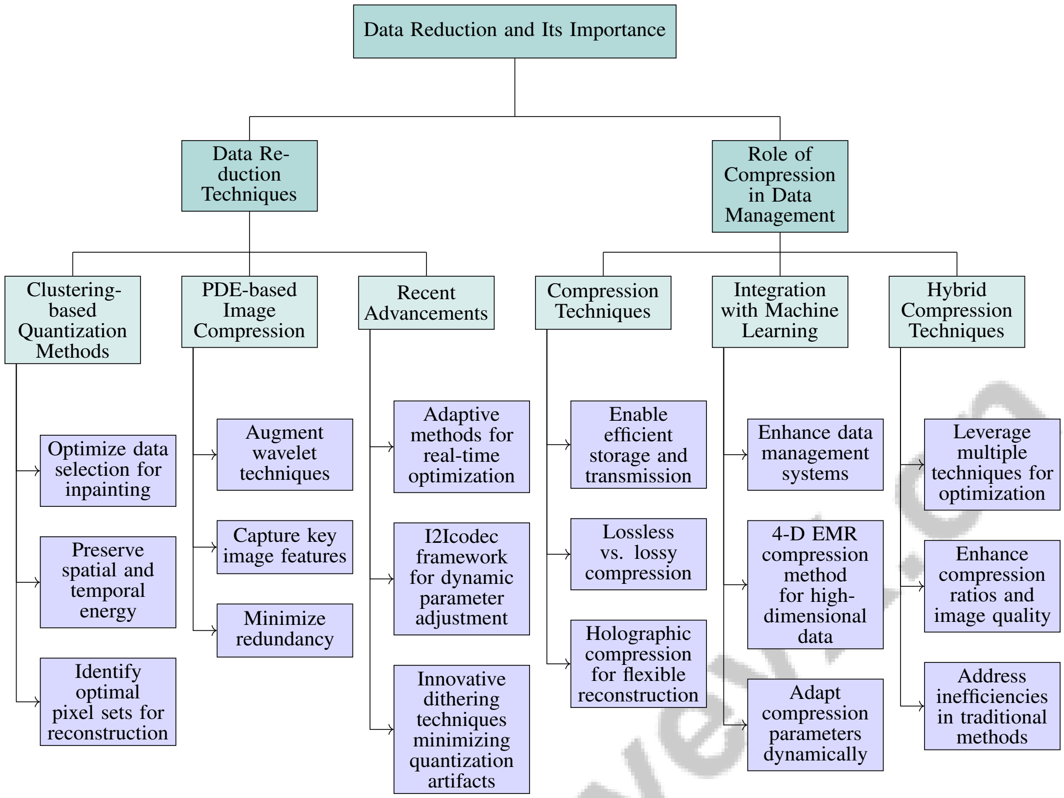

Figure 4: This figure illustrates the hierarchical structure of data reduction techniques and their roles in data management. It categorizes the primary methods and recent advancements in data reduction, emphasizing clustering-based quantization, PDE-based image compression, and adaptive techniques. Additionally, it highlights the integration of machine learning into compression frameworks and the evolution of hybrid compression techniques to address the challenges posed by high-resolution images and complex datasets.

image translation with compression to dynamically adjust parameters for optimal performance across diverse applications [33]. Innovative dithering techniques utilizing parametric distributions have emerged, effectively minimizing quantization artifacts while maintaining low entropy in compressed data [46]. Such advancements enhance compression performance across various applications, from multimedia to scientific research, where efficiency and quality are paramount.

Ongoing research reflects a shift towards more adaptive and efficient data reduction methods. The integration of machine learning techniques is expected to advance image and video compression technologies. For instance, the method proposed by [7] reduces exponential complexity associated with single-layer approaches while maintaining high fidelity and efficient memory storage. Moreover, CARP's adaptability to various image dimensions, minimal tuning requirements, and capability for progressive transmission offer substantial advantages in data reduction [2].

Future research may focus on optimizing energy ratio calculations in SVD methods, particularly for color images and hybrid compression algorithms [1]. Additionally, exploring the computational efficiency of methods like IAMBTC for real-time image and video transmission could further propel the field [82].

6.2 Role of Compression in Data Management

Compression is crucial to data management and storage, particularly given the exponential growth of digital data volumes. It enables efficient storage and transmission by reducing file sizes through techniques like lossless and lossy compression. Lossless compression allows for exact data recovery, while lossy compression prioritizes visual fidelity over perfect accuracy, making it especially useful

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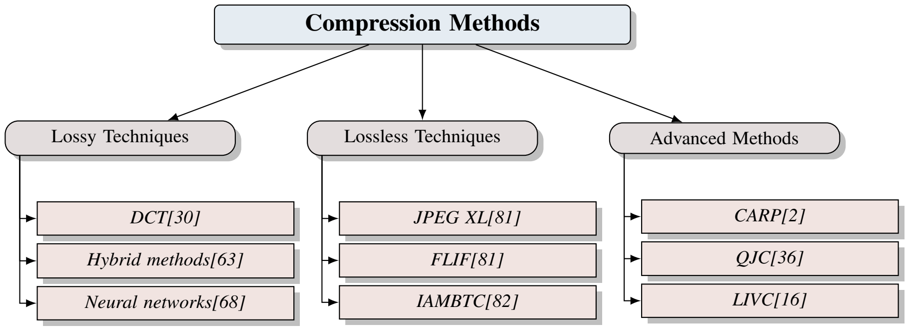

Figure 5: This figure illustrates the hierarchical classification of image compression methods, highlighting key lossy, lossless, and advanced techniques. It emphasizes the integration of traditional and modern approaches, including neural networks and hybrid methods, to optimize compression efficiency and quality.

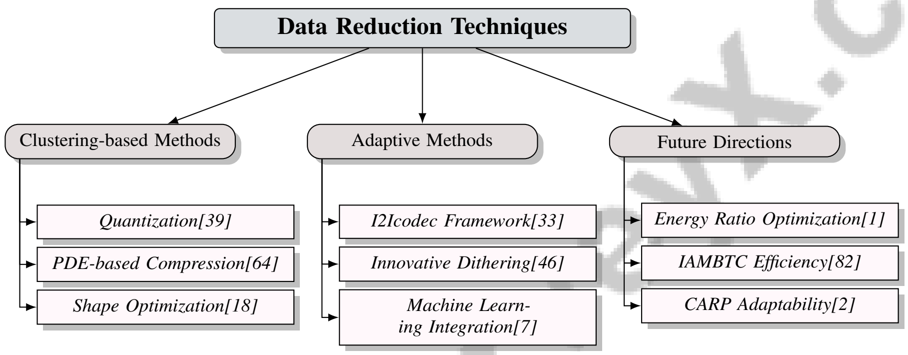

Figure 6: This figure illustrates the hierarchical categorization of data reduction techniques, highlighting clustering-based methods, adaptive methods, and future directions. Each category includes specific techniques and frameworks that contribute to enhancing data reduction efficiency and performance.

for multimedia files like images and videos. Advanced methods, such as holographic compression, create multiple compressed representations of data, allowing flexible reconstruction quality based on the number of representations used, optimizing storage efficiency without sacrificing data integrity [26, 28, 25]. By effectively reducing data sizes while preserving the integrity and quality of the original content, compression techniques facilitate more efficient data storage and management solutions. Traditional methods like JPEG, JPEG2000, and H.264 have significantly reduced file sizes by leveraging techniques such as the DCT and wavelet-based approaches, which minimize data redundancy and optimize compression ratios.

Despite their widespread use, traditional compression methods often encounter limitations with high-resolution images, particularly regarding compression ratios and decoding speeds. This has spurred the development of more advanced techniques that promise better compression efficiency and quality preservation. Deep learning-based compression methods have emerged as a significant advancement, outperforming traditional methods in both compression ratio and reconstruction quality, with minimal impact on downstream predictions [3].

The integration of machine learning into compression frameworks shows significant promise in enhancing data management systems. For instance, the 4-D EMR compression method improves coding efficiency and visual quality, effectively addressing the unique challenges posed by high-dimensional data [86]. This advancement underscores the capacity of machine learning algorithms to dynamically adapt compression parameters based on input data characteristics, ensuring optimal performance across diverse applications.

In medical imaging, compression techniques are crucial for managing large datasets generated by high-resolution imaging modalities. Deep learning-based methods have demonstrated significant reductions in storage costs and improved data transfer efficiency, particularly for high-color medical images. The integration of compression techniques with image-to-image translation frameworks further emphasizes the importance of encoding efficiency in distributed data management systems [57].

The evolution of hybrid compression techniques highlights the changing landscape of compression technologies. These methods leverage the strengths of multiple techniques to optimize data selection for inpainting, effectively addressing inefficiencies in traditional methods by enhancing compression ratios while maintaining high image quality. For instance, the 4-D EMR method significantly enhances coding efficiency and visual quality, providing a robust solution for managing complex datasets [86].

The challenges posed by high-resolution images, particularly in fields like electron microscopy, underscore the need for advanced compression techniques capable of achieving high compression ratios and fast decoding speeds. Developing efficient algorithms tailored to the unique demands of microscopy and other data-intensive applications is essential for optimizing data management and storage solutions [87].

7 Applications and Case Studies

Compression techniques are integral across various fields, particularly in medical imaging, where managing large datasets is critical. This section delves into the application of these methods in medical imaging, emphasizing their role in enhancing diagnostics and optimizing resource utilization.

7.1 Medical Imaging Applications

Compression is crucial for handling the extensive datasets generated by imaging modalities like MRI, CT, and electron microscopy, facilitating the storage, transmission, and analysis of high-resolution medical images while preserving essential diagnostic information. Methods like IAMBTC improve Peak Signal-to-Noise Ratio (PSNR) from 33.62 to 34.83 and reduce bits per pixel (bpp) from 2 to 1.75, demonstrating efficiency in medical imaging data management [82]. Advanced compression techniques support diverse datasets related to medical conditions and anatomical studies, with setups involving adult drosophila brain and human heart images providing a framework for evaluating algorithm performance in maintaining diagnostic quality [65].

These algorithms not only enhance data management efficiency but also aid in developing AI-driven diagnostic tools. Lossless techniques like JPEG XL and innovative methods such as Deep Semantic Image Compression (DeepSIC) integrate semantic information, reducing computational burdens in tasks like object recognition, thus boosting AI application performance in MRI and CAT scan analysis [88, 42, 89, 66]. These techniques decrease storage and transmission requirements of high-resolution images, enabling faster processing and real-time decision-making, particularly beneficial for telemedicine under bandwidth constraints.

The integration of machine learning into compression frameworks promises improved efficiency in medical imaging systems by dynamically adjusting compression parameters based on input data characteristics. Recent methods have produced smaller compressed files than traditional codecs like JPEG and WebP while maintaining high fidelity, as indicated by PSNR and SSIM metrics. Joint optimization frameworks in medical imaging, like MRI, demonstrate that lossy compression can enhance reconstruction quality, achieving notable PSNR gains [29, 30, 2, 90, 91].

7.2 Scientific Research and Data Handling

In scientific research, image and video compression are vital for managing large datasets. Efficient storage and transmission of high-resolution images and videos facilitate handling vast data generated by advanced imaging technologies like electron and optical microscopy [14]. Balancing data reduction with preserving essential information is a primary challenge; lossy methods significantly reduce file sizes but require careful trade-off considerations between compression efficiency and image quality [5, 17].

Machine learning integration enhances data management systems' efficiency, with architectures like cResNet optimizing processing by working directly on compressed representations, eliminating the need for decoding [12]. Adaptive methods optimize compression parameters in real-time based on input characteristics [33]. Functionally lossless methods, such as Quantum JPEG Compression (QJC), achieve high efficiency while maintaining image quality, suitable for medical imaging and scientific research applications [36].

Wavelet-based techniques, including SPIHT and EBCOT, show promise in managing large datasets by decomposing images into coefficients, achieving high compression ratios while preserving visual fidelity, crucial for accurate analysis and interpretation [51, 30, 18]. Clustering-based quantization optimizes data selection for inpainting, reducing size while preserving essential features [39]. Machine learning integration enhances data management efficiency, allowing real-time adaptation of compression parameters [33].

The evolution of compression technologies, driven by the demand for efficient solutions, significantly impacts scientific research and data handling. As digital data volume grows, developing advanced techniques—such as lossless methods in JPEG XL and holographic approaches—aims to enhance storage efficiency and transmission solutions while maintaining data integrity and quality. Research emphasizes predictive coding, transform coding, and context modeling to improve compression ratios, facilitating effective data recovery and reconstruction [26, 42].

7.3 Digital Media and Entertainment

The digital media and entertainment industries have grown significantly, driven by high-quality visual content demand and digital device adoption. Advancements in video compression, such as collaborative compression and intelligent analytics, enhance visual content delivery and optimize feature extraction for machine vision applications. The industry increasingly utilizes methods like deep learning-based coding tools and MPEG standards to meet evolving consumer and machine needs [92, 72]. Compression techniques are crucial, enabling efficient storage, transmission, and streaming of multimedia content across various devices and platforms.

Traditional standards like JPEG, JPEG2000, and H.264 have been instrumental in digital media development, delivering high-quality content at reduced sizes. However, the demand for high-resolution content, such as 4K and 8K videos, exposes limitations in compression efficiency and quality preservation [30]. Recent advancements focus on developing efficient algorithms using machine learning. Neural network-based methods improve compression efficiency and visual quality, optimizing rate-distortion performance for high-quality content delivery with minimal data usage [8, 33].

Machine learning integration leads to adaptive techniques that dynamically adjust compression parameters, ensuring optimal performance across multimedia applications, from streaming services to digital media storage [33]. Hybrid video compression methods with binary random coding patterns illustrate ongoing technological evolution, enhancing efficiency and quality for critical applications [53].

Research in compression techniques reflects the adaptive landscape of digital media, with innovations like the "Hybrid-Analyze-Then-Compress" approach and Video Coding for Machines (VCM), emphasizing collaborative compression and intelligent analytics. These methods address bandwidth limitations and demand for efficient processing, enhancing visual content delivery [29, 72, 92, 56]. As digital content continues to proliferate, advanced compression methods, including neural network-based and hybrid techniques, will play a pivotal role in shaping the industry's future, ensuring high-quality media can be efficiently stored, transmitted, and streamed across diverse platforms [11].

8 Future Trends and Challenges

8.1 Integration of AI and Machine Learning in Compression

Integrating AI and ML into image and video compression is revolutionizing the field by enhancing efficiency and preserving image quality. These technologies adaptively process data, achieving superior PSNR and SSIM scores compared to traditional methods like DCT. Frameworks such as Kuchen improve codec performance, enhancing data transmission and storage without sacrificing perceptual fidelity [30, 32]. AI-driven methods, like the I2Icodec framework, streamline data management through image-to-image translation, eliminating separate codecs [11]. CNNs significantly enhance neural network-based compression by learning complex visual patterns, optimizing both encoding and decoding [33]. Studies highlight learned compression methods' potential to balance file size reduction with image quality [8].

Neural network-based techniques are transforming adaptive strategies for managing digital visual data, addressing the limitations of traditional hybrid coding frameworks. Deep CNNs enhance compression by jointly compressing semantic and visual information, optimizing representation for both human and machine vision [29, 67, 68, 83, 93]. As digital content grows, neural networks' role in optimizing compression is expected to expand, driving advancements in the field. Machine learning algorithms, like the cResNet architecture, improve data management by operating directly on compressed images, preserving essential visual features for tasks such as object detection [12, 52].

AI and ML integration signifies a shift towards adaptive methods for digital data management. Video Coding for Machines (VCM) unifies video and feature compression, enhancing data representation efficiency with deep learning and predictive models. Codebook-based hyperpriors improve entropy estimation, enabling effective compression for applications like smart cities and IoT [71, 72, 73, 52, 88]. Lightweight hybrid methods, using binary random coding patterns, exemplify neural network-based advancements, enhancing compression efficiency and quality for multimedia and scientific applications [53]. Future compression technology will increasingly rely on AI and ML, promising transformative adaptive methods for managing growing digital data volumes. Emerging techniques, including deep learning-based coding tools, aim to optimize visual data representation, supporting applications from smart city analytics to advanced visual recognition [71, 72, 73, 94, 88]. As demand for high-quality content rises, advanced compression techniques will be vital for efficient storage and transmission.

8.2 Challenges and Future Directions

The rapid growth of digital data necessitates efficient compression solutions. Despite progress, challenges remain in high-resolution image compression and integrating ML techniques into existing frameworks. Standardized approaches are needed to retain salient image features for downstream ML applications. While traditional algorithms and learning-based methods show promise, optimizing them for both efficiency and quality is challenging. Unified preprocessing frameworks attempt to address these issues, but learning-based methods face standardization and complexity hurdles [95, 30, 88, 32].

High-resolution compression must balance data reduction with quality preservation. Analyses of lossy algorithms like DCT and Wavelet Transform emphasize maintaining high PSNR and SSIM scores. Semantic image compression can drastically reduce data size while preserving quality, indicating ongoing evolution in the field [30, 79, 96]. Traditional codecs often struggle with high-resolution demands, introducing artifacts that degrade quality, particularly in precision-critical fields.

ML integration offers promising efficiency and quality enhancements. Neural network-based methods using CNNs improve rate-distortion performance, balancing file size reduction with quality retention [8, 5]. Hybrid and adaptive techniques integrate traditional and advanced methods, addressing conventional standards' limitations while achieving high compression ratios without quality loss. Ongoing research in compression technologies, including DCT and innovative representations, highlights adaptive strategies for managing digital data volumes. These advancements aim to reduce file sizes while preserving quality, addressing bandwidth and machine vision task challenges. The evolution of compression techniques is crucial for data transmission efficiency and high-quality visual analytics in the big data era [26, 74, 52, 28, 76].

High-resolution compression challenges, especially in electron microscopy, require advanced techniques that achieve high ratios while maintaining quality. Functionally lossless methods, like Quantum JPEG Compression (QJC), represent significant steps in optimizing complex dataset compression [36].

9 Future Trends and Challenges

The rapid evolution of technology necessitates innovative solutions in image and video compression to manage the burgeoning digital visual data. The integration of AI and machine learning within these frameworks emerges as transformative, redefining efficiency and quality. The following subsection

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explores methodologies and applications of AI and machine learning in compression, highlighting their potential to revolutionize the field and address contemporary challenges.

9.1 Integration of AI and Machine Learning in Compression

AI and machine learning integration into image and video compression frameworks marks a pivotal advancement, enhancing both efficiency and quality. Modern technologies have birthed adaptive methods that leverage machine learning algorithms to dynamically adjust parameters based on input data characteristics. Techniques like real-time adaptive image compression and redundancy removal in video encoding significantly boost efficiency, achieving superior compression ratios compared to traditional codecs such as JPEG and WebP, while maintaining high-quality visual reconstructions at low bitrates. Generative compression and machine-oriented video coding further enhance adaptability and resilience to data loss, underscoring their relevance in big data and intelligent analytics [72, 42, 97, 90, 56].

Convolutional Neural Networks (CNNs) for learned image compression capture complex visual data patterns, improving compression ratios and visual fidelity. Their integration into compression frameworks has led to end-to-end optimized methods focusing on balancing rate-distortion performance, thus reducing file sizes while preserving image quality [8]. The I2Icodec framework exemplifies a novel approach by integrating image-to-image translation with compression, facilitating efficient visual data processing without separate codecs [11]. Lightweight hybrid video compression methods, such as those utilizing binary random coding patterns, signify the ongoing evolution of neural network-based techniques [53].

Functionally lossless image compression through Quantum JPEG Compression (QJC) introduces a new dimension by storing quantized JPEG coefficients in qubits, reducing data redundancy while preserving high-quality visual representations [36]. This innovation underscores the potential of integrating quantum computing concepts with traditional compression techniques for superior performance. Machine learning techniques also optimize data management systems; for example, the cResNet architecture operates directly on compressed image representations, eliminating the need for decoding and enhancing processing efficiency [12]. These methods emphasize preserving crucial visual features, bolstering machine vision analytics tasks such as object detection and classification [52].

Exploration of functionally lossless image compression methods, such as the Fully Lossless Image Compression (FLIC) approach, illustrates potential for achieving high compression efficiency while maintaining original image quality [36]. These methods serve as viable alternatives to conventional techniques, particularly for applications demanding high-quality image preservation.

Ongoing research in AI and machine learning integration into compression frameworks signifies a shift toward more adaptive and efficient methods for managing digital visual data. As digital content surges due to the proliferation of acquisition devices, traditional methods struggle to keep pace. Neural networks, particularly deep CNNs, are emerging as essential tools to enhance compression processes. These methodologies not only address conventional coding framework limitations but also significantly improve performance by leveraging deep learning techniques. Recent studies highlight neural networks' capability to optimize coding efficiency and explore innovative approaches, such as joint compression of semantic and visual information, catering to both human and machine vision. Thus, neural network integration is poised to drive substantial advancements, shaping the future of image and video coding standards [67, 69, 68].

9.2 Digital Media and Entertainment

The digital media and entertainment sectors have experienced transformative growth, driven by the demand for high-quality visual content and widespread digital device adoption. Central to this evolution are compression techniques, crucial for enabling efficient storage, transmission, and streaming of multimedia content across diverse platforms. Advanced methods facilitate seamless access to high-quality media on various devices, including mobile phones and high-definition televisions. Techniques like keypoint encoding enhance feature extraction from compressed video, while lossy compression algorithms such as Discrete Cosine Transform (DCT) minimize delays and maintain visual fidelity. Innovations in machine learning for video encoding, such as redundancy removal in subsequent frames, further optimize storage efficiency while preserving content quality, ensuring a smooth user experience [30, 92, 98, 56].

Traditional standards like JPEG, JPEG2000, and H.264 have significantly influenced the media landscape by providing solutions for reducing file sizes while maintaining acceptable quality. JPEG employs DCT to minimize storage and bandwidth requirements, albeit with potential blocking artifacts. JPEG2000 enhances efficiency through wavelet transforms, allowing better quality at lower bit rates. H.264 optimizes video quality and compression, essential for streaming applications. These standards have shaped digital content management and transmission across various platforms, addressing the growing demand for efficient data handling in fields like medicine, remote sensing, and archival [55, 42, 74]. JPEG, widely used for lossy compression, leverages DCT for significant data reduction by quantizing less perceptible frequency components. JPEG2000, an advancement over JPEG, employs wavelet transform techniques to achieve higher compression ratios and better image quality at low bit rates. H.264, known for high compression efficiency, is suitable for diverse applications from streaming to high-definition video storage.

Despite their prevalence, traditional methods encounter limitations, particularly regarding compression efficiency and quality preservation for high-resolution content like 4K and 8K videos [30]. Recent advancements have focused on developing more efficient algorithms leveraging machine learning, which have demonstrated significant improvements in compression efficiency and visual quality, optimizing rate-distortion performance for high-quality visual content delivery with minimal data usage [33].

Machine learning integration into compression frameworks has led to adaptive techniques that dynamically adjust parameters based on processed content, ensuring optimal performance across diverse multimedia applications [33]. The I2Icodec framework, which combines image-to-image translation with compression, exemplifies this evolution [11]. Additionally, lightweight hybrid video compression methods, incorporating binary random coding patterns, signify ongoing technological advancement in digital media and entertainment sectors [53]. These methods yield substantial improvements in efficiency and quality, making them suitable for applications demanding both efficiency and high-quality output.

Exploration of functionally lossless image compression methods, such as the Fully Lossless Image Compression (FLIC) approach, showcases viable alternatives to conventional techniques, particularly for applications requiring high-quality image preservation [36].

10 Future Trends and Challenges

10.1 Integration of AI and Machine Learning in Compression

The integration of AI and ML into image and video compression frameworks significantly enhances both efficiency and quality. Deep learning models, particularly CNNs, dynamically adjust compression parameters based on input data, optimizing the balance between compression and visual fidelity [8]. These learned methods focus on rate-distortion performance, crucial for achieving efficient compression while maintaining high image quality [33]. Frameworks like I2Icodec demonstrate the potential of neural networks by integrating image-to-image translation with compression, eliminating the need for separate codecs [11]. Lightweight hybrid video compression methods, using binary random coding patterns, highlight the evolution of neural network-based techniques [53].

Quantum JPEG Compression (QJC) introduces a novel approach by storing quantized JPEG coefficients in qubits, reducing data redundancy while preserving high-quality visuals, showcasing the potential of combining quantum computing with traditional methods [36]. Machine learning also enhances data management systems, as seen in the cResNet architecture, which processes compressed images directly, optimizing efficiency without decoding [12]. These methods bolster machine vision analytics, crucial for tasks like object detection and classification [52].

Advanced algorithms utilizing clustering-based quantization and PDE-based techniques are part of ongoing efforts to enhance compression efficiency and quality [44]. Hybrid and adaptive methods that combine various techniques present promising solutions to contemporary compression challenges, ensuring efficient storage without compromising quality. Innovations like NCode, which replaces hand-crafted transforms with neural networks, exemplify AI's transformative role in compression [97]. Future research should explore improvements in JND estimation techniques and their application

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across diverse compression types [99]. Additionally, quantum algorithms, such as Grover's algorithm, offer exciting prospects for improving encoding processes in VQ through quantum computing [100].

In light field compression, machine learning applications, including JPEG enhancement and depth estimation networks, have shown promise in improving reconstruction quality [101]. Future investigations could focus on integrating deep learning techniques and establishing benchmarks for a wider range of scenarios [102].

10.2 Challenges and Future Directions

The image and video compression field faces significant challenges in meeting the demand for efficient storage and transmission of high-resolution data. Traditional codecs like JPEG and JPEG2000 often struggle to maintain quality at high compression ratios, particularly in precision-critical applications such as microscopy and medical imaging. DCT-based methods excel in preserving image fidelity, achieving high PSNR and SSIM scores, underscoring the need for advanced techniques to address high-resolution dataset demands [30, 42]. Techniques like NIC and SQLC aim to retain high-level information while minimizing data size, crucial for fields like medicine and remote sensing [20, 30, 42, 103, 14].

The integration of ML into compression frameworks offers promising solutions. CNNs improve efficiency and quality through optimized rate-distortion performance, learning complex visual data patterns [33]. Hybrid and adaptive techniques merge traditional and advanced methodologies to overcome conventional standards' limitations, meeting the demand for high compression ratios without compromising quality. The I2Icodec framework exemplifies hybrid methods' potential by combining image-to-image translation with compression [33]. ML integration leads to adaptive methods capable of real-time optimization based on data characteristics [33].

As digital content demand surges, driven by streaming media and smart city applications, future compression technologies are poised for transformation. Innovations like ML-based encoding models, collaborative techniques for human and machine vision, and unified preprocessing frameworks pave the way for efficient and adaptable solutions. These advancements enhance existing codecs' performance and address video data growth challenges, which constitute a significant portion of internet traffic [56, 32, 72]. AI and ML integration is anticipated to play a pivotal role in shaping future compression technologies, ensuring efficient storage and transmission for growing digital visual data volumes.

Future research directions include optimizing reference frame selection and enhancing robustness in dynamic video contexts [53]. Exploring functionally lossless methods like QJC illustrates the potential for high efficiency while preserving original quality [36]. These methods offer novel approaches to reducing data redundancy while maintaining high-quality visuals, highlighting the promise of integrating quantum computing with traditional techniques.

11 Conclusion

The survey underscores the pivotal role of image and video compression techniques in managing the escalating volumes of digital data across diverse fields, including microscopy, medical imaging, and digital media. While traditional methods such as JPEG and JPEG2000 have established a foundation for data reduction, the demand for high-resolution content necessitates the development of more advanced techniques. Wavelet-based compression methods have demonstrated considerable promise in enhancing image quality and compression efficiency [59], indicating a pathway for future advancements.

The incorporation of AI and machine learning into compression frameworks marks a significant evolution, facilitating the creation of adaptive methods that optimize compression parameters based on the characteristics of input data. This integration has led to notable improvements in both compression efficiency and quality preservation, as evidenced by neural network-based and hybrid techniques. Ongoing research in this domain emphasizes the need for continual innovation to tackle the challenges posed by high-resolution data and the requirements for efficient storage and transmission solutions.

Future investigations will aim to broaden the evaluation of compression techniques to encompass additional machine vision tasks and codecs, thereby validating and enhancing the proposed methodologies [94]. As digital content proliferates, the advancement of compression technologies will be essential for effective data management and storage across various applications, ranging from scientific research to entertainment. The exploration of novel methodologies, such as functionally lossless image compression and the application of quantum computing concepts, reflects the dynamic nature of the field and its potential for groundbreaking developments.

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