A Survey of Lossy Image Compression Techniques

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***Abstract*—The field of lossy picture compression techniques is thoroughly examined in this overview study, which highlights the importance of these techniques for managing multimedia content. Significant file size reductions are possible with lossy techniques, such as transformational coding and neural network-based algorithms, without sacrificing much visual quality. Our investigation highlights the robustness to compression of several models, ranging from the traditional Discrete Cosine Transform (DCT) and Convolutional Neural Networks (CNNs) based models to the more current pixel diffusion models that are contributing to Generative AI.**

***Keywords*—Lossy Image Compression, Discrete Cosine Transform (DCT), Convolutional Neural Networks (CNN), Pixel Diffusion, Neural Network-based Compression, Transformative Coding, Multimedia Content Management, Compression Algorithms, Quantization Techniques, Entropy Coding, Medical Imaging, Telecommunications, Visual Fidelity, Compression Efficiency, Emerging Technologies, Virtual Reality (VR), Augmented Reality (AR), Recurrent Neural Networks (RNN), Real-Time Recurrent Learning (RTRL), Unbiased Online Recurrent Optimization (UORO), AutoEncoder, Generative Adversarial Networks (GAN), Challenges, Compression Ratios, Visual Quality, Image Processing, Hierarchical Pixel Diffuser (HPD), Machine Learning, Entropy Scheme, Rate-Distortion Performance**

I. Introduction

The effective management of multimedia content—especially images—is essential in the digital age for a variety of applications, from entertainment to telecommunications. A key technological advancement that makes it possible to transmit and store enormous volumes of visual data while using fewer resources is image compression. Among the various compression algorithms, lossy techniques have become a popular approach to accomplish substantial file size reductions without sacrificing visual quality significantly. This study explores these lossy picture compression methods in depth, examining their foundations, uses, and ramifications in several fields.

Effective visual data storage and transmission are becoming more and more important due to the quick growth of digital imaging applications. The objective of image compression methods is to lower the amount of data in an image while preserving a satisfactory degree of visual quality. In comparison to lossless techniques, lossy compression methods, in particular, employ controlled information loss to obtain better compression ratios. They are essential in situations when bandwidth or storage capacity constraints necessitate large data reductions without appreciably lowering perceived quality.

Lossy image compression methods work by taking advantage of the limits of human vision to eliminate unnecessary or unimportant information from the image. These methods include transform coding, predictive coding, quantization techniques, and other algorithms and methodologies.

Using transforms like the Discrete Cosine Transform (DCT) or Discrete Wavelet Transform (DWT), transform coding entails transforming the picture data into a transformed domain, such as the frequency domain. By predicting pixel values based on nearby pixels, predictive coding drastically reduces redundancy. A key element of lossy compression is quantization, which lowers the modified coefficients' precision to increase compression ratios.

Applications of lossy image compression techniques are found in many domains, including entertainment, medical imaging, and telecommunications. These methods allow images to be transmitted over networks with limited bandwidth more quickly in telecommunication systems, which makes data transfer for applications like multimedia messaging, picture sharing, and video conferencing more effective.

Furthermore, lossy compression makes it possible to transmit and store large-scale medical images without sacrificing diagnostic quality, which is important in the field of medical imaging where diagnostic accuracy and storage efficiency are paramount.

Concerns about the trade-off between compression ratio and visual integrity are brought up by the use of lossy compression techniques. While it may not be noticeable in some applications, the amount of information loss might negatively affect image quality in others. Thus, it is crucial to comprehend the trade-offs and choose the right compression parameters, particularly for applications that require a high level of visual fidelity.

Ongoing research in lossy picture compression concentrates on resolving innate difficulties as technology keeps developing. The main research focus is still to maximize compression efficiency while minimizing perceptual loss.
Furthermore, because emerging imaging technologies like virtual reality (VR) and augmented reality (AR) require higher resolutions and immersive visual experiences, adapting compression techniques to these technologies presents new challenges.

An important component of lossy compression is quantization. It involves transferring the continuous values of changed coefficients to a discrete range of values. By rounding off values, this process adds to the irreversible nature of lossy compression by introducing information loss.

The quantized data is further compressed using entropy coding methods like Arithmetic or Huffman coding. By assigning shorter codes to more frequent symbols, these techniques take advantage of the different probability distributions of symbols, allowing for additional compression without appreciably lowering the quality of the reconstructed image.

To sum up, lossy image compression methods are an essential tool for effectively organizing and sending large volumes of visual data. The objective of this paper is to conduct a thorough investigation and analysis of these methodologies, elucidating their fundamentals, practical uses, and the dynamic array of obstacles and prospects they offer across diverse fields.

The implications of lossy image compression methods are multifaceted. Effective compression techniques enable the quick transfer of medical images in telemedicine, guaranteeing prompt diagnosis and treatment. These methods allow large amounts of data to be transmitted from spaceborne platforms to ground stations in an efficient manner, which is useful in the fields of satellite imaging and remote sensing.

II. Algorithms

A. CNN

Deep convolutional neural networks have emerged as a crucial asset in the field of computer vision, surpassing human capabilities in tasks like image classification, object detection, and semantic segmentation. Moreover, they are increasingly valuable for regression applications in basic image and video processing, generating saliency maps, and optical flow fields, and achieving top-tier performance in single-image super-resolution. [60]

a. Semantic Segmentation: Semantic segmentation at the pixel level entails attributing individual pixels in an image with their corresponding class labels. This process employs a neural network architecture with an encoder-decoder structure, ultimately leading to pixel-wise classification. [61]

b. Depth Estimation: To assess the effectiveness of GAN architecture in compression scenarios, it's essential to have a task that isn't intertwined with producing high-quality outputs, where compression might negatively impact results. An instance of such a task involves deriving the depth map of a scene from sequences of monocular images. [61]

c. Object Detection: In the realm of object detection, the task involves locating and categorizing foreground objects within a scene. This stands in contrast to semantic segmentation, which is responsible for assigning labels to individual pixels. Additionally, the computation of confidence levels accompanies each classification. [62]

d. Human Pose Estimation: The process of Human Pose Estimation entails determining and superimposing the skeletal configuration of individuals identified in a scene. Current advancements utilize part affinity fields to establish connections between body parts and individuals, effectively discerning similarities among visual features. [63]

e. Human Action Recognition: For the accurate classification of individual action, ranging from a handstand to knitting, it is essential to analyze spatial details within each frame and temporal information across the complete video sequence. [64]

This research has explored the influence of lossy image compression on various deep CNN architectures. We've investigated the extent of compression achievable while maintaining acceptable performance and the potential improvement in performance by retraining networks with compressed images [65]. Retraining the network on compressed images has shown a partial recovery of performance across all challenges. Notably, our study highlights that in widely used yet previously unexamined network architectures, it's possible to compress images at exceptionally high rates. Specifically, segmentation and depth estimation exhibit resilience even under significant compression, facilitated by an encoder-decoder pipeline. With retrained models, compression can be safely applied up to 85% across all domains, leading to substantial reductions in storage costs before noticeable performance impacts. Further optimization of hyperparameters in retrained models could potentially enhance these gains. In certain domains like segmentation, we can already achieve a twentieth of the original storage cost. However, it's crucial to note that in safety-critical applications, even a small performance loss, such as 1 or 2%, may be unacceptable, particularly in operations like depth estimation for vehicular visual odometry.

B. RTRL and UORO

Compared to CNNs and auto-encoders, image compression networks based on RNNs have not advanced significantly, as far as we are aware. These methods combine residual scaling, entropy coding based on deep learning, and recurrent neural networks (RNNs) to propose a comprehensive picture resolution network. During training, this network produces three models simultaneously [23].

Recurrent neural networks (RNNs) have become a potent tool in image compression due to their ability to capture extensive dependencies within images. Two notable algorithms for training RNNs in image compression are Real-Time Recurrent Learning (RTRL) and Unbiased Online Recurrent Optimization (UORO).

Real-Time Recurrent Learning (RTRL):
RTRL[21], a gradient-centric algorithm, adjusts RNN weights over time by back-propagating the error (BPTT). This method involves iteratively computing derivatives of the loss function concerning the network's parameters, incurring computational expenses. Furthermore, RTRL necessitates the storage of past activations and gradients, posing challenges for handling extended dependencies. Gradient information is carried forward rather than backward in real-time recurrent learning. It delivers parameter updates at each time step while running concurrently with the model. However, to achieve that, it needs to hold onto a sizable matrix that connects the parameters and internal state of the model. Updating this matrix is unreasonably expensive, even if it can be saved at all [19].

Unbiased Online Recurrent Optimization (UORO):
In contrast, UORO is an online algorithm that mitigates RTRL's limitations. UORO is an online, forward differentiation method used for training neural image compression models. It eliminates the need for storing past activations or gradients, substantially enhancing computational efficiency and scalability for extended dependencies. UORO employs an unbiased approximation of RTRL, using "forward-mode differentiation" to calculate derivatives during a forward pass, eliminating the necessity for retaining past information [19, 12].

Comparative Analysis with Traditional Techniques:
Corentin Tallec and Yann Ollivier [12] report that deep learning-based lossy image compression methods, such as those employing RTRL and UORO, provide advantages over traditional approaches. Their capacity to learn from extensive datasets allows them to achieve superior compression ratios while maintaining acceptable visual quality. Despite their adaptability to diverse image types, these techniques have drawbacks, including computationally demanding training processes and challenges in real-time application deployment.

Testing UORO[12] in artificial scenarios with temporal dependencies that TBPTT finds challenging to master due to visual impairments or incorrect time scale balance reveals that UORO performs on par with or occasionally better than TBPTT.

Another experiment conducted by Ankur Mali[11] highlights that UORO, along with RTRL (Real-Time Recurrent Learning), appears to struggle with adaptive learning rate rules such as Adam and Adagrad, unlike BPTT (Backpropagation Through Time) and SAB (Sparse Attentive Backtracking). This suggests that UORO and RTRL may not work as favorably with backpropagation-based -based heuristics, impacting their performance. The paper also notes that UORO is quite sensitive to hidden layer sizes and interacts negatively with various optimizers compared to RTRL. It requires a careful grid search to obtain the best settings. Additionally, UORO generates good reconstruction in terms of perceptual quality, but it struggles to match the performance of BPTT and SAB, particularly on test sets and in terms of transfer performance on unseen data.

Another study evaluates the potential application of an RNN trained with the Unbiased Online Recurrent Optimization (UORO) algorithm to predict respiratory motion during lung cancer radiotherapy treatment[51]. The study reveals in application RNN with UORO better results and compares it to RNN with RTRL, LMS, and linear regression. UORO achieved the lowest error overall, making it suitable for online adaptive training.

C. AutoEncoder/Decoder

AutoEncoders is an algorithm based on unsupervised deep learning, which takes an input, compresses it, and gives an output that is very close/similar to our input. In the context of image compression, AutoEncoders come under lossy compression, where the quality of the image is traded for reduced size. The scope of AutoEncoders is not limited to compression. These models can be trained and developed for specific problem statements. Other uses of AutoEncoders include feature selection, data denoising, and data compression[29].

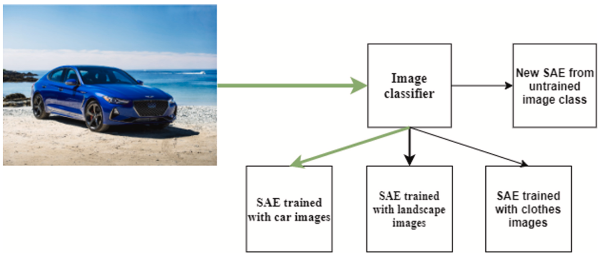

Figure 1 - Algorithm Overview

AutoEncoders have three layers in their architecture: encoder, encoded layer, and decoder[30]. The number of nodes in the encoder(input) and the decoder(output) is the same, whereas the encoded layer generally has reduced nodes(compressed data). AutoEncoders have been widely used for data compression, coupled with different algorithms and CNN models to enhance performance. Some of the work includes using a Kalman filter for image compression to enhance the training of the AutoEncoders [32]. In [33] AutoEncoder was trained using a Kodak dataset. The results of this model were better in terms of performance than the traditional compression models such as JPEG and Zip.

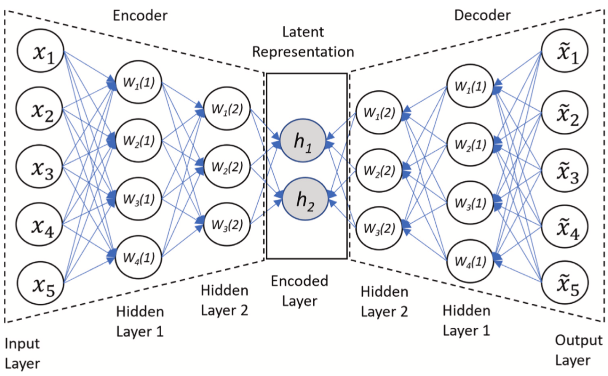

Figure 2 - AutoEncoder Architecture

The image compression process using Stacked AutoEncoders can be divided into three parts - i. Model training ii. Compression iii. Decompression. The SAE consists of three phases - Input layer, latent layer, and output layer. The training is done such that our sample dataset is passed through all three layers. Based on the results the SAE is customized or auto-tuned to get more accurate results of our input image [34]. The next step is to use the trained SAE to compress our image. We then pass our input image to the Encoder layer(input layer) of SAE for compression.

Lastly, the decompression of the image is done by utilizing the Decoder layer(output layer) of our SAE, with the goal of reconstructing the output image as close to the original image as possible.

Zip, proposed (enhanced) image, and JPEG encoded CR comparison.

Dataset	Original size (Bytes)	Zip size (Bytes)	Zip CR	CR enhanced	CR JPEG
MNIST	5,866,822	7,424,526	−26.55%	85.37%	65.91%
Grayscale car images	71,347,847	71,065,028	0.40%	86.31%	85.51%
Color car images	88,748,154	90,026,670	−1.44%	68.54%	66.39%

Figure 3 - Compression Rate Comparison

After experimenting with three different datasets - MNIST, grayscale, and color, the lossy image compression using stacked AutoEncoders performed better than traditional compression algorithms like JPEG for the MNIST and grayscale datasets. For colored image datasets, this compression algorithm is very close to JPEG compression in terms of compression rate and decompressed image size. Please find the examples below.

Figure 4 - Results

D. GAN

Importance maps or feature vectors are widely popular in Deep Learning based lossy compression methods but many times they lead to image distortion and low bpp because bit allocation depends upon important features of the image. GAN-based approaches have been more successful in performing lossy image compression at low bit rates.

GANs (Generative Adversarial Networks) are used for image compression to reconstruct non-important regions of an image, reducing distortion caused by insufficient bit allocation to those regions. This approach improves compression performance at low bits per pixel (bpp) and outperforms conventional compression algorithms such as JPEG, JPEG2000, and BPG, as well as state-of-the-art DNN-based compression methods at low bpp. Generative Adversarial Network (GAN)[42]-based image compression systems offer tunability, enabling compression to specific ratios without necessitating retraining of the model.The use of GANs in image compression has shown significant performance improvements, especially at low bpp, by preserving texture, color, and other details of the image.

The discriminator and generator neural networks make up the architecture of a Generative Adversarial Network (GAN)[43]. The discriminator assesses the created images and separates them from genuine ones, whereas the generator is in charge of producing new data instances, such as photos, that resemble the training data. These two networks are trained concurrently through a competitive process[44]. In this process, the generator aims to produce realistic images to deceive the discriminator, while the discriminator strives to enhance its accuracy in distinguishing real images from the generated ones.

In the realm of image compression, a GAN-based tunable image compression system[45] typically features a generator tasked with reconstructing non-essential regions of the image to minimize distortion resulting from inadequate bit allocation to those regions. Simultaneously, the discriminator undergoes training in tandem with the generator to enhance the overall performance of image generation. The use of GAN in image compression has shown significant performance improvements, especially at low bits per pixel (bpp), by preserving texture, color, and other details of the image. The GAN architecture in image compression systems is designed to be tunable, allowing compression to specific ratios without retraining the model

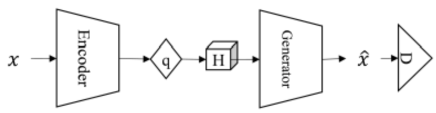

Figure 5 - GAN Architecture

x is the image that is encoded to get a latent version z which in turn is passed to the Generator which is a Decoder network. xˆ is the output of the generator which is passed to the Discriminator which compares the output from the generator with the original image. Overall Loss is a combination of adversarial[47] and distortion[48] loss.

The adversarial loss in the context of a GAN-based tunable image compression system is a part of the overall loss function[49] and is composed of the losses from the generator and the discriminator.

The distortion loss[50] measures the difference between the original image and the reconstructed image in a GAN-based tunable image compression system.

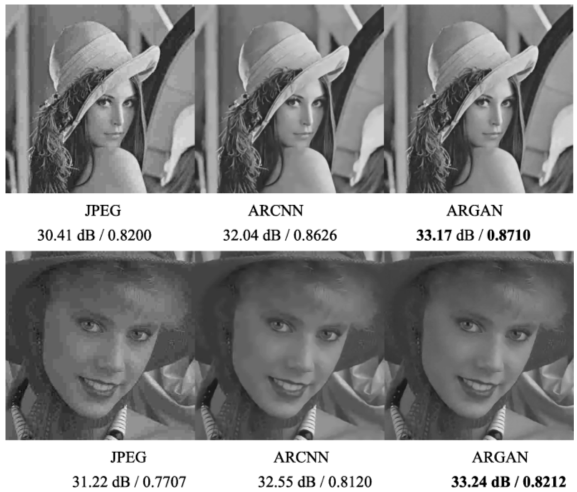

Figure 6 - Comparison of JPEG, CNN, and GAN Results

E. Pixel Diffuser

One kind of diffusion model that can be used to produce high-quality images from low-resolution representations is the Pixel Diffuser. This model is very effective for image compression [1], achieving state-of-the-art results on a variety of benchmarks. It’s interesting to know that the inception of image compression based on diffusion models is sort of inspired by thermodynamics with a unique approach to adding noise to an image - the very reverse process of image generation. This forms the fundamental idea behind pixel diffusion.

Diving deeper into image compression based on pixel diffusion - there is a possibility of a training strategy for Pixel Diffuser that could result in improved performance for image compression[3]. The proposed strategy uses a combination of supervised learning and self-supervised learning. The supervised learning task is to reconstruct the original image from a compressed representation. The self-supervised learning task is to learn a representation of the image that is robust to noise.

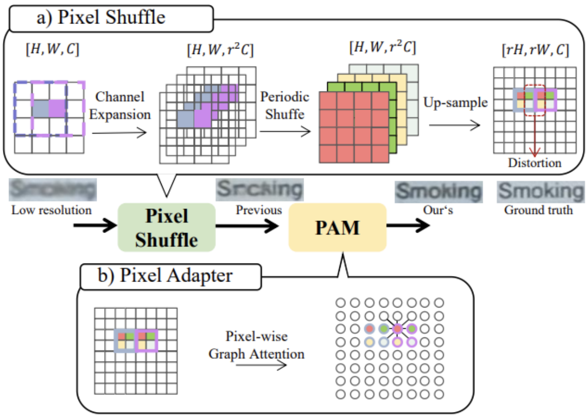

Figure 7 - Pixel Shuffle[58]

But is there any backbone architecture in place for image compression based on diffusion models? Surprisingly yes! Our survey exposed a new architecture for Pixel Diffuser that improves its performance for image compression. The proposed architecture is called the Hierarchical Pixel Diffuser (HPD). HPD uses a hierarchical structure that allows it to capture both high-frequency and low-frequency information in the image. Pixel Diffuser is also a U-Net-based architecture that is trained to learn the inverse process of diffusion. It can achieve state-of-the-art results on a variety of benchmarks, including the ImageNet Compression Challenge (ICCC) 2021 and the Codec dataset. We were amazed to see diffusion based on adaptive encoding techniques where the proposed scheme was able to improve the rate-distortion performance of the Pixel Diffuser by up to 0.2 dB. While adaptive encoding[5] gave amazing results, it was interesting to learn about the context-aware entropy scheme as well which improved the rate-distortion performance of the Pixel Diffuser by up to 0.3 dB.

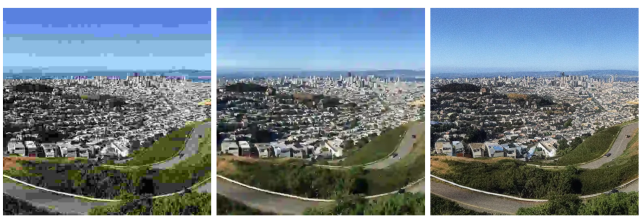

Figure 8 - Stable Diffusion[59]

It's vital to remember that, despite having a far better subjective appearance than the JPG and WebP compressed images, the Pixel Diffusion outputs do not considerably outperform them in terms of common measurement criteria like PSNR. Just that the types of artifacts created are less noticeable because they have a greater impact on image content than on image quality, which brings up another potential risk with this method: The clarity of the reconstructed features should not be taken as gospel; even when the information appears to be crystal clear, it may still contain compression artifacts. In the years to come, pixel diffusers—a potential new method for picture compression—are probably going to have a big influence on the industry.

F. DCT

Bridging the gap in image processing between the frequency and spatial domains. It is an essential bridge between neural network-based applications and image compression in the pipeline. The combined effect of neural networks, pixel diffusers, and the Discrete Cosine Transform (DCT) improves the quality and efficiency of compressed images.

Pixel diffusers have a more significant role in image compression than merely reducing aberrations. These diffusers actively aid in maintaining the fine features of the image and minimizing compression-related artifacts brought on by quantization mistakes. Pixel diffusers ensure a more aesthetically pleasing and accurate reproduction of the source image by dispersing compression faults across nearby pixels[28]. Together with DCT, the intelligent use of pixel diffusers in the compression process creates a pleasing balance between image quality and compression efficiency.

Moreover, the joint efforts of pixel diffusers and DCT prove crucial in controlling the frequency components of an image. DCT's capacity to convert spatial data into frequency components enhances pixel diffusers' function in error minimization. This combination method produces compressed photos of exceptional quality by preserving important features while also maintaining image quality.

Neural networks add a learning component to the compression procedure[24], which helps to further optimize the compression process. Neural networks are very good at recognizing complex patterns, representations, and details in images. Because of their adaptability, they can optimize compression parameters according to the unique qualities of various kinds of image content.

The compression process is made more dynamic and sensitive to the subtleties of various image contents by utilizing neural networks' learning capabilities[24]. This produces compressed images that are both aesthetically beautiful and precisely represented.

DCT acts as a connection in this networked structure, enabling communication between the neural network and the pixel image. It serves as a channel for the conversion of spatial data into frequency components, which enables the neural network to function on a more streamlined and abstract representation. With the help of pixel diffusers, neural networks, and DCT working together, this cooperative method offers a complete solution for producing high-quality compressed images that nevertheless contain important visual information.

III. Challenges

The project presented several challenges: comprehending and clearly explaining complex algorithms, keeping pace with rapidly evolving trends in image compression research, discerning the most impactful and relevant papers within this vast field, and striking a delicate balance between providing sufficient detail for each algorithm while maintaining conciseness. Overcoming these hurdles demanded rigorous research, meticulous selection of key information, and careful crafting of explanations that were both accurate and accessible.

Lossy image compression methods are essential for handling the growing amount of digital images, allowing for effective transmission, storage, and retrieval. Although there are trade-offs between compression ratios and image quality, ongoing algorithmic developments and new technologies such as machine learning promise to push the limits of compression efficiency while preserving perceptual fidelity.

IV. Conclusion

In conclusion, this survey paper provides a comprehensive overview of lossy image compression techniques, encompassing traditional methods such as Discrete Cosine Transform (DCT), Convolutional Neural Networks (CNN), and emerging approaches like Pixel Diffusion. Lossy compression, by deliberately sacrificing some visual information, proves indispensable for effectively transmitting and storing large volumes of visual data, especially in applications like telecommunication, medical imaging, and emerging technologies such as virtual and augmented reality. The paper highlights the pivotal role of quantization, entropy coding, and transformative coding in achieving optimal compression ratios.

The survey delves into specific algorithms like DCT, CNN, Recurrent Neural Networks (RNNs) with Real-Time Recurrent Learning (RTRL) and Unbiased Online Recurrent Optimization (UORO), AutoEncoder/Decoder, GANs, and Pixel Diffusers, elucidating their strengths, challenges, and applications. Furthermore, the study explores the intersection of neural networks, pixel diffusers, and DCT, showcasing their synergistic effect on compression. efficiency and image quality. The challenges and potential breakthroughs identified underscore the dynamic nature of ongoing research in this field, emphasizing the need to balance compression efficiency with visual fidelity, especially in emerging applications like virtual and augmented reality. Overall, this survey contributes valuable insights into the current landscape of lossy image compression, pointing towards a future where advancements in machine learning and emerging technologies continue to shape the evolution of compression techniques.

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