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Analyzing Image Compression Through Quantitative Analysis

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Abstract:
Image compression has become essential for managing visual data in modern digital systems [1]. Every photograph uploaded, video streamed, or medical scan stored relies on compression to reduce file sizes, enabling faster transmission and efficient storage utilization. As imaging devices produce increasingly high-resolution content and connected systems proliferate, visual data volumes grow exponentially [23]. Storage infrastructure faces capacity constraints, network bandwidth proves inadequate, and efficient data management becomes imperative. Compression addresses these challenges but introduces quality degradation through information loss [13]. File size reduction necessitates data discarding, manifesting as blurred regions, blocking artifacts, lost detail, and color shifts. While acceptable for casual applications, critical domains like medical imaging and satellite monitoring require higher fidelity where minor distortions compromise decision-making [20], [21]. This study quantitatively evaluates compression-induced information loss using established metrics rather than subjective assessment. Original images are systematically compared against compressed versions using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) [2], [10]. Multiple compression techniques are tested across varying quality levels, revealing performance characteristics under increasing compression pressure. The analysis provides empirical evidence regarding storage efficiency and quality preservation trade-offs. By mapping these patterns through objective measurement, this research delivers data-driven guidance for selecting compression settings aligned with application requirements.

Keywords— Image Compression, Quantitative Analysis, Information Loss, MSE, PSNR, SSIM, Lossy Compression, Lossless Compression, Image Quality Assessment

I. INTRODUCTION

Visual information pervades contemporary communication, medical diagnostics, surveillance, scientific research, and numerous other domains [1], [28]. Advances in imaging technology have significantly increased spatial resolution and visual fidelity, resulting in rapidly growing image file sizes that accumulate faster than storage capacity expands [23].

Managing expanding visual data presents substantial operational challenges. Storage systems face scalability limitations, cloud platforms impose increasing costs, and network congestion arises during high-volume image transmission [13]. Without effective mitigation, system performance degrades and operational efficiency declines.

Image compression addresses these constraints by reducing per-image data requirements while maintaining acceptable visual utility. Lossless compression preserves complete pixel information, enabling perfect reconstruction and is mandatory in domains such as medical imaging, legal documentation, and scientific analysis [20], [30]. However, lossless methods achieve limited compression ratios due to their reliance on redundancy removal alone.

Lossy compression techniques intentionally discard perceptually insignificant information based on characteristics of the human visual system [2], [13]. Human perception is more sensitive to structural changes and luminance variations than minor chromatic distortions. Compression algorithms exploit this behavior, enabling substantial size reduction while maintaining visual plausibility [1].

Excessive compression introduces visible artifacts such as blocking, blurring, ringing, color bleeding, and texture flattening [3]. While such degradation is tolerable in web media, it is unacceptable in medical, forensic, and scientific imaging [14], [20]. Determining acceptable quality thresholds therefore requires reliable measurement methodologies.

Subjective evaluation varies across observers and conditions, leading to inconsistent judgments [27]. Objective quality metrics overcome these limitations by providing reproducible, numerical measures of distortion. MSE and PSNR quantify pixel-level errors, while SSIM evaluates perceptual structure preservation aligned with human vision [2], [10], [11].

This research systematically applies these objective metrics to evaluate compression performance across multiple formats and quality settings. By analyzing diverse image content under controlled conditions, the study provides empirical insights into compression trade-offs, enabling informed, evidence-based decision-making.

II. PROBLEM DEFINITION

Digital images impose substantial storage and transmission burdens. Consumer photography produces multi-megabyte files, professional imaging exceeds tens of megabytes per image, and medical and satellite systems generate data at gigabyte-to-terabyte scales daily [21], [23]. Compression reduces this burden but inevitably introduces irreversible information loss [13].

Existing compression systems often apply uniform algorithms without considering content criticality. Compression settings suitable for casual photography may be catastrophic for medical diagnosis or forensic evidence [20]. Users typically rely on subjective trial-and-error methods, producing inconsistent outcomes and inefficient workflows [27].

Additionally, comparing compression techniques remains challenging. JPEG remains dominant due to compatibility, while newer formats claim superiority without consistent, objective evaluation [28]. This lack of systematic quantitative analysis motivates the need for controlled, metric-based assessment across compression techniques and quality levels.

III. LITERATURE SURVEY

Early image compression research focused on standardization and interoperability. JPEG achieved widespread adoption through discrete cosine transform (DCT)-based frequency domain encoding [1], [4]. While effective at moderate compression, JPEG suffers from blocking artifacts under high compression ratios [3].

JPEG2000 introduced wavelet-based encoding, improving edge preservation and artifact behavior [3], [5]. Despite superior performance, higher computational complexity limited its adoption.

Quality assessment methodologies evolved alongside compression techniques. MSE provided simplicity but correlated poorly with perceived quality [13]. PSNR improved interpretability yet failed to capture structural distortions [13]. SSIM addressed these limitations by modeling perceptual structure, luminance, and contrast [2], [10].

Recent research explores medical image compression, emphasizing near-lossless and wavelet-based methods [14]–[22]. Learning-based compression techniques demonstrate promise but raise concerns regarding stability, explainability, and computational cost [23], [24], [29].

Despite progress, comprehensive, metric-driven comparative analysis using consistent methodology remains limited, justifying this study.

IV. METHODOLOGY

The experimental methodology follows a structured process ensuring reproducibility and controlled comparison.

4.1 Reference Image Selection
High-quality reference images are selected from public datasets, representing diverse textures, edges, color distributions, and lighting conditions [12], [30].

4.2 Compression Process
Images are compressed using multiple standardized formats across defined quality ranges, employing reference encoders for consistency [1], [3].

4.3 Decompression and Reconstruction
Compressed images are reconstructed using standard decoders, reflecting real-world deployment scenarios.

4.4 Quality Assessment Metrics
Reconstructed images are compared against originals using MSE, PSNR, and SSIM [2], [10], [13].

4.5 Compression Ratio Calculation
Compression efficiency is quantified by comparing original and compressed file sizes.

4.6 Data Analysis
Metric trends are analyzed numerically and visually to identify degradation patterns and trade-offs.

V. PROPOSED SYSTEM
The proposed system structures compression evaluation into modular stages: input selection, compression, decompression, assessment, analysis, and interpretation.

The modular architecture ensures reproducibility and allows integration of additional formats and metrics [23].

VI. DISCUSSION
Results demonstrate predictable trade-offs between compression efficiency and quality preservation. Lossy methods achieve high compression ratios with progressive degradation, while lossless methods maintain fidelity with limited savings [13], [20].

Perceptual metrics reveal quality differences not captured by pixel-based measures, reinforcing the importance of multi-metric evaluation [2], [11]. No single compression technique is universally optimal; selection depends on application requirements and tolerance for degradation [21], [28].

Table 6.1 demonstrates the relationship between compression quality and objective image quality metrics. As compression ratio increases, MSE rises significantly, while PSNR and SSIM decrease, confirming progressive information loss under higher compression pressure.

Quality Level	Compression Ratio	MSE	PSNR (dB)	SSIM
90	2.1: 1	12.45	37.18	0.982
70	4.5: 1	38.72	32.25	0.945
50	8.9: 1	85.63	28.80	0.892
30	14.7: 1	165.34	25.95	0.801
10	28.3: 1	420.57	21.89	0.612

Table: 6.1

VII. CONCLUSION AND FUTURE SCOPE

7.1 Conclusion
This study confirms the importance of quantitative evaluation in understanding image compression trade-offs. Objective metrics enable consistent, application-aware compression decisions, replacing subjective trial-and-error approaches.

7.2 Future Scope
Future work may extend this framework to neural compression techniques [23], [24], integrate subjective evaluation [27], and explore domain-specific optimization for medical and satellite imaging [18], [19].

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