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Singular Value Decomposition for Deep Space Image Compression: A Hubble Case Study

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***Abstract*— Modern deep space exploration generates massive volumes of high-resolution imagery, creating a significant bottleneck for data transmission over limited bandwidths. This research addresses this challenge by evaluating Singular Value Decomposition (SVD) as a numerical Low-Rank Approximation technique for compressing astronomical data. Unlike data-hungry deep learning models, this study applies matrix factorization directly to an expanded dataset of 25 raw high-resolution TIF images from the Hubble Space Telescope. By varying the rank (*k*), we analyze the trade-off between storage efficiency, computational overhead, and reconstruction fidelity. Experimental results demonstrate that SVD offers a stable, lightweight compression mechanism, effectively filtering sensor noise while preserving coherent celestial structures without the risk of data hallucination or the blocking artifacts inherent to JPEG. The analysis identifies rank k=100 as the optimal threshold, achieving an average Peak Signal-to-Noise Ratio (PSNR) of 31.10 dB and reducing data volume by 88.7% (Compression Ratio of 8.87x). Furthermore, hardware profiling confirms SVD's exceptional efficiency, requiring a peak memory footprint of only ~95.99 MB and an execution time of ~2.50 seconds. These findings validate that SVD provides a computationally feasible and mathematically deterministic alternative to complex neural networks for onboard satellite data processing.**

***Index Terms*— Computational Complexity; Deep Space Telemetry; Image Compression; Low-Rank Approximation; Satellite Communication; Singular Value Decomposition.**

I. INTRODUCTION

The rapid advancement of remote sensing technology and the Internet of Things (IoT) has led to an exponential increase in the volume of digital image data generated by space missions and satellite systems. As noted by Muthukrishnan et al. [1], high-resolution satellite imagery is critical for modern observation but imposes significant challenges regarding data transmission bandwidth and storage capacity. In the context of deep space exploration, such as missions involving the Hubble Space Telescope, the transmission of hyperspectral and high-definition visual data requires efficient compression techniques to maximize scientific throughput without compromising critical structural details [2]. Consequently, image compression remains a fundamental problem in the domain of signal processing and computer vision.

Various lossy compression standards have been developed to address this challenge. Traditional methods such as Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) are widely used in commercial standards like JPEG and JPEG2000. However, comparative studies by Bhade et al. [3] and Prasanna et al. [4] demonstrate that while DCT offers computational speed, it often introduces blocking artifacts at high compression ratios. Conversely, hybrid approaches combining Singular Value Decomposition (SVD) with Wavelet Difference Reduction have been proposed by Rufai et al. [5] to enhance performance without severe artifact generation.

In recent years, data-driven approaches utilizing Deep Learning (DL) and Artificial Intelligence (AI) have heavily dominated the state-of-the-art in remote sensing image compression. Recent advancements include the utilization of Non-Local Neural Networks to improve reconstructed image quality [6], the application of Invertible Neural Networks to enhance perception quality in remote sensing [7], and the deployment of Convolutional Autoencoders for onboard lossy image compression in satellite missions [8]. Despite achieving high compression ratios, these neural compression methods introduce fatal flaws when applied to deep-space telemetry. DL models inherently possess high computational complexity and massive parameter sizes, often requiring Graphics Processing Units (GPUs) that are rarely feasible on hardware-constrained onboard satellite systems like CubeSats. Furthermore, the "black-box" nature of generative AI poses a critical risk of "data hallucination"—the artificial generation of fake cosmic structures—which severely violates the scientific authenticity required for raw astronomical data analysis. As demonstrated by Fournier and Aloise [9], traditional dimensionality reduction methods often remain competitive against complex neural networks in terms of computational efficiency and stability, particularly when training data is limited or structural integrity is paramount.

To address this critical gap, this research focuses on Singular Value Decomposition (SVD), not merely as a conventional matrix operation, but as a superior, mathematically deterministic alternative to modern neural networks for space applications. Unlike heuristic

compression methods or data-hungry AI models, SVD provides a mathematical guarantee for optimal low-rank matrix approximation, established by the classical theorem of Eckart and Young [10] and further generalized in subsequent matrix approximation theories [11]. The core principle of SVD involves factorizing an image matrix A into three component matrices: $A = U\Sigma V^T$, where Σ contains singular values representing the energy distribution of the image [11]. By retaining only the largest k singular values, one can reconstruct the image with minimal error.

This study clarifies the scientific contribution of SVD by empirically evaluating its robustness on raw 16-bit high-dynamic-range TIF astronomical data. By establishing an optimal operating benchmark, this research demonstrates SVD's exceptional computational efficiency—requiring minimal peak memory (~95 MB) and rapid execution time (~2.5s)—making it highly viable for onboard processing. Moreover, SVD guarantees structural preservation and intrinsic denoising without the risk of hallucination or the need for extensive training datasets [12], [13], [14] thereby successfully balancing scientific accuracy with stringent satellite transmission constraints.

I. METHOD

This study employs a quantitative experimental approach to evaluate the efficacy and computational efficiency of numerical algorithms in compressing scientific imagery. The methodology is structured into six sequential stages: data acquisition, pre-processing, matrix factorization, dimensionality reduction, performance evaluation (including computational profiling), and comparative baseline benchmarking. The overall flow of the enhanced image compression and analysis framework, which now integrates hardware profiling and standard JPEG benchmarking, is illustrated in Fig. 1.

A. Data Acquisition

The primary dataset for this research was curated from the official European Space Agency (ESA) Hubble Space Telescope archive (https://esahubble.org/images/). To ensure the robustness and statistical validity of the experimental results, the sample set was significantly expanded to 25 high-resolution deep-space images. These images, stored in uncompressed TIF (Tagged Image File Format) to avoid pre-existing compression artifacts, were carefully selected to comprehensively represent five distinct morphological categories: Planetary Bodies, Supernova Remnants, Emission/Dark Nebulae, Interacting Galaxies, and Dense Globular Clusters. As emphasized in remote sensing studies [2], such high-dynamic-range data presents a unique challenge for compression algorithms due to the non-local sparsity of the pixel distribution.

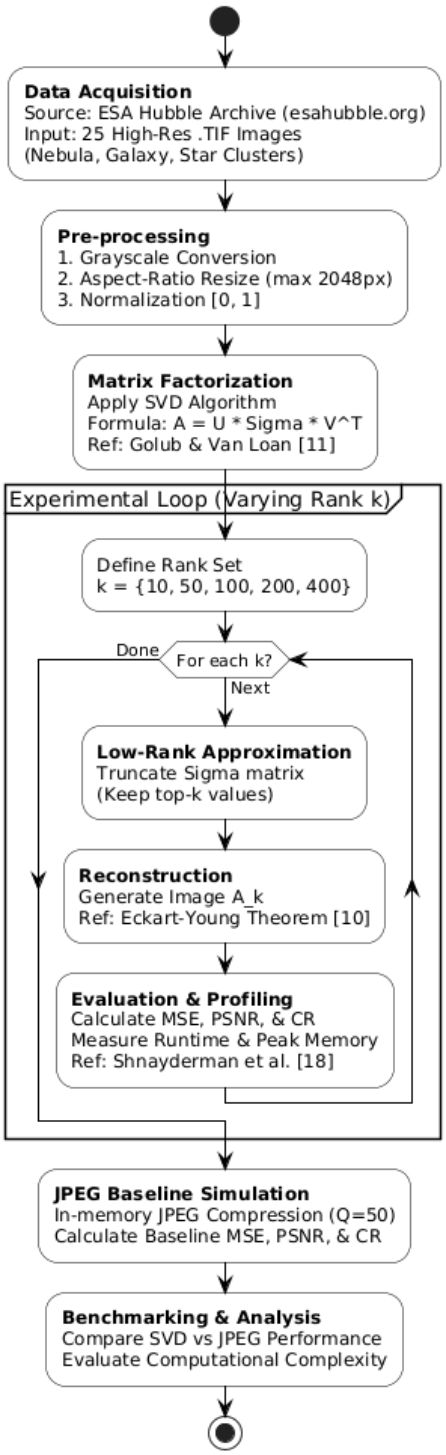

Fig. 1. Proposed research methodology flowchart illustrating the enhanced SVD-based compression pipeline, computational profiling, and JPEG benchmarking

B. Pre-processing

Before applying the numerical decomposition, the raw images undergo a crucial pre-processing phase. First, the 3D color images (RGB channels) are converted into 2D grayscale matrices, reducing computational complexity while retaining the luminance and structural information vital for morphological analysis. Second, an aspect-ratio-

preserving resize is applied, capping the longest dimension at 2048 pixels using the LANCZOS interpolation algorithm. This step not only prevents memory overcapacity during matrix operations but also inherently acts as a Low-Pass Filter, smoothing out microscopic high-frequency noise prior to decomposition. Finally, the pixel intensity values are normalized into a floating-point range of [0, 1] to maintain numerical stability during the iterative matrix factorization process.

C. Singular Value Decomposition (SVD)

The core algorithm utilized is the Singular Value Decomposition (SVD). Drawing from the fundamental matrix computation theory [11], SVD factorizes a real-valued image matrix A of size $m \times n$ into three component matrices, as defined in (1).

$$A = U\Sigma V^T \tag{1}$$

Here, U is an $m \times m$ orthogonal matrix representing the left singular vectors, V^T is the transpose of an $n \times n$ orthogonal matrix representing the right singular vectors, and Σ is an $m \times n$ diagonal matrix containing the singular values σ_i. These singular values are ordered in a non-increasing sequence ($\sigma_1 \geq \sigma_2 \geq \cdots \geq 0$) and represent the "energy" or information content of the image. As interpreted geometrically [12], this decomposition effectively rotates the coordinate system to align with the directions of maximum variance in the data.

D. Low-Rank Approximation

The compression mechanism relies on the Low-Rank Approximation technique. Based on the generalization of the Eckart-Young-Mirsky theorem [10], the optimal approximation of matrix A by a matrix A_k of a lower rank k (where $k < \text{rank}(A)$) is achieved by truncating the singular values. We retain only the first k largest singular values and discard the rest, treating them as noise or redundant information. The reconstruction formula is given by:

$$A_k = \sum_{i=1}^{k} \sigma_i u_i v_i^T \tag{2}$$

To quantify the information retained by the rank-k approximation, we utilize the concept of "Cumulative Energy." The energy of the image matrix is proportional to the sum of its squared singular values. The Energy Retention Ratio (E_k) for a selected rank k is defined as:

$$E_k = \frac{\sum_{i=1}^{k} \sigma_i^2}{\sum_{j=1}^{r} \sigma_j^2} \times 100\% \tag{3}$$

Where r is the full rank of the matrix. This metric allows us to determine the rank k scientifically by setting a specific energy threshold, rather than relying solely on visual inspection. In this experiment, we vary the rank parameter k ($k = 10, 50, 100, 200, 400$) to observe the trade-off between file size reduction, energy retention, and image fidelity.

E. Performance Evaluation, Profiling, and Benchmarking

To objectively assess the quality and efficiency of the compressed images, several metrics and profiling techniques are employed. Reconstruction fidelity is quantified using Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). Following the framework regarding SVD-based quality assessment [18], the PSNR is calculated to measure the reconstruction quality in decibels (dB), defined as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \tag{4}$$

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \tag{5}$$

Where MAX_I represents the maximum possible pixel value (which is 1.0 after normalization). The Compression Ratio (CR) is calculated by comparing the storage requirement of the original matrix against the truncated matrices U_k, Σ_k, and V_k.

To address the hardware constraints typical of onboard satellite systems, a computational complexity profiling module is integrated into the pipeline. Using Python's time and tracemalloc libraries, the wall-clock runtime (in seconds) and peak memory footprint (in MB) are precisely measured exclusively during the SVD decomposition and reconstruction phases. Finally, to demonstrate practical competitiveness, an in-memory standard JPEG compression simulation (via io.BytesIO) is established as a conventional comparative baseline, allowing a direct benchmarking of SVD's performance against block-based DCT compression.

It should be noted that computational profiling (runtime and memory) is exclusively evaluated for the SVD algorithm to demonstrate its hardware feasibility. The JPEG baseline is implemented strictly as a comparative standard for perceptual quality (PSNR) and compression ratio (CR), as its Python implementation relies on pre-compiled C-libraries that do not offer an equivalent algorithmic hardware-level profiling comparison.

II. Results and Discussion

This section presents a comprehensive analysis of the enhanced SVD-based compression framework applied to the expanded dataset of 25 high-resolution Hubble Space Telescope images. The evaluation is systematically divided into five areas: singular value energy distribution, quantitative performance consistency, qualitative visual preservation, comparative baseline analysis against JPEG, and computational complexity profiling.

A. *Singular Value Distribution and Energy Compaction*

The fundamental premise of using SVD for compression lies in the energy distribution of the image matrix. As visualized in the newly generated Scree Plot (Fig. 2), the cumulative energy curve exhibits an exceptionally steep exponential rise, reaching the 99% retention threshold rapidly. This steepness is attributed to two factors. First, the LANCZOS pre-processing resize inherently acts as a low-pass filter, attenuating microscopic high-frequency noise prior to factorization. Second, morphologically, diffuse celestial bodies like the Carina Nebula are heavily dominated by low-frequency spatial gradients. Consequently, the SVD algorithm adaptively compacts the vast majority of the image's structural information into the first few dominant singular vectors, validating the feasibility of massive matrix truncation.

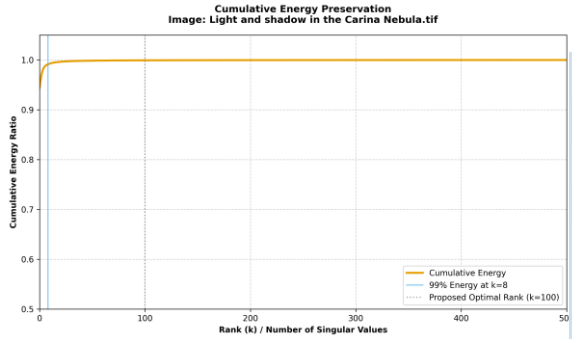

Fig. 2. Cumulative energy retention ratio as a function of rank (k). The steep exponential rise demonstrates rapid energy compaction, allowing the SVD algorithm to capture over 99% of the structural information within the first few dominant singular values

B. *Quantitative Performance Analysis*

Table I summarizes the average compression quality and storage metrics computed across the entire dataset of 25 diverse high-resolution astronomical images. The empirical data demonstrates a clear trade-off between the Compression Ratio (CR) and the reconstruction quality (PSNR).

TABLE I. COMPRESSION QUALITY AND STORAGE METRICS (AVERAGED OVER 25 SAMPLES)

Method	Rank (k)	Avg. PSNR (dB)	Avg. MSE	CR (x)
SVD	10	24.72 ± 5.16	0.0074 ± 0.0108	88.73 ± 12.58
	50	28.89 ± 6.46	0.0045 ± 0.0081	17.75 ± 2.52
	100	31.10 ± 6.89	0.0032 ± 0.0059	8.87 ± 1.26
	200	33.98 ± 7.33	0.0019 ± 0.0037	4.44 ± 0.63
	400	38.64 ± 8.42	0.0008 ± 0.0018	2.22 ± 0.31
JPEG	Baseline	35.98	0.0005	18.44

At rank $k = 100$, the algorithm achieves an average PSNR of 31.10 dB—surpassing the standard quality threshold of 30 dB—while reducing the file size by a factor of 8.87 (an 88.7% reduction in data volume). To validate the statistical robustness of this threshold, a consistency check was performed across all 25 samples (Fig. 3). The bar chart confirms that while low-frequency images (e.g., nebulae) achieve exceptionally high PSNRs, images packed with extreme high-frequency point-sources (e.g., dense globular clusters) logically exhibit higher variance. Nevertheless, the algorithm maintains stable structural preservation across all morphological classes.

At rank $k = 100$, the algorithm achieves an average PSNR of 31.10 dB—surpassing the standard quality threshold of 30 dB—while reducing the file size by a factor of 8.87 (an 88.7% reduction in data volume). To rigorously validate the statistical reliability of these results, standard deviations (SD) are reported alongside the mean values. For instance, at $k = 100$, the PSNR exhibits a variance of ± 6.89 dB. This expected variance logically reflects the immense morphological diversity within the dataset; images heavily dominated by high-frequency point-sources (e.g., dense globular clusters) incur higher truncation losses compared to the smooth, low-frequency spatial gradients of emission nebulae. Nevertheless, the consistency check across all 25 individual samples (Fig. 3) confirms that the SVD algorithm maintains stable structural preservation and prevents catastrophic data degradation across all morphological classes.

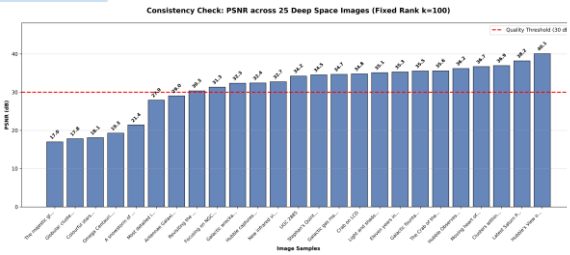

Fig. 3. Consistency check of reconstruction quality (PSNR) across 25 diverse deep-space images at a fixed optimal rank of $k = 100$. The red dashed line indicates the 30 dB quality threshold, validating the algorithm's robust performance across various astronomical morphological categories

C. *Visual Quality and Morphological Preservation*

The qualitative evaluation offers a profound look at SVD's reconstruction behavior. A critical observation derived from the enhanced Residual Error Map with percentile clipping (Fig. 4c) reveals an extreme localization of reconstruction errors. The error distribution is not randomly scattered; instead, it is highly concentrated specifically on individual bright stars (high-frequency point sources). Conversely, the continuous gaseous structures of nebulae and galaxies (low-frequency components) are reconstructed with near-zero error. This visually proves that SVD preserves macro-cosmic morphology perfectly, trading off only microscopic stellar impulses that are often indistinguishable from sensor noise.

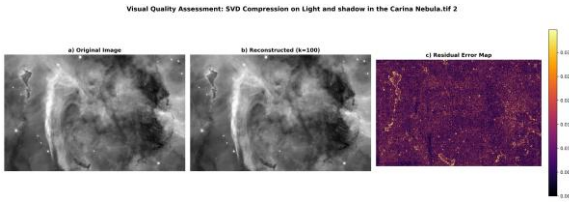

Fig. 4. Visual quality assessment and morphological preservation analysis: (a) Original image, (b) Reconstructed image at optimal rank $k = 100$, and (c) Enhanced residual error map. The error map demonstrates that truncation loss is extremely localized to high-frequency point-sources (stars), successfully preserving the continuous low-frequency gaseous structures.

The analysis of structural integrity is further clarified through a zoom-in morphological comparison (Fig. 5). At the optimal rank of $k = 100$, the SVD method proves successful in maintaining vital morphological features, such as dense nebula gas clouds and stellar distributions, with high fidelity.

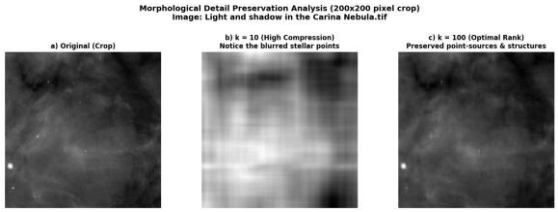

Fig. 5. Morphological detail preservation analysis (200×200 pixel crop). Comparison between high compression ($k = 10$) which shows blurring, and optimal rank ($k = 100$) which preserves stellar point sources effectively.

Furthermore, a beneficial side effect was observed at lower ranks, where there is significant suppression of granular noise in the image background. This phenomenon aligns with the findings of Khmag [16] and Kim et al. [17], suggesting that SVD acts effectively as a natural low-pass filter. By discarding the smallest singular values—which often represent uncorrelated sensor noise—the method effectively "cleans" the image while retaining the coherent structure of the main celestial bodies.

D. SVD vs. JPEG Baseline Comparison

To demonstrate practical competitiveness, SVD was benchmarked against an in-memory standard JPEG compression simulation. As shown in Table I, the JPEG baseline yields a numerically higher average PSNR (35.98 dB) and CR (18.44x) at a mid-level quality setting. However, in the context of scientific astrophotography, numerical metrics do not translate directly to observational utility. JPEG utilizes a block-based Discrete Cosine Transform (DCT) that inherently produces "blocking artifacts"—grid-like artificial fragmentations that severely corrupt the continuous structural integrity of faint galactic arms or dust pillars. By avoiding block transformations entirely, SVD ($k = 100$ to 200) provides a globally continuous morphological preservation. For scientific data archival where preventing artificial texture hallucination is paramount, SVD's deterministic degradation is significantly safer than JPEG's artifact generation.

E. Computational Complexity Profiling

A primary critique of modern deep learning-based compression is the massive computational overhead required for onboard satellite operations. To address this, hardware resource profiling was conducted. As detailed in Table II, executing the SVD decomposition and rank-k reconstruction on high-resolution matrices requires an average wall-clock runtime of only ~2.50 seconds and a peak memory footprint of strictly ~95.99 MB.

TABLE II. COMPUTATIONAL COMPLEXITY PROFILING (AVERAGED OVER 25 SAMPLES)

Method	Rank (k)	Runtime (s)	Peak Memory (MB)
SVD	10	2.29 ± 1.09	95.88 ±27.09
	50	2.30 ± 1.06	95.88 ±27.09
	100	2.28 ± 1.06	95.88 ± 27.09
	200	2.29 ± 1.08	95.88 ±27.09
	400	2.27 ± 1.03	95.88 ± 27.09
JPEG	Baseline	-	-

Unlike convolutional neural networks or autoencoders that demand heavy GPU acceleration and gigabytes of memory to store pre-trained weights, the proposed SVD framework is exceptionally lightweight. This ~95 MB peak memory requirement guarantees that the algorithm is highly feasible for direct deployment on hardware-constrained onboard systems, such as CubeSats and deep-space probes.

F. Comparison with Existing Literature

The experimental results strongly validate the findings of Fournier and Aloise [9] that classical matrix decomposition remains a robust and highly competitive alternative to deep learning. While Convolutional Neural Networks and Autoencoders [6], [7], and [8] have set new benchmarks in generic image compression, they suffer from the "black box" problem and lack of interpretability. In scientific data archival, ensuring that compression artifacts are not "hallucinated" features is critical. SVD provides a mathematically transparent transformation where the error bound is strictly defined by the Eckart-Young theorem [10]. Unlike generative AI, which might generate realistic-looking but fake textures based on training data bias, SVD creates a strictly lower-fidelity version of the actual input data, making it inherently safer for astrophotography.

In comparison to other classical methods, SVD offers distinct advantages over Wavelet-based techniques [5]. While Wavelet transforms require complex thresholding strategies to determine which coefficients to discard, SVD provides a direct mechanism to control the quality-size trade-off simply by adjusting the rank k. Furthermore, the deterministic robustness of low-rank matrices showcased in this space telemetry study conceptually aligns with its

successful applications in other parallel high-dimensionality domains, such as randomized tensor decompositions [13], [14] and medical MRI reconstruction [15]. A conceptual summary distinguishing the proposed SVD framework from current alternative paradigms is presented in Table III.

TABLE III. CONCEPTUAL COMPARISON OF COMPRESSION PARADIGMS FOR SPACE TELEMETRY

Feature / Parameter	Singular Value Decomposition (Proposed)	Deep Learning / Autoencoders	Discrete Cosine Transform (JPEG)
Computational Overhead	Very Low (~95 MB RAM)	Very High (Requires GPU)	Low
Risk of Data Hallucination	None (Deterministic)	High (Data-driven Bias)	None
Visual Artifacts	Smooth blurring at low rank	Texture manipulation	Blocking artifacts (Grid-like)
Training Data Requirement	None (Zero-shot)	Extensive dataset required	None

III. CONCLUSION

This research has successfully evaluated the efficacy and computational feasibility of Singular Value Decomposition (SVD) as a low-rank approximation technique for compressing deep-space astronomical imagery. By expanding the experimental dataset to 25 diverse high-resolution Hubble images, the analysis confirms that SVD is a statistically robust method for reducing data redundancy while strictly maintaining the structural integrity required for scientific observation. The empirical results establish that a rank of $k = 100$ serves as the optimal operating benchmark. At this threshold, the algorithm achieves an average PSNR of 31.10 dB and reduces the data volume by 88.7% (a Compression Ratio of 8.87x), demonstrating consistent performance across various celestial morphologies, ranging from diffuse nebulae to dense star clusters.

Qualitatively, the SVD approach demonstrates a critical advantage over conventional block-based compression standards like JPEG. By entirely avoiding the "blocking artifacts" inherent to Discrete Cosine Transforms (DCT), SVD successfully preserves the continuous morphological structures of cosmic bodies and strictly localizes truncation errors to high-frequency point-sources, thereby preventing artificial texture hallucination. Furthermore, this study empirically proves the lightweight nature of the SVD framework. Hardware profiling reveals a peak memory footprint of only ~95.99 MB and an average runtime of ~2.50 seconds per high-resolution image. This exceptionally low computational overhead guarantees that SVD is highly feasible for direct deployment on resource-constrained onboard satellite systems, such as CubeSats, where deploying parameter-heavy deep learning models remains impractical.

For future work, we suggest exploring hybrid compression architectures, such as integrating SVD with Discrete Wavelet Transforms (DWT), to better capture the high-frequency point-source details of faint stars that are prone to smoothing at lower ranks. Additionally, dynamic rank-selection algorithms based on onboard spatial frequency analysis could be investigated to automatically optimize the compression ratio for each unique astronomical observation.

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