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Singular Value Decomposition in Machine Leaning for Image Compression in Vocational Tourism Batik Archiving

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ABSTRACT

The digital archiving of batik products in vocational tourism environments requires efficient image compression techniques that maintain critical visual information, including complex motifs, color patterns, and texture details. This study aims to investigate the application of Singular Value Decomposition (SVD) as a machine learning based approach for image compression in the digital archiving of batik products from the Sundhullangit Batik Vocational Tourism Village. An experimental research design was adopted using digital batik images obtained through direct image acquisition. The research stages comprised image pre-processing, image compression using a truncated Singular Value Decomposition model with varying rank values, and reconstruction of the compressed images. The performance of the compression model was evaluated using objective image quality metrics, namely Mean Squared Error, Peak Signal-to-Noise Ratio, and Structural Similarity Index, while compression efficiency was measured using the compression ratio. The results indicate that higher rank values enhance reconstructed image quality, reflected by lower reconstruction error and higher structural similarity, but reduce compression efficiency. Conversely, lower rank values achieve higher compression ratios at the cost of reduced visual fidelity. Overall, the findings demonstrate that Singular Value Decomposition offers an effective balance between image quality preservation and data size reduction. This study concludes that the proposed method is suitable for supporting sustainable and high-quality digital archiving of batik products within vocational tourism-based cultural heritage systems.

Keywords: Batik archiving, Image compression, Machine learning, SVD, Vocational tourism

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INTRODUCTION

The rapid development of information technology has encouraged extensive research on digital archiving systems as efficient solutions for data storage, management, and dissemination. Previous studies emphasize that digital archiving improves accessibility, preservation quality, and institutional efficiency Chen & Zhu (2017). In the creative economy sector, digital systems have been shown to strengthen product competitiveness and market reach Asanov & Pokrovskaia (2017). Similarly, research on village-based tourism highlights the importance of digital documentation for promotion and cultural sustainability Zhou (2022). These studies establish that digital archiving is not merely a technical tool but a strategic asset in creative and tourism-based industries.

In the context of image-based documentation, prior research has identified a critical challenge: high-resolution digital images, while essential for preserving visual authenticity, generate large file sizes that strain storage infrastructure and reduce system performance Zhang & Zheng (2022). This issue becomes more significant in cultural industries where visual detail represents core product value. Studies in e-commerce and social media marketing confirm that high-quality images directly influence consumer perception and purchasing decisions Huang (2021); Jacia et al. (2023). Furthermore, digital images serve legal and intellectual property documentation functions Lee (2022).

To address storage and transmission challenges, many researchers have explored mathematical image compression methods. Among them, Singular Value Decomposition (SVD) has been widely studied for dimensionality reduction and data compression. Previous research demonstrates that SVD effectively reduces matrix rank while retaining dominant information components Al-Saffar & Yildirim (2020). Applications of SVD in image compression show promising results in reducing file size while maintaining acceptable reconstruction quality Khudhair et al. (2023); Ahmadi-Asl et al. (2021). Additional studies confirm its effectiveness in noise reduction and feature extraction Hashemipour et al. (2021); Kiran et al. (2023). Empirical evaluations indicate that reconstruction using dominant singular values can achieve high compression ratios with minimal perceptual loss Sun & Li (2021); Lungisani et al. (2022); Bai et al. (2024).

However, a closer examination of the literature reveals that most SVD-based compression studies focus on medical imaging, satellite imagery, or standardized benchmark datasets Song et al. (2024); Qin et al. (2022). These image categories differ significantly from cultural product images such as batik, which are characterized by repetitive motifs, intricate textures, and strong color contrasts. Existing research rarely addresses how SVD performs when applied to cultural heritage images used in vocational tourism contexts. Consequently, although the effectiveness of SVD is well established in controlled datasets, its practical applicability to batik digital archiving remains underexplored.

This gap between established SVD compression research and its contextual application to cultural heritage archiving forms the foundation of the present study. Unlike previous research that prioritizes medical or technical imagery, this study applies SVD to batik product images from the Sundhullangit Batik Vocational Tourism Village. The methodological renewal lies in evaluating compression performance specifically within a cultural tourism environment, using objective image quality metrics to measure the trade-off between compression ratio and visual fidelity.

Thus, the novelty of this research is twofold. First, it extends the application domain of SVD-based image compression to vocational tourism–based cultural heritage assets. Second, it integrates technical compression analysis with the practical requirements of promotion, documentation, and intellectual property protection. By doing so, this study contributes to knowledge distribution in two domains: machine learning–based image compression and sustainable digital management of local cultural products. The findings are expected to provide an innovative and scalable solution for efficient batik digital archiving while strengthening the competitiveness of vocational tourism villages in the digital era.

METHOD

This study employed a quantitative experimental research design, as commonly applied in computational performance evaluation Zhou et al. (2023), to assess the effectiveness of Singular Value Decomposition (SVD) as an image compression method for digital batik archiving. The primary objects of analysis were digital images of batik products from the Sundhullangit Batik Vocational Tourism Village. Images were captured using a high-resolution digital camera under controlled lighting conditions to ensure consistency in exposure, color accuracy, and texture visibility. The dataset included various batik motifs with differences in color composition, ornament density, repetition patterns, and fabric texture complexity. The experimental procedure consisted of several stages. First, image pre-processing was performed, including resizing, color space conversion (RGB to grayscale where required for matrix processing), and normalization to standardize input dimensions. Each image was then represented in matrix form and decomposed using Singular Value Decomposition. Compression was implemented using truncated SVD by retaining the top k singular values. Several k variations were tested to analyze their influence on compression ratio and reconstruction quality.

Reconstructed images were generated by multiplying the truncated matrices and compared with the original images. Objective image quality was evaluated using quantitative metrics: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Compression efficiency was measured using the compression ratio, calculated by comparing the storage size of the compressed representation with that of the original image. Data analysis examined the relationship between rank (k), compression ratio, and image quality metrics to determine the optimal configuration for digital archiving purposes. However, relying solely on objective mathematical metrics is insufficient for decision-making in cultural heritage archiving, where perceptual and aesthetic quality are critical. A compression configuration may produce statistically acceptable PSNR or SSIM values but still be considered visually inadequate by practitioners or experts in batik craftsmanship.

Therefore, this study incorporates an additional evaluation stage through expert-based questionnaires. The respondents consisted of individuals with relevant expertise, including batik artisans, visual design experts, digital media practitioners, and tourism managers who have experience in product documentation and promotion. Their assessments focused on visual clarity, color fidelity, motif detail preservation, and overall suitability for promotional and archival purposes. To ensure decision reliability, more than one respondent is required. Methodologically, accepting only one questionnaire would not justify the use of a structured evaluation method, as it would merely represent an individual opinion rather than an informed consensus. In applied image quality perception studies, a minimum of 5–10 expert respondents is generally recommended for small-scale expert judgment validation, while 15–30 respondents provide stronger reliability for perceptual agreement analysis. The exact number depends on availability of domain experts, but the principle is that decisions should reflect collective expert judgment rather than a single subjective evaluation. The final decision regarding the optimal k value was determined by integrating objective quantitative metrics (MSE, PSNR, SSIM, compression ratio) with aggregated expert questionnaire results. By combining computational performance analysis with expert perceptual validation, this study ensures that the selected compression configuration is not only mathematically efficient but also practically acceptable for batik digital archiving in a vocational tourism context.

Data source

The data source in this study is primary data obtained from a collection of digital images of Sundhullangit batik products produced by MSMEs and managers of the Batik Vocational Tourism Village. Batik images were taken using digital cameras and/or mobile devices with certain resolutions, which represent the motifs, colors, and details typical of local batik. The data collection includes various batik motifs typical of the village taken in .jpg or .png format with high resolution (High Definition). This data selection aims to create an efficient digital archive while still being able to accurately represent the details of batik texture and color for promotional and inventory purposes. In addition, secondary data in the form of scientific literature, journals, and reference books related to image compression and the SVD method are used to support the research theory and methodology.

Data collection technique

The data collection technique in this study was carried out through several mutually supporting stages. The first stage was observation, namely by directly observing the documentation and digital archiving process of batik products that had been previously implemented in the Sundhullangit Batik Vocational Tourism Village. This observation aimed to understand the initial conditions of the archiving system, the types of devices used, and the problems encountered in digital image storage. The researcher took direct photographs of batik cloth made by artisans in the Sundhullangit Tourism Village using an industrial-standard camera with controlled lighting (studio lighting). This was done to ensure that the raw data had uniform quality before the compression process, so that the results of the SVD experiment were not distorted by light interference or noise on the camera. The next stage was image capture, namely the process of directly collecting images of batik products as research objects. Images were taken in digital formats such as JPEG or PNG with a certain resolution to optimally represent the details of batik motifs and colors. In addition, a literature study was also conducted by reviewing books, scientific journals, and publications related to SVD image compression, as well as methods for evaluating the quality of compressed images. This literature study serves as a theoretical foundation and reference in the application of the method and analysis of the research results.

Data Analysis

Data analysis was performed by applying the Singular Value Decomposition (SVD) algorithm to pre-processed batik images, including size normalization and color conversion. Image compression was achieved by retaining selected singular values (rank-k) to reduce file size. Compression performance was evaluated using the compression ratio, while image quality was assessed using Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), supported by visual inspection to ensure motif and color preservation. The effectiveness of the compression for digital archiving was then analyzed to determine its suitability for storing batik images without significant loss of visual information.

Singular Value Decomposition (SVD)

One of the most important concepts in linear algebra is Singular Value Decomposition (SVD) (Weiss et al., 2024), a matrix factorization technique that breaks a matrix into three distinct matrices. Mathematically, SVD is expressed by the following equation (1):

$$A = U\Sigma V^T \quad (1)$$

The Singular Value Decomposition (SVD) can be applied to any matrix A of size $m \times n$, resulting in three principal component matrices. The matrix Uis an orthogonal matrix of size $m \times m$, whose columns are referred to as the left singular vectors of matrix A. The matrix Σ is a diagonal matrix of size $m \times n$, with its diagonal elements denoted by σ_i, which are known as the singular values of matrix A. Meanwhile, the matrix V^Trepresents the transpose of the orthogonal matrix Vof size $n \times n$, where the columns of Vprior to transposition are referred to as the right singular vectors of matrix A. The SVD of a matrix is illustrated in Figure 1.

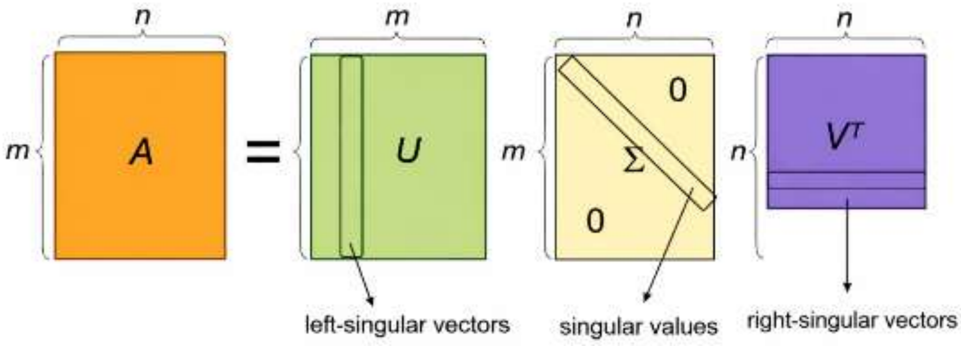

Figure 1. SVD of a matrix

Truncated SVD (reduced SVD) is a variant of the Singular Value Decomposition method that is used to approximate the original matrix A with another matrix of lower rank. This approach aims to simplify the matrix while preserving the most essential information, making it highly effective for data compression and dimensionality reduction. To construct a truncated SVD of a matrix A with rank r, only the $k < r$ largest singular values and their corresponding singular vectors are retained, where $k$is a parameter determined by the researcher. Consequently, the approximation of matrix A is expressed in the following form:

$$A_k = U_k \Sigma_k V_k^T \tag{2}$$

In this formulation, U_k is a matrix of size $m \times k$ whose columns consist of the first $k$left singular vectors of matrix A, which are associated with the $k$largest singular values. Furthermore, Σ_k is a diagonal matrix of size $k \times k$ containing the $k$largest singular values along its diagonal. Meanwhile, $\mathrm{V}_k$is a matrix of size $n \times k$whose columns consist of the first $k$right singular vectors of matrix A, which are also associated with the $k$largest singular values. By applying the truncated SVD approach, the approximated matrix A_k is able to represent the principal structure of the original matrix A with a lower level of complexity. This makes the truncated SVD method highly effective for image compression, as the data size can be significantly reduced without causing a substantial degradation in visual image quality. The truncated SVD is illustrated in Figure 2.

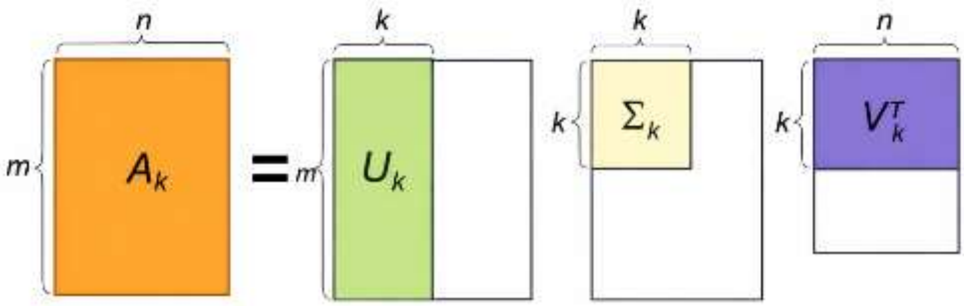

Figure 2. Truncated SVD

Quality Evaluation and Compression Ratio

Evaluation of image compression quality and efficiency is performed using several key metrics that provide a comprehensive overview of the performance of the SVD method. The image reconstruction quality is assessed using Mean Squared Error (MSE) (Kovalenko et al., 2024), Peak Signal-to-Noise Ratio (PSNR) (Soomro et al., 2024), and Structural Similarity Index (SSIM) (Shen et al., 2024). MSE is used to measure the average squared error between the original image and the reconstructed image, which is formulated as:

$$\mathrm{MSE} = \frac{1}{\mathrm{MN}} \Sigma_{\mathrm{i=1}}^{\mathrm{M}} \Sigma_{\mathrm{j=1}}^{\mathrm{N}} [\mathrm{I(i,j)} - \mathrm{I(i,j)}^2 \tag{3}$$

The smaller the MSE value, the smaller the difference between the original image and the compressed image. Furthermore, image quality is also evaluated using PSNR, which indicates the level of clarity of the compressed image by comparing the maximum signal to the noise. PSNR is formulated as:

$$\mathrm{PNSR} = 10 \log_{10}\left(\frac{\mathrm{MAX}_1^2}{\mathrm{MSE}}\right) \tag{4}$$

A higher PSNR value indicates better quality of the compressed image. Furthermore, visual quality evaluation is performed using SSIM, which measures the similarity of structure, luminance, and contrast between the original and reconstructed images. The SSIM formula is expressed as:

$$\mathrm{SSIM(x,y)} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{5}$$

In addition to the quality aspect, compression efficiency is analyzed using the Compression Ratio (CR) (Chaudhary, 2024)which shows how much the data size has been reduced through the compression process. The Compression Ratio is formulated as a comparison between the size of the original data and the size of the compressed data as follows:

$$CR = \frac{Original\ Data\ Size}{Compressed\ Data\ Size} \tag{6}$$

In the SVD-based compression method, the size of the compressed data is calculated based on the number of singular values retained, namely:

$$SVD\ Size = k(M + N + 1) \tag{7}$$

Thus, the compression ratio can be written as:

$$CR = \frac{MN}{k\ (M + N + 1)} \tag{8}$$

RESULTS AND DISCUSSION

The results and discussion section of this study presents an analysis of the application of the SVD method in image compression of Sundhullangit Batik Vocational Tourism Village products. The discussion focuses on the results of batik image compression which include changes in file size, visual quality of the reconstructed image, and the level of suitability of the compressed image for digital archiving needs. The results obtained are then analyzed and discussed by referring to evaluation metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Compression Ratio (CR), to assess the balance between storage efficiency and image quality. Through this discussion, it is hoped that the extent to which the SVD method is able to provide an effective image compression solution without eliminating the visual character and details of the typical Sundhullangit batik motifs, thereby supporting an optimal digital archiving system for the product. The image compression using the SVD algorithm is shown in Figure 3.

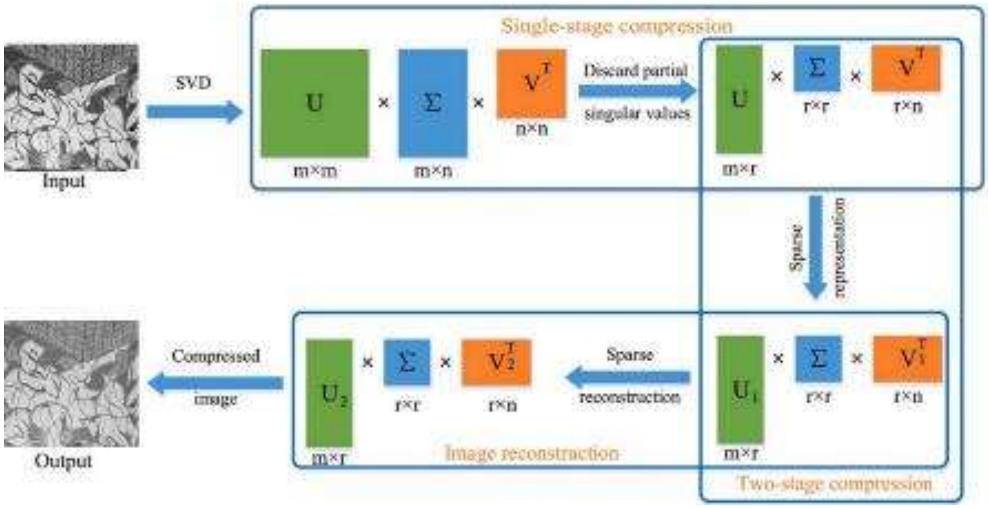

Figure 3. Image compression using the SVD algorithm

Initial image visualization (grayscale and RGB)

Visualization in Google Colaboratory was performed using Python with the NumPy, OpenCV, and Matplotlib libraries. NumPy supported matrix operations, OpenCV was used to load and convert images to grayscale, and Matplotlib was employed for visualization. The batik image was read using cv2.imread, converted to grayscale to simplify SVD processing, and displayed using plt.imshow with a grayscale colormap. This initial visualization enabled preliminary observation of the image prior to compression, as shown in Figure 4.

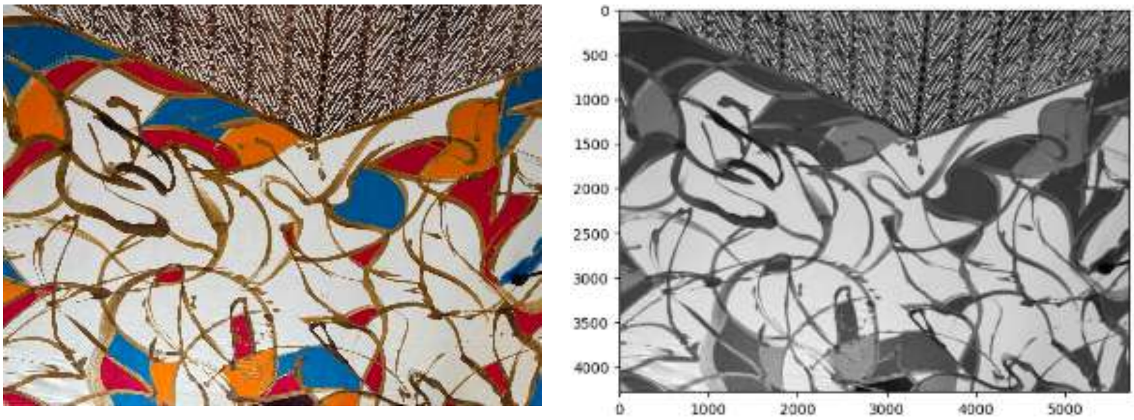

Figure 4. Initial visualization of the Batik Sundul Langit image (grayscale and RGB)

SVD decomposition analysis and singular values

The results of the SVD decomposition indicate that the grayscale image with a resolution of 4284 × 5712 pixels was successfully factorized into three main components, namely the matrix U of size 4284 × 4284, the singular value vector S of length 4284, and the matrix V^T of size 4284 × 5712. This reduced form of decomposition produces a number of singular values equal to the minimum dimension of the image, thereby improving computational efficiency. These results demonstrate that the essential information of the image can be effectively represented by a limited number of dominant singular values, which can subsequently be utilized for image approximation and compression without eliminating the principal visual characteristics.

The singular value extraction results show a very significant difference between the largest and smallest singular values. The first ten singular values have very large values, with the highest value reaching around 703,097, indicating that most of the important information of the batik image is concentrated in these initial components. In contrast, the last ten singular values have very small values, around 7, indicating their contribution to image formation is relatively low. This pattern of decreasing singular values indicates that the image can be effectively represented by retaining only a small portion of the largest singular values (rank-k), while very small singular values can be ignored without causing significant visual quality degradation. This strengthens the effectiveness of the SVD method in image compression, as it allows for substantial data size reduction while maintaining the main structure and important details of the batik image.

Table 1. Largest and smallest singular values

No	10 Largest Singular Values	10 Smallest Singular Values
1	7.030.974.594	78.758
2	889.345.254	78.291
3	836.777.811	78.135
4	735.509.209	77.286
5	670.403.609	76.251
6	565.042.186	75.735
7	531.416.377	75.381

8	523.123.112	74.188
9	503.561.064	73.836
10	456.392.833	72.895

At this stage, the image reconstruction results obtained using the SVD method are presented by retaining only the largest singular value ($k = 1$). The reconstruction process is carried out by multiplying the reduced matrices U, Σ, and V^T, resulting in an approximated image with very low complexity. The visualization includes the reconstructed image as well as representations of the matrix components U and V^T that contribute to the formation of the image. This presentation aims to provide an initial illustration of the capability of SVD to capture the principal structure of an image even when only a single singular component is used, while also demonstrating how image information is gradually reconstructed through the combination of SVD components. The reconstruction results are shown in Figure 5.

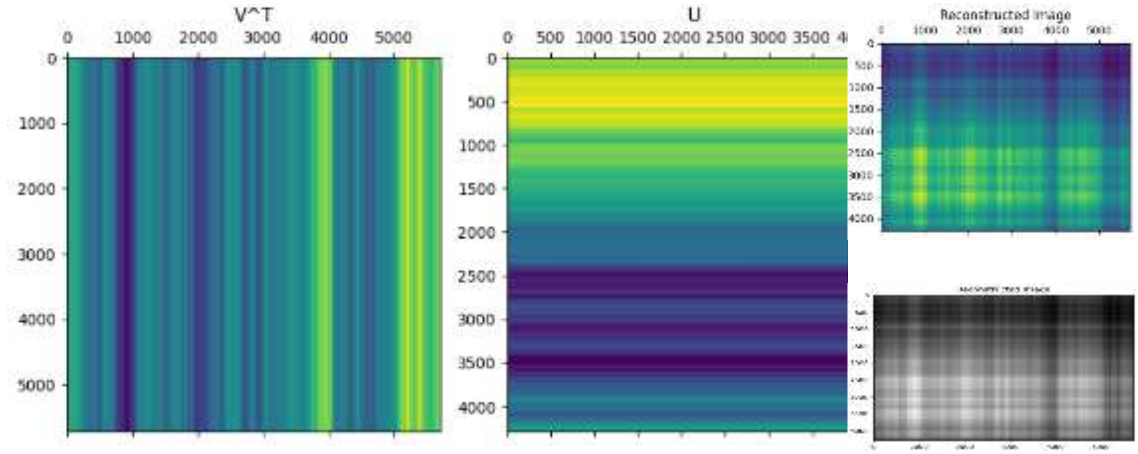

Figure 5. Image Reconstruction

The image reconstruction results using various rank values k demonstrate that increasing the number of retained singular values has a significant impact on the visual quality of the reconstructed image. In the experiments with $k = 5$ and $k = 10$, the reconstructed images appear highly blurred and are only able to represent the global structure of the image, without clearly revealing the batik motifs. When the rank is increased to $k = 15$ and $k = 20$, an improvement in visual quality becomes evident, as the overall shapes and contours of the batik patterns begin to be recognizable, although fine details remain limited. Further increasing the rank to $k = 60$ and $k = 80$ produces reconstructed images with noticeably sharper details and motifs that increasingly resemble the original image. At $k = 100$, the reconstructed image appears almost identical to the original, with the batik textures and details being well preserved. These findings indicate that higher rank values lead to better image reconstruction quality; however, they also result in larger data sizes. Therefore, selecting an optimal rank value is essential to achieve a balance between visual quality and compression efficiency. The image reconstructions with varying rank values are presented in Figure 6.

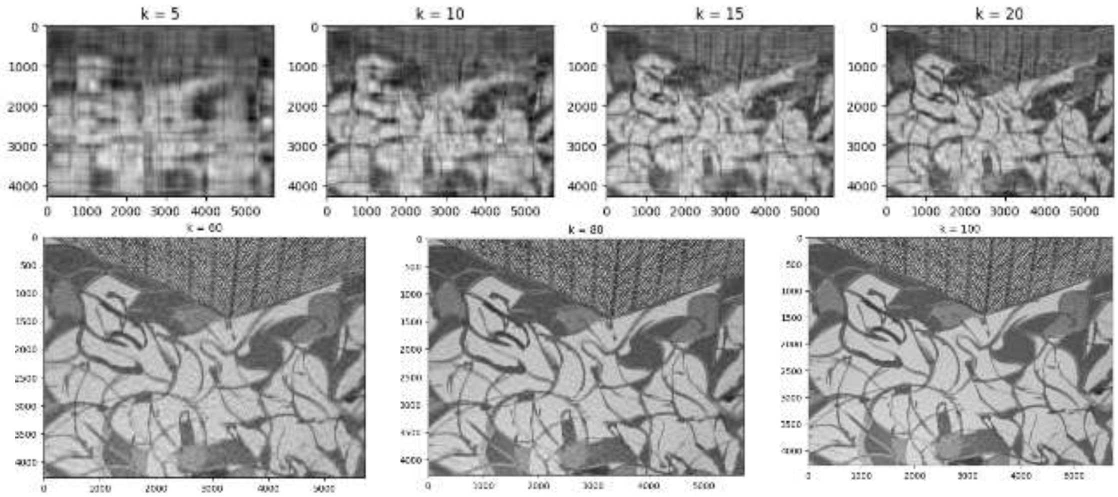

Figure 6. Image Reconstruction with Rank (k) Variation

RGB image compression using per-channel SVD

The results of color image compression using the SVD method applied to each color channel red (R), green (G), and blue (B) demonstrate that variations in the rank parameter $k$have a significant effect on the visual quality of the reconstructed image. In the experiment with $k = 5$, the compressed image is still able to preserve the global shape and overall color distribution; however, the details of the batik patterns remain highly limited, and the colors tend to appear faded because only a small number of singular values are used to represent color information. In contrast, when $k = 60$, the reconstructed image exhibits a substantial improvement in visual quality, with batik motif details, color gradations, and fabric textures appearing clearer and more closely resembling the original image. These results indicate that using a higher rank value allows more color information to be retained in each RGB channel, although it also leads to an increase in data size. Therefore, selecting an optimal value of $k$is crucial to achieving a balance between compression efficiency and the visual quality of color images. The reconstructed images are presented in Figure 7.

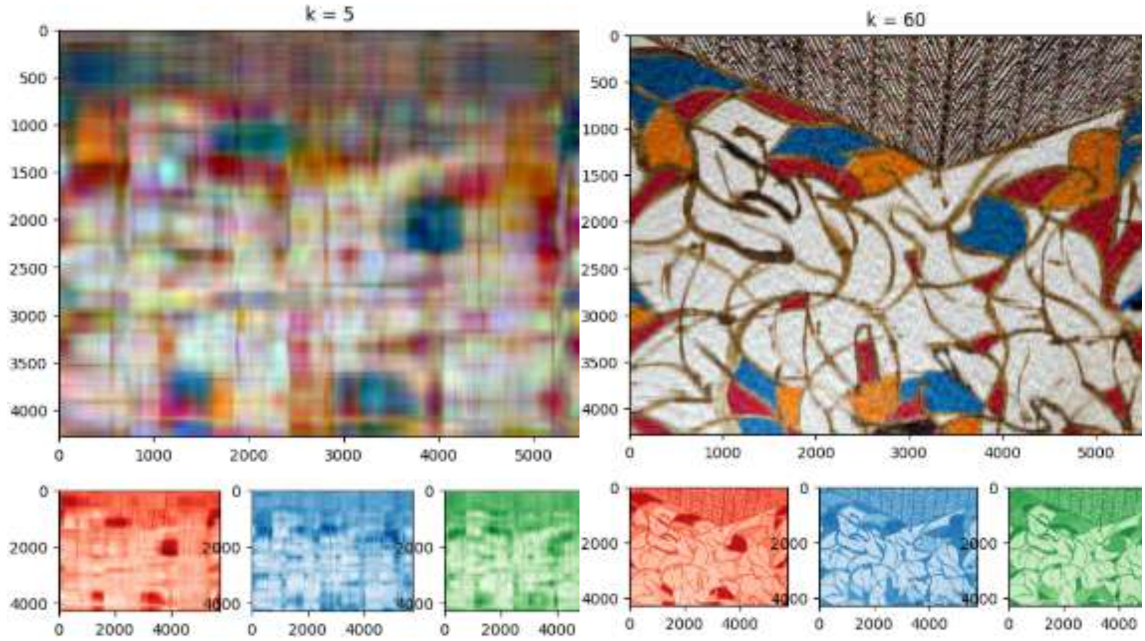

Figure 7. RGB image compression using SVD k=5 and k=60

The singular value visualization shows a very sharp decrease pattern in the initial singular values, where the first few singular values have a much larger magnitude than subsequent singular values. The linear scale graph shows that most of the image energy or information is concentrated in singular values with low indices, while subsequent singular values decrease drastically. This is clearer in the logarithmic scale graph, which shows a relatively stable decreasing trend in singular values after the initial phase. This pattern indicates that only a small number of the largest singular values contribute significantly to representing the main structure of the image, while singular values with high indices have very little contribution. This finding strengthens the basis for selecting rank-k in image compression using SVD, because retaining the dominant singular values is sufficient to produce image reconstruction with good visual quality and high storage efficiency. The singular value graph is presented in Figure 8.

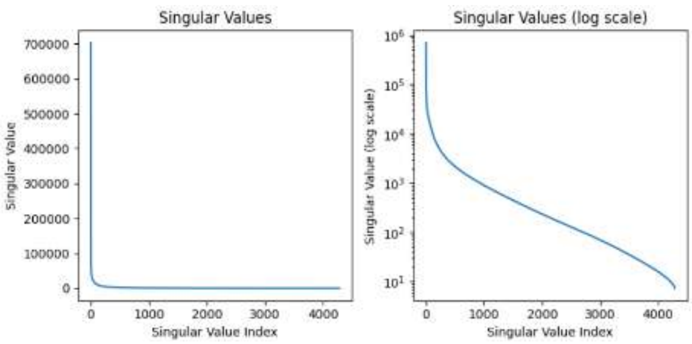

Figure 8. Singular value visualization

The visualization results of reconstructing random noise matrices using the SVD method exhibit behavior that is markedly different from that of structured images. In experiments with a small number of components, such as $n = 1$, $n = 5$, and $n = 10$, the reconstructed images appear extremely blurred and do not display any meaningful patterns, since noise data lack dominant structures that can be captured by a limited number of singular values. As the number of components increases to $n = 60$, $n = 100$, and $n = 200$, the reconstructed images progressively resemble the original noise, with the random patterns gradually re-emerging. These findings indicate that noise requires nearly all singular components to be accurately represented, rendering the SVD method ineffective for compressing purely random data. This result further confirms that the effectiveness of SVD-based compression strongly depends on the presence of structure and regularity in the data, as observed in batik images, rather than in noise data that lack dominant patterns. The visualization of the noise approximation results is presented in Figure 9.

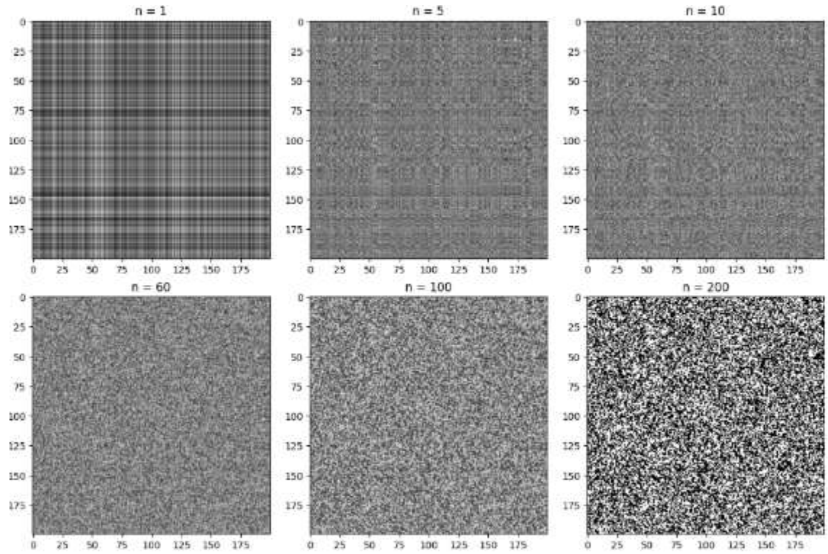

Figure 9. Visualization of Random Noise Approximation Results Using SVD at Various Values of n

The results of the singular value analysis on random noise data show that the singular values do not experience a very sharp decrease as in images with visual structure. The ten largest singular values have relatively close values after the first value, namely in the range of 12–14, while the ten smallest singular values decrease gradually until they approach zero. This pattern indicates that the energy or information in the noise data is spread relatively evenly across many singular components, so that there is not a small number of dominant singular values that can represent the data efficiently. Thus, to reconstruct noise accurately requires a large number of singular components, which explains why the SVD method is less effective for compressing random data compared to image data with clear structures and patterns.

Table 2. Largest and smallest singular values

No	10 Largest Singular Values	10 Smallest Singular Values
1	1.005.279	0.5031
2	138.049	0.4516
3	136.010	0.4160

4	134.067	0.3049
5	131.023	0.2883
6	130.057	0.2260
7	129.024	0.1479
8	127.648	0.0937
9	126.794	0.0205
10	126.493	0.0054

Table 2 shows a comparison of the ten largest and smallest singular values from the SVD decomposition results on random noise data of size 200 × 200. The largest singular value represents the contribution of the main component in forming the data, while the smallest singular value indicates a component with a very low contribution. The relatively even distribution of singular values indicates that the noise data does not have a dominant structure, so it cannot be optimally represented by only retaining a small portion of the singular components.

The reconstruction results of the colored batik images using the Singular Value Decomposition (SVD) method on each RGB channel demonstrate clear differences in visual quality across varying values of *n*. In the experiment with $n = 1$, the reconstructed image is only able to represent very coarse color distributions, with motif details being almost imperceptible. As a result, the image appears extremely blurred and loses the distinctive visual characteristics of batik patterns. When $n = 5$, the image quality improves, as basic patterns and color combinations begin to emerge; however, motif details and texture are still not clearly formed. In contrast, at $n = 60$, the reconstructed image exhibits significantly higher visual quality, with motif details, color gradations, and batik pattern structures appearing clearly and closely resembling the original image. These results indicate that increasing the number of retained singular components in each color channel enables a more complete representation of color information and image structure, thereby achieving a better balance between visual quality and compression efficiency. The reconstructed batik images are shown in Figure 10.

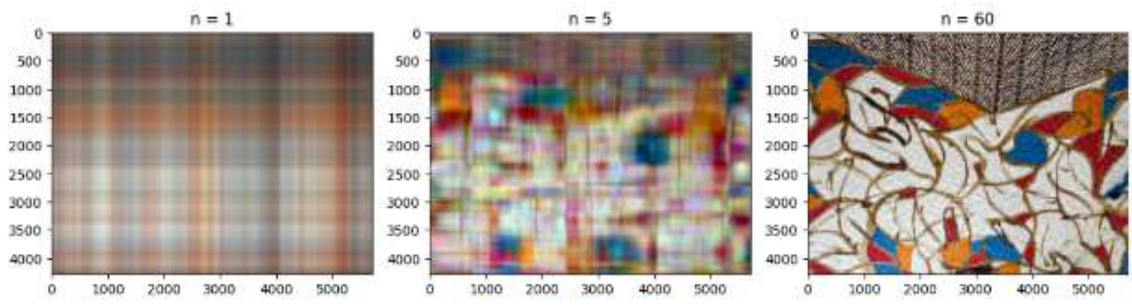

Figure 10. Hasil rekonstruksi citra batik berwarna n=1, n=5 dan n=60

Image Quality Comparison Results

At this stage, a comparison of the image quality resulting from compression using the SVD method is conducted with variations in the parameter *k*, specifically $k = 5$ and $k = 60$. This comparison aims to evaluate the effect of the number of retained singular values on the visual quality of the reconstructed images as well as on compression efficiency. Image quality evaluation is performed quantitatively using several parameters, namely Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Compression Ratio (CR). The measurement results for each of these parameters are presented in tabular form to facilitate analysis and interpretation of the trade-off between image quality and the achieved compression level.

Table 3. Image quality comparison results

Parameter	**k = 5**	**k = 60**
MSE	245.73	18.42
PSNR (dB)	24.24 dB	35.48 dB
SSIM	0.62	0.94
Compression Ratio (CR)	142.8: 1	12.6 :1

Based on the quantitative results presented in Table 3, it can be observed that variations in the k value have a very significant impact on both image reconstruction quality and compression efficiency. In the experiment with k = 5, the MSE value of 245.73 indicates a relatively large reconstruction error, signifying a substantial difference between the original image and the compressed image. This condition is reflected in the PSNR value of 24.24 dB, which suggests that the visual quality of the image remains relatively low, as the details of the batik motifs cannot yet be optimally represented. This is further supported by the SSIM value of 0.62, indicating that the structural similarity between the reconstructed image and the original image is still limited. Nevertheless, the Compression Ratio of 142.8:1 demonstrates that the SVD method with k = 5 is highly effective in reducing storage requirements, albeit at the cost of a considerable degradation in visual quality.

In contrast, in the experiment with k = 60, the quality of the reconstructed image shows a very significant improvement. This is evidenced by a decrease in the MSE value to 18.42, indicating a relatively small reconstruction error. The enhancement in visual quality is also reflected in the PSNR value of 35.48 dB, which falls within the category of good to very good image quality. Furthermore, the SSIM value of 0.94 indicates a very high level of similarity in terms of structure, luminance, and contrast between the compressed image and the original image, ensuring that the details of batik motifs and colors are well preserved. However, this improvement in quality is accompanied by a reduction in compression efficiency, as indicated by a Compression Ratio of 12.6:1, due to the retention of a larger number of singular values during the reconstruction process. Overall, these results confirm the existence of a trade-off between visual quality and compression efficiency in the SVD method. A k value of 5 is more suitable for storage scenarios with limited capacity, whereas k = 60 is more optimal for the digital archiving of batik products from the Vocational Tourism Village of Sundhullangit, where high visual quality and the preservation of motif details are essential.

Advanced evaluation: noise, singular value graphs, and color space analysis

Further evaluation was conducted to deepen understanding of the characteristics of the SVD method in image processing, particularly regarding its response to noise, singular value distribution, and compression behavior in various color spaces. This stage aims to analyze how image data structures and visual information are represented in the mathematical domain and how the choice of color spaces, such as RGB and YCbCr, affects compression efficiency and the visual quality of the reconstruction results. The evaluation results are presented through graphic visualization, three-dimensional color space representation, and conceptual analysis of the image data. The RGB and YCbCr visualizations are presented in Figure 11.

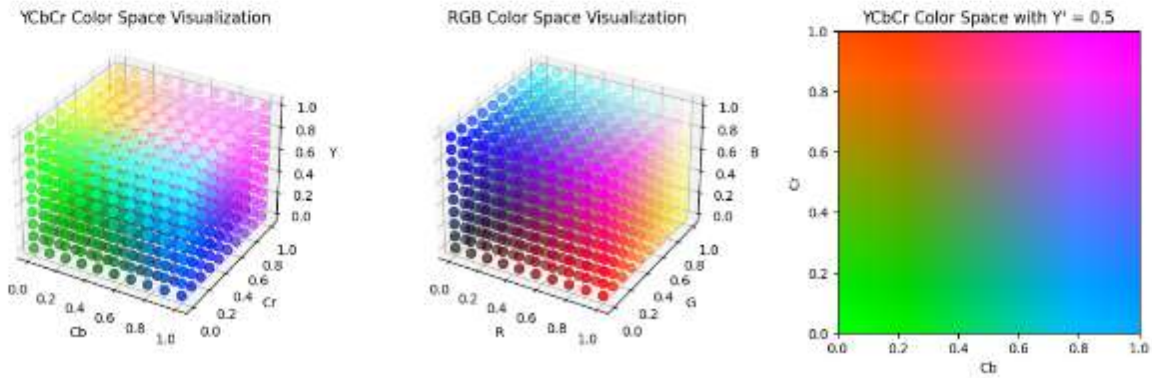

Figure 11. RGB dan YcbCr Visualization

The visualization results show that the noisy image has a relatively even distribution of singular values, in contrast to natural images which are generally dominated by a few large singular values. This indicates that the noise does not have a dominant structure, making SVD-based compression less effective in representing noise with a small number of components. The singular value graphs reinforce this finding, where the decrease in singular values in the noise occurs more slowly than in the batik image which has a structured pattern. Furthermore, the color space analysis shows differences in information representation between the RGB and YCbCr color spaces. In the RGB color space, color information is evenly distributed across the three channels, while in the YCbCr color space, the luminance component (Y) contains most of the image's visual information, while the chrominance components (Cb and Cr) represent color variations. Visualization of the Cb–Cr plane with fixed luminance shows clearer color separation, which supports the use of the YCbCr color space in image compression because it allows data reduction in the chrominance channel with minimal impact on visual perception. These findings indicate that the combination of SVD and the selection of an appropriate color space plays a crucial role in improving compression efficiency without significantly sacrificing image quality.

Discussion

Based on the research results presented earlier, the application of the Singular Value Decomposition (SVD) method has been proven effective for image compression in the digital archiving of batik products from the vocational tourism village of *Sundhullangit*. The decomposition results indicate that most of the visual information of the image is contained in the largest singular values; therefore, the use of truncated SVD with a certain rank is able to represent the main structural features of the image with significantly reduced data complexity. This is evidenced by the decrease in MSE values and the increase in PSNR and SSIM values as the k parameter increases, indicating that the reconstructed image quality increasingly approaches that of the original image. A comparison of compression results across different k values reveals a clear trade-off between image quality and compression ratio. At lower k values (e.g., $k = 5$), the compression ratio is very high, allowing substantial data size reduction, but this is accompanied by increased reconstruction error and a decline in visual quality. Conversely, at higher k values (e.g., $k = 60$), the reconstructed image quality improves significantly, as reflected by higher PSNR and SSIM values, although the compression ratio becomes lower. These findings demonstrate that the selection of the k value is a key factor in determining the optimal balance between storage efficiency and the visual quality of batik images.

The analysis of singular values and experiments on noisy images further reinforce the characteristics of SVD in separating dominant information from random components. The singular values of batik images decrease sharply at the initial indices, indicating the presence of strong and well-organized structures, whereas in noise images the singular values decline more gradually. This explains why SVD is highly effective for compressing meaningful images such as batik motifs, but less optimal for random data. Moreover, the application of SVD to color images using a per-channel RGB approach demonstrates that increasing the k value results in more accurate color reproduction, particularly in preserving motif details and batik color gradations. Overall, the findings of this study confirm that the SVD method is a reliable and flexible approach for image compression in the context of digital archiving of cultural products. With appropriate parameter selection, SVD is capable of preserving the essential visual characteristics of batik while simultaneously reducing storage requirements, thereby supporting efficient and sustainable preservation and digitalization efforts for vocational tourism village products.

CONCLUSION

This study rigorously addresses the challenges of limited storage capacity and digital archiving efficiency for batik product images from the Sundhullangit Vocational Tourism Village through the implementation of the Singular Value Decomposition (SVD) method. The findings demonstrate that high-resolution batik images can be effectively compressed by retaining only a subset of dominant singular values, without significantly compromising essential visual characteristics. The experimental process confirms that image pre-processing, including resizing and normalization, plays an important role in ensuring stable matrix decomposition and consistent compression performance. The distribution of singular values in batik images shows a rapid decay pattern, indicating that much of the structural and visual information is concentrated in the leading components, thereby validating the suitability of SVD for patterned cultural images with repetitive motifs and rich textures.

The results further reveal a clear and systematic relationship between rank selection, compression efficiency, and reconstruction quality. Lower rank values substantially reduce storage size but may lead to noticeable degradation in fine details and texture sharpness, while higher rank values better preserve image fidelity but provide smaller compression gains. The optimal rank is identified at a moderate level, where objective metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) indicate high similarity to the original image alongside significant file size reduction. This trade-off analysis confirms that the rank parameter serves as a critical control variable in balancing visual quality and storage optimization. Moreover, expert-based questionnaire validation aligns with the quantitative findings, indicating that the statistically optimal configuration is also perceptually acceptable for documentation, promotion, and intellectual property purposes.

Overall, the study concludes that SVD functions not only as a mathematical compression technique but also as a selective representation mechanism that preserves dominant structural patterns and aesthetic elements of batik motifs. By integrating objective computational evaluation with expert perceptual assessment, the research establishes a reliable and practical framework for sustainable digital archiving of cultural heritage products. These findings contribute to the development of scalable digital archiving systems for vocational tourism villages and highlight the strategic role of applied linear algebra methods in supporting efficient, long-term preservation of local cultural assets in the era of digital transformation.

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REFERENCES

B. A. Lungisani, C. K. Lebekwe, A. M. Zungeru and A. Yahya, "Image Compression Techniques in Wireless Sensor Networks: A Survey and Comparison," in *IEEE Access*, vol. 10, pp. 82511-82530, 2022, doi: 10.1109/ACCESS.2022.3195891.

B. Kovalenko, V. Lukin and B. Vozel, "MSE Prediction in BPG-Based Lossy Compression of Grayscale Images," *2024 IEEE 5th KhPI Week on Advanced Technology (KhPIWeek)*, Kharkiv, Ukraine, 2024, pp. 1-6, doi: 10.1109/KhPIWeek61434.2024.10877996.

B. P. Bondžulić, N. M. Stojanovic, V. V. Lukin and S. S. Kryvenko, "Visually Lossless Image Compression: From JPEG to BPG and Vice Versa," in *IEEE Signal Processing Letters*, vol. 32, pp. 2942-2946, 2025, doi: 10.1109/LSP.2025.3587601

C. Xie, X. Xia, H. Shishido, T. Matsui and I. Kitahara, "A VR Assisted Image Gathering Method for Digital Archiving of Cultural Properties," *2022 IEEE 11th Global Conference on Consumer Electronics (GCCE)*, Osaka, Japan, 2022, pp. 152-155, doi: 10.1109/GCCE56475.2022.10014128.

E. Jacia, G. Dyan, A. Ifan, F. L. Gaol and T. Matsuo, "The Social Media Implications on the Sales of Business Products," *2023 3rd International Conference on Smart Data Intelligence (ICSMDI)*, Trichy, India, 2023, pp. 73-79, doi: 10.1109/ICSMDI57622.2023.00021.

F. Sun and X. Li, "Star Chart Recognition Algorithm Based on Singular Value Decomposition," *2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Chongqing, China, 2021, pp. 124-129, doi: 10.1109/IAEAC50856.2021.9391032.

G. Yang, M. A. Jan, A. U. Rehman, M. Babar, M. M. Aimal and S. Verma, "Interoperability and Data Storage in Internet of Multimedia Things: Investigating Current Trends, Research Challenges and Future Directions," in *IEEE Access*, vol. 8, pp. 124382-124401, 2020, doi: 10.1109/ACCESS.2020.3006036.

H. Dai, Y. Wang, K. B. Kent, L. Zeng and C. Xu, "The State of the Art of Metadata Managements in Large-Scale Distributed File Systems — Scalability, Performance and Availability," in *IEEE Transactions on Parallel and Distributed Systems*, vol. 33, no. 12, pp. 3850-3869, 1 Dec. 2022, doi: 10.1109/TPDS.2022.3170574.

H. -K. Lee, "Changes in the Technological Industry Environment and the Direction of Copyright Protection Policy," *2022 IEEE/ACIS 7th International Conference on Big Data, Cloud Computing, and Data Science (BCD)*, Danang, Vietnam, 2022, pp. 208-210, doi: 10.1109/BCD54882.2022.9900652.

H. Qiu, Q. Zheng, G. Memmi, J. Lu, M. Qiu and B. Thuraisingham, "Deep Residual Learning-Based Enhanced JPEG Compression in the Internet of Things," in *IEEE Transactions on*

Industrial Informatics, vol. 17, no. 3, pp. 2124-2133, March 2021, doi: 10.1109/TII.2020.2994743.

H. Zhou, W. Wu, Y. Zhang, J. Ma and H. Ling, "Semantic-Supervised Infrared and Visible Image Fusion Via a Dual-Discriminator Generative Adversarial Network," in *IEEE Transactions on Multimedia*, vol. 25, pp. 635-648, 2023, doi: 10.1109/TMM.2021.3129609.

I. F. Asanov and N. N. Pokrovskaia, "Digital regulatory tools for entrepreneurial and creative behavior in the knowledge economy," *2017 International Conference "Quality Management,Transport and Information Security, Information Technologies" (IT&QM&IS)*, St. Petersburg, Russia, 2017, pp. 43-46, doi: 10.1109/ITMQIS.2017.8085759.

J. Al-Asad, H. Mewada, A. Flah and A. V. Patel, "Discrete Cosine Stockwell Transform vs. Discrete Cosine Transform in Despeckling OCT images," *2023 International Conference on Electrical, Computer and Energy Technologies (ICECET)*, Cape Town, South Africa, 2023, pp. 1-6, doi: 10.1109/ICECET58911.2023.10389363.

J. García-Sobrino, A. J. Pinho and J. Serra-Sagristà, "Competitive Segmentation Performance on Near-Lossless and Lossy Compressed Remote Sensing Images," in *IEEE Geoscience and Remote Sensing Letters*, vol. 17, no. 5, pp. 834-838, May 2020, doi: 10.1109/LGRS.2019.2934997.

Kiran, B. D. Parameshachari, D. S. Sunil Kumar, P. S. Prafulla and J. Yashwanth, "Singular Value Decomposition (SVD) Based Optimal Image Compression Technique," *2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT)*, Bengaluru, India, 2023, pp. 1-6, doi: 10.1109/EASCT59475.2023.10392294.

M. A. A. Abdelgawad, R. C. C. Cheung and H. Yan, "IncTSVD: Incremental Tensor Singular Value Decomposition of Multidimensional Streaming Data," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 36, no. 10, pp. 18666-18680, Oct. 2025, doi: 10.1109/TNNLS.2025.3578117.

N. Hashemipour *et al*., "Optimal Singular Value Decomposition Based Big Data Compression Approach in Smart Grids," in *IEEE Transactions on Industry Applications*, vol. 57, no. 4, pp. 3296-3305, July-Aug. 2021, doi: 10.1109/TIA.2021.3073640.

P. K. Chaudhary, "FBSE-Based JPEG Image Compression," in *IEEE Sensors Letters*, vol. 8, no. 2, pp. 1-4, Feb. 2024, Art no. 7001104, doi: 10.1109/LSENS.2023.3349112.

S. Ahmadi-Asl *et al*., "Randomized Algorithms for Computation of Tucker Decomposition and Higher Order SVD (HOSVD)," in *IEEE Access*, vol. 9, pp. 28684-28706, 2021, doi: 10.1109/ACCESS.2021.3058103.

S. Song, G. Yeo, H. -W. Kim, M. Cho and M. -C. Lee, "Improved 3D photon counting imaging using singular value decomposition (SVD)," *2024 24th International Conference on*

Control, Automation and Systems (ICCAS), Jeju, Korea, Republic of, 2024, pp. 602-607, doi: 10.23919/ICCAS63016.2024.10773141.

S. Weiss, I. K. Proudler, G. Barbarino, J. Pestana and J. G. McWhirter, "On Properties and Structure of the Analytic Singular Value Decomposition," in *IEEE Transactions on Signal Processing*, vol. 72, pp. 2260-2275, 2024, doi: 10.1109/TSP.2024.3387726.

T. A. Soomro, M. Rathi, S. A. Soomro, M. U. Keerio, P. Kumar and E. N. Baro, "Image Enhancement Technique for MRI Brain Images," *2024 Global Conference on Wireless and Optical Technologies (GCWOT)*, Malaga, Spain, 2024, pp. 1-5, doi: 10.1109/GCWOT63882.2024.10805684.

W. Qin, H. Wang, F. Zhang, J. Wang, X. Luo and T. Huang, "Low-Rank High-Order Tensor Completion With Applications in Visual Data," in *IEEE Transactions on Image Processing*, vol. 31, pp. 2433-2448, 2022, doi: 10.1109/TIP.2022.3155949.

W. Shen, M. Zhou, J. Luo, Z. Li and S. Kwong, "Graph-Represented Distribution Similarity Index for Full-Reference Image Quality Assessment," in *IEEE Transactions on Image Processing*, vol. 33, pp. 3075-3089, 2024, doi: 10.1109/TIP.2024.3390565.

W. Zhou, "Research on the Application of UAV Oblique Photography Algorithm in the Protection of Traditional Village Cultural Heritage," *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, 2022, pp. 1303-1306, doi: 10.1109/ICCMC53470.2022.9753856.

X. Wang, L. Wang and P. Liu, "Digital Revival of Traditional Batik Patterns: Accurate Extraction With Mask Attention AR-Net and AIGC Design Application," in *IEEE Access*, vol. 13, pp. 166254-166272, 2025, doi: 10.1109/ACCESS.2025.3607435.

Y. Bai, X. Liu, K. Wang, X. Ji, X. Wu and W. Gao, "Deep Lossy Plus Residual Coding for Lossless and Near-Lossless Image Compression," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 46, no. 5, pp. 3577-3594, May 2024, doi: 10.1109/TPAMI.2023.3348486.

Y. Chen, Z. Jia, Y. Peng and Y. Peng, "Efficient Robust Watermarking Based on Structure-Preserving Quaternion Singular Value Decomposition," in *IEEE Transactions on Image Processing*, vol. 32, pp. 3964-3979, 2023, doi: 10.1109/TIP.2023.3293773.

Y. Huang, "Research on E-commerce Precision Marketing Strategy Based on Big Data Technology," *2021 2nd International Conference on E-Commerce and Internet Technology (ECIT)*, Hangzhou, China, 2021, pp. 87-90, doi: 10.1109/ECIT52743.2021.00026.

Y. Zhang and X. Zheng, "Development of Image Processing Based on Deep Learning Algorithm," *2022 IEEE Asia-Pacific Conference on Image Processing, Electronics and*

Computers (IPEC), Dalian, China, 2022, pp. 1226-1228, doi: 10.1109/IPEC54454.2022.9777479.

Z. A. Al-Saffar and T. Yildirim, "A Novel Approach to Improving Brain Image Classification Using Mutual Information-Accelerated Singular Value Decomposition," in *IEEE Access*, vol. 8, pp. 52575-52587, 2020, doi: 10.1109/ACCESS.2020.2980728.

Z. Chen and Y. Zhu, "Personal Archive Service System using Blockchain Technology: Case Study, Promising and Challenging," *2017 IEEE International Conference on AI & Mobile Services (AIMS)*, Honolulu, HI, USA, 2017, pp. 93-99, doi: 10.1109/AIMS.2017.31.

Z. N. Khudhair *et al*., "Color to Grayscale Image Conversion Based on Singular Value Decomposition," in *IEEE Access*, vol. 11, pp. 54629-54638, 2023, doi: 10.1109/ACCESS.2023.3279734.

Z. Xu, X. Zhang, W. Chen, J. Liu, T. Xu and Z. Wang, "MuralDiff: Diffusion for Ancient Murals Restoration on Large-Scale Pre-Training," in *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 8, no. 3, pp. 2169-2181, June 2024, doi: 10.1109/TETCI.2024.3359038.