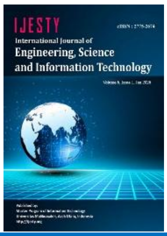
International Journal of Engineering, Science and Information Technology
Volume 6, No. 1 (2026) pp. 9-20
eISSN: 2775-2674
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v6i1.1794
Research Paper, Short Communication, Review, Technical Paper



Application of Singular Value Decomposition for Image Compression of Yogyakarta Cosmological Axis in Digital Learning in Vocational Education

Yoga Sahria[1]*, Putu Sudira[1], Mohamad Hidir Mhd Salim[2]

[1]*Department of Technological and Vocational Education, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia*
[2]*Institute of Visual Informatics, Universiti Kebangsaan Malaysia, Selangor, Malaysia*

**Corresponding author Email: yoga.sahria@uny.ac.id*

The manuscript was received on 17 June 2025, revised on 18 August 2025, and accepted on 28 November 2025, date of publication 1 January 2026

Abstract

This study examines the application of the Singular Value Decomposition (SVD) method as a digital image compression technique on the Yogyakarta Cosmological Axis object which is used as a digital learning medium in vocational education. The background of this study is based on the need for high-quality visual media with efficient file sizes for easy storage, transmission, and access through digital-based learning systems. The study uses an experimental quantitative approach with data in the form of high-resolution digital images processed through SVD-based compression stages. The research procedure includes image transformation into matrix form, matrix decomposition using SVD, selection of a number of dominant singular values (ranks), and reconstruction of the compressed image. The research data were analyzed using image quality evaluation parameters, namely Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Compression Ratio (CR). The results show that an increase in the rank value is directly proportional to an increase in the quality of the reconstructed image, as indicated by a decrease in the MSE value and an increase in the PSNR and SSIM values. Conversely, a decrease in the rank value results in a higher compression rate but is followed by a degradation in the visual quality of the image. Experimental data also shows that most of the visual information of an image can be represented by a small number of principal singular values, thus allowing for significant file size reduction without losing the important visual structure of the image object. Visually, the compressed image at a medium rank value is still considered suitable for use as a learning medium because the main details, object contours, and visual characteristics of the Yogyakarta Cosmological Axis can still be recognized well. These findings prove that the SVD method is effective as a mathematical-based image compression technique to support the development of efficient, informative, and contextual digital learning media based on local wisdom in vocational education.

Keywords: *Digital Image, Compression, Vocational Education, Yogyakarta Cosmological Axis, Singular Value Decomposition.*

1. Introduction

The development of digital technology in education has encouraged the use of visual media as the primary means of delivering learning materials [1][2][3]. In vocational education, the use of digital images is crucial because it supports practice-based learning, observation, and visual analysis [4][5]. One relevant material to be packaged in digital form is the Yogyakarta Cosmological Axis, which is a world cultural heritage and has high historical, philosophical, and architectural value. However, the large size of image files is often an obstacle in the implementation of digital learning, especially when distributed through a Learning Management System (LMS) or accessed by devices with limited storage capacity [6][7]. Various previous studies have examined image compression using mathematical transformation methods, including Singular Value Decomposition (SVD), which has proven effective in reducing file size without losing significant visual information [8]–[12]. However, its application to local cultural content, particularly the Yogyakarta Cosmological Axis, is still rarely discussed [13][14].

Various studies have shown that SVD is able to reduce image dimensions effectively through the selection of appropriate singular values [15] [16]. This approach allows image reconstruction with good visual quality despite a significant reduction in file size [17] [18]. In addition, the digitization of cultural objects has become a global research focus as an effort to preserve and improve public access [19]. However, the integration of mathematical compression methods in the context of local culture-based vocational learning is still limited, so this study attempts to fill this gap [20]. SVD is an effective matrix decomposition method used in digital image compression by breaking down images into main components that represent the important features of the image [21] [22]. The use of SVD in image compression allows data size reduction without significant loss of visual quality, making it very relevant for digital learning applications, especially in vocational education that requires efficient presentation of multimedia materials [23]. Previous studies have shown that the SVD method is able to reduce image data with uncomplicated calculation complexity and good quality compression results according to application needs [24].

The main problem faced is the relatively large size of the Yogyakarta Cosmological Axis image, which hinders the efficiency of digital learning. In addition, there are not many studies evaluating the effectiveness of SVD in compressing cultural heritage images while maintaining important visual aspects [25]. In the context of vocational education, the presentation of digital learning materials often faces obstacles in terms of data size and access speed, especially for images used as learning media. The image of the Yogyakarta cosmological axis as one of the learning objects has quite complex details, so it requires a compression method that is able to maintain the quality of its visual information [26]. The specific problem to be addressed is how to optimize the compression of the image using SVD so that data storage and transmission efficiency can be achieved without sacrificing learning quality [27]. This is important to support the effectiveness of digital learning in the current technological era.

The urgency of this research is increasing along with the increasing need for digitalization of cultural content and the demands of adaptive, fast vocational learning that prioritizes accessibility. The specific problem faced is how to implement compression of cultural heritage images (Yogyakarta Cosmological Axis) for digital learning materials in vocational education effectively while maintaining the visual integrity and accuracy of the image data [28]. The urgency of this research lies in the need to ensure the accessibility and effectiveness of image-based digital learning materials. In the context of vocational education, where visual understanding of real objects is crucial, lossy compression can reduce the didactic value of the material. Therefore, an adaptive compression method is needed that balances the compression ratio and image quality (fidelity) [29].

This study aims to implement and evaluate the effectiveness of the SVD method in compressing the Yogyakarta Cosmological Axis image to support the efficiency of storage and distribution of digital learning materials in vocational education. The main objective of this study is to implement and test the performance of the SVD method in compressing the Yogyakarta Cosmological Axis image as digital learning materials in vocational education. Specifically, this study aims to analyze the effect of selecting the rank value (singular value) on the compression ratio and image quality produced by SVD. Determine the optimal rank (the number of singular values retained) that produces the best balance between storage efficiency and acceptable visual quality for vocational learning needs.

The contribution of this research lies in the application of the SVD method specifically to the image of the Yogyakarta Cosmological Axis as vocational learning material, resulting in a compression model that is more adaptive to local cultural content. This research is expected to provide a practical contribution in the form of a prototype implementation of efficient image compression for digital learning materials, which can be adopted by vocational education institutions. Scientifically, this research presents an in-depth quantitative analysis of the effectiveness of SVD in the context of local cultural heritage images, which have unique visual characteristics. In the context of vocational education, which has not been widely studied before, it is hoped that it can be a real solution to improve the quality and efficiency of digital learning while providing new contributions in image processing for vocational education applications. The novelty of this research lies in the integration of mathematical compression technology with the context of cultural and vocational education, an approach that has not been widely explored in previous studies. This research also provides an empirical overview of the optimal limits of SVD compression for cultural images without reducing the visual quality relevant for learning. This research lies in the application of SVD specifically to the Image of the Yogyakarta Cosmological Axis as digital learning material in the realm of vocational education. Although SVD is well-known as a compression technique, no research has explicitly tested its performance on Indonesian cultural heritage images, focusing on meeting the need for crucial visual details in the context of vocational learning. This study provides a proven SVD rank selection guide for this specific image case, ensuring that educational aspects (architectural/cosmological details) are maintained post-compression.

2. Literature Review

This chapter discusses the theoretical basis that serves as the conceptual basis for the research on the Application of Singular Value Decomposition (SVD) for Image Compression of the Yogyakarta Cosmological Axis in Digital Learning in Vocational Education. This literature review includes theories related to digital image compression, the use of the SVD method in image processing, an understanding of the Yogyakarta Cosmological Axis as a compressed image object, the concept of digital learning in vocational education, and the integration of image compression technology in learning to improve the effectiveness of visual material management. Overall, this review provides a theoretical framework that strengthens the arguments and direction of research development.

2.1. Digital Image Compression

Digital image compression is the process of reducing the number of bits required to represent a digital image without significantly reducing visual quality [30]. The main purpose of compression is to save storage space and speed up data transmission over a network. Compression techniques exploit the data redundancy present in images, which can be classified into three: spatial redundancy occurs when adjacent pixels have the same or very similar values, spectral redundancy occurs in color images, where color channels (e.g., Red, Green, Blue) are correlated with each other. Psychovisual redundancy refers to information in an image that is less sensitive to the human eye. Image compression improves storage space efficiency, processing speed, and increases accessibility in the distribution of digital-based materials. Compression is divided into two types, namely lossless and lossy [31], each of which has different characteristics and levels of data reduction depending on the application needs. In the context of digital learning, image compression plays an important role in ensuring that visual materials can be accessed quickly and easily by students, without sacrificing important information contained in the image. This becomes particularly relevant when learning materials utilize cultural imagery or historical sites, such as the Yogyakarta Cosmological Axis, which typically feature complex visual details. By applying appropriate compression techniques, visual materials can be optimally presented on devices with varying specifications and limited internet connections, thus supporting effective and inclusive vocational learning.

2.2. Singular Value Decomposition (SVD) in Image Processing

Singular Value Decomposition (SVD) is a fundamental matrix factorization technique in linear algebra that has wide applications in signal processing, statistics, and in particular, digital image processing [32]. SVD is a matrix decomposition method that breaks down an image matrix into three main components, namely orthogonal matrices [33]. Diagonal matrices containing singular values, and orthogonal matrices. In image processing, SVD has the ability to represent the energy of image information in an ordered manner at the singular values, where most of the visual information is concentrated in a small number of the largest singular values. This characteristic makes SVD very effective for use in image compression, because file size can be reduced significantly by retaining only a portion of the most dominant singular values. In addition to efficient data representation, SVD also has high numerical stability, so it is able to produce compressed images with relatively good quality even though the compression level is increased. In the context of digital learning, the use of SVD offers advantages in the form of flexible compression performance and ease of implementation in various image processing platforms. Thus, SVD becomes one of the relevant methods to support the distribution and management of visual learning materials including the image of the Yogyakarta Cosmological Axis more efficiently without losing the quality of information that is essential for the vocational learning process.

2.3. Cosmological Axis of Yogyakarta

The Yogyakarta Cosmological Axis is an imaginary line connecting three main points: Mount Merapi in the north, the Yogyakarta Palace as the center, and Parangtritis Beach in the south [34]. This concept reflects the Javanese cosmological view of the balance between humans, nature, and spiritual power [35][36]. In 2023, UNESCO designated the Yogyakarta Philosophical Axis as a World Cultural Heritage, making it an important cultural object to be preserved and introduced to the younger generation. Visualization of the Yogyakarta Cosmological Axis usually involves imagery with rich architectural details, landscapes, and symbolic elements, thus requiring high-quality visual media management. In the context of vocational education, the image of the Yogyakarta Cosmological Axis presented in Figure 1 is often used as a learning medium to introduce cultural values, history, and architectural design to students, especially in the fields of technology, art education, and multimedia. However, the large image file size can be an obstacle in the distribution of digital learning materials, especially in environments with limited devices and bandwidth. Therefore, compression techniques such as SVD become relevant to ensure that imagery remains well accessible without compromising the visual quality needed to understand the cultural and aesthetic context of the historic site.

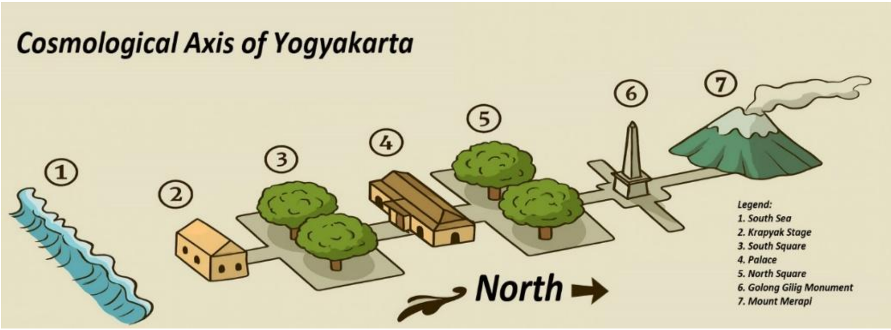


Fig 1. Cosmological Axis Of Yogyakarta

2.4. Digital Learning in Vocational Education

Digital learning in vocational education is becoming an important strategy in addressing increasingly complex technological developments and industrial needs [37]. The use of digital media such as video, animation, simulations, interactive modules, and high-resolution imagery enables the delivery of material that is more contextual, applicable, and skills-oriented. Digital learning also supports self-paced learning, flexibility of time, and allows for the visual presentation of technical concepts, which is crucial in vocational fields that emphasize practice, procedures, and demonstrations. The use of digital learning also faces challenges, particularly related to device availability, bandwidth, and storage capacity. High-quality digital materials such as architectural or cultural imagery are often large in size, which can hinder accessibility for learners. Therefore, efficiency in digital media management is a key requirement for effective and inclusive learning. The integration of image compression technologies, such as SVD, is one approach that can improve the performance of digital learning by ensuring visual materials remain easily accessible without sacrificing the quality of essential information required in the vocational education process.

2.5. Integration of Compression Technology in Learning

In the context of vocational education, where teaching materials often require detailed technical visualizations, the application of image compression helps maintain display quality while reducing file size [38] .This supports faster distribution of teaching materials, more efficient use of storage, and wider access for students. In addition to technical benefits, the integration of compression technologies such as SVD also provides new learning opportunities for students, particularly in the fields of information technology, multimedia, and image processing. Students can learn the working principles of compression algorithms, analyze the quality of compression results, and understand how the technology is applied in various industries. Thus, the use of compression technology not only improves the efficiency of material presentation but also provides added pedagogical value that strengthens students' digital competence. This integration is a strategic step in facing the demands of vocational education in the era of digital transformation.

3. Methods

The method used in this study was designed to apply the Singular Value Decomposition (SVD) [39][40] technique in the image compression process of the Yogyakarta Cosmological Axis, so that it can support the efficiency of material presentation in digital learning in vocational education. In general, the SVD-based compression procedure is carried out through five main steps, starting from image data representation to evaluation of the quality of the compression results. The Philosophical Axis image is taken from the page https://whc.unesco.org/. These steps ensure the compression process runs systematically, measurably, and can be replicated in the context of digital image processing.

3.1. Image Representation as a Matrix

In the initial stage, digital images are represented in matrix form so that they can be mathematically processed using the Singular Value Decomposition (SVD) approach. Each image, whether in RGB or grayscale format, consists of a collection of pixels, each of which has a specific intensity value. In RGB images, this process involves separating the image into three color channels, red, green, and blue, where each channel is formed into a two-dimensional matrix containing the intensity value at each pixel position. Meanwhile, grayscale images are represented as a single matrix with intensity values ranging from 0 to 255. This image conversion into a numeric matrix is a fundamental step that allows the decomposition process to be carried out precisely, while ensuring that the visual structure of the image can be analyzed and manipulated through linear operations in the subsequent compression stage. The schematic diagram of the SVD compression structure is presented in Figure 2.

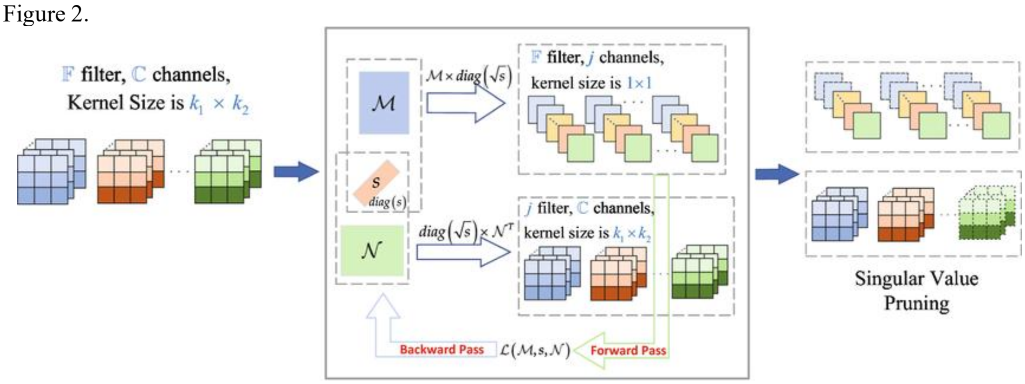


Fig 2. Schematic diagram of the SVD compression structure

3.2. Matrix Decomposition Using SVD

At this stage, each image channel that has been represented as a matrix is then decomposed using the SVD method. This process breaks down the image matrix A into three main components, namely orthogonal matrices U, diagonal matrix Σ which contains singular values, and orthogonal matrices V^T, so that the decomposition form is obtained $A = U\Sigma V^T$. Matrix Σ stores singular values ordered from largest to smallest, and these values represent the most important energy or information of the image. Thus, the singular value at Σ is the main basis in the compression process, because most of the visual information of an image can be preserved by simply taking the largest number of singular values. This decomposition allows the separation of the main structure of the image from the minor components, allowing for a more compact image reconstruction without significant loss of visual quality. The SVD of a matrix is presented in Figure 3.

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

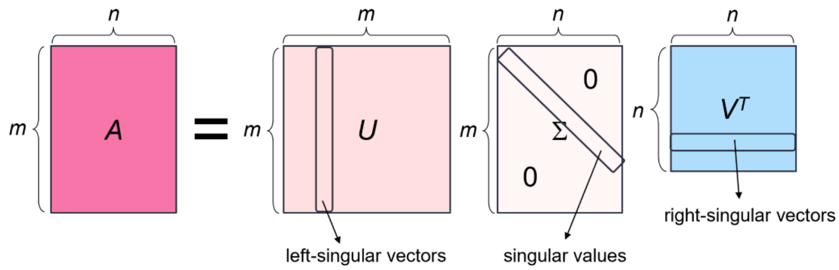


Fig 3. SVD of a matrix

3.3. Rank (k) Selection for Compression

The selection of rank (k) is an important stage in the SVD-based image compression process because it determines how many largest singular values are in the matrix Σ which will be maintained. These singular values represent the primary information that forms the visual structure of the image, so the larger the k chosen, the higher the quality of the reconstructed image. However, using a smaller k will result in a higher compression rate because only a small portion of the information is retained. Thus, selecting k becomes a process of finding a balance between reconstruction quality and compression efficiency. The determination of the k value is usually based on the percentage of cumulative energy of the singular values or the need for specific visual quality in the context of digital learning, so that the compressed image can still convey important information without reducing readability or visual aesthetics.

3.4. Compressed Image Reconstruction

After the largest singular value is selected based on rank k, The next step is to reconstruct the compressed image. This process is done by reconstructing the image matrix using only the most important components, namely U_k, Σ_k, dan V_k^T, so that the reconstruction matrix is obtained which is formulated as $A_k = U_k\Sigma_k V_k^T$. Despite using fewer singular values than the original image, this reconstruction is still able to preserve the main visual shape and structure of the image. The resulting images have a significantly smaller file size due to the significantly reduced amount of data stored, yet their visual quality remains good enough for use in digital learning contexts. Thus, this reconstruction process is at the heart of SVD compression efficiency, enabling lighter distribution of visual content without sacrificing critical image information.

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

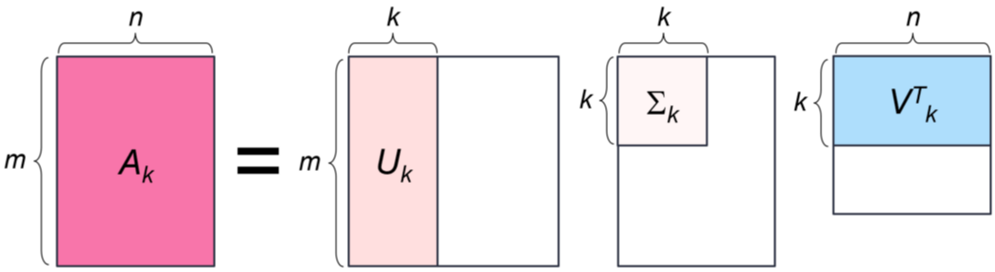


Fig 4. Truncated SVD

3.5. Quality Evaluation and Compression Ratio

Evaluation of image compression quality and efficiency is carried out using several key metrics that provide a comprehensive overview of the performance of the SVD method. Reconstruction quality is assessed using Mean Squared Error (MSE) (3), Peak Signal-to-Noise Ratio (PSNR) (4), and Structural Similarity Index (SSIM) (5), where MSE measures the average error between the original and reconstructed images, PSNR indicates the level of image clarity after compression through a comparison between the maximum signal and noise, while SSIM assesses the similarity of structure, luminance, and contrast between two images. In addition, compression efficiency is analyzed using Compression Ratio (CR) (6) which describes how much data size savings are obtained from the compression process. The combination of these metrics provides a comprehensive understanding of the balance between visual quality and data reduction effectiveness achieved through the application of SVD.

Measuring the average squared error between the original image and the reconstructed image with Mean Squared Error (MSE):

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

The higher the PSNR, the better the quality of the compressed image with Peak Signal-to-Noise Ratio (PSNR):

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

Measuring structural similarity, luminance, and contrast with the Structural Similarity Index (SSIM):

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

Shows how much the data size was successfully reduced with the Compression Ratio (CR):

$$CR = \frac{Original\ Data\ Size}{Compressed\ Data\ Size} \quad (6)$$

In SVD compression, the size of the compressed data is calculated as:

$$Size\ SVD = k(M + N + 1) \quad (7)$$

So that:

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

4. Result and Discussion

This Results and Discussion section presents the main findings of the study entitled "Application of Singular Value Decomposition (SVD) for Image Compression of the Yogyakarta Cosmological Axis in Digital Learning in Vocational Education." The results are presented systematically to illustrate the image compression process, the performance of the SVD algorithm, and the quality of the compressed images based on various evaluation metrics. Furthermore, the discussion focuses on the interpretation of the findings, the relevance of SVD implementation in the context of digital learning, and its contribution to the efficiency of learning media in vocational education environments. It is hoped that this section will provide a comprehensive understanding of the effectiveness of the SVD method in image compression and serve as a basis for further research development and implementation.

4.1. Initial image visualization (grayscale and RGB)

In the first stage, an initial visualization of the Yogyakarta Cosmological Axis image is displayed in two formats, namely grayscale and RGB. The grayscale image is obtained using *cv2.IMREAD_GRAYSCALE*, while the RGB image is generated through the *cv2.split()* process to separate each color channel. This visualization shows the quality of the original image, including the sharpness of architectural details and spatial contours that are characteristic of the Cosmological Axis. This stage is an important foundation before the compression process, because the quality of the initial image will determine the accuracy of the singular value calculation and the results of the compressed image reconstruction in the next stage.

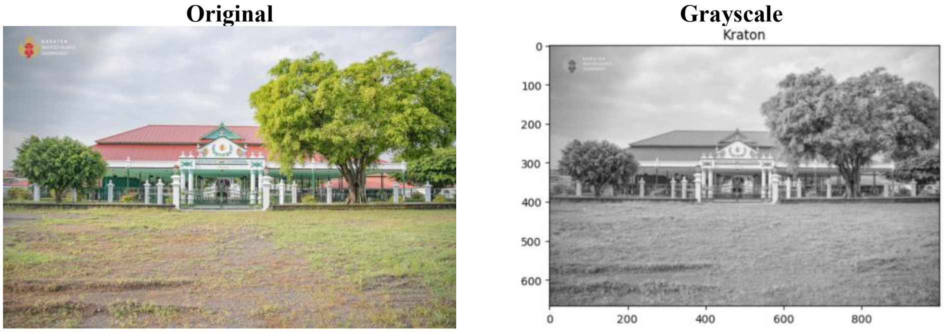


Fig 5. Visualisasi awal citra (grayscale & RGB)

4.2. SVD decomposition analysis and singular values

The results of the SVD decomposition produce three main components in the form of matrices U, S, and V^T with the respective dimensions (667, 667), (667,), and (667, 1000). Singular value analysis shows that the ten largest values are in the high range, such as 133493.67 to 3457.05, while the ten smallest values are in the low range between 5.74 to 4.01 see in Table 1. The singular value graphs on the linear and logarithmic scales show a very sharp decrease, indicating that most of the image information is concentrated in the largest singular values see in. In contrast, small singular values only contribute minor details or noise so they can be eliminated for compression without significantly reducing visual quality. This rapid decrease is also a common characteristic of natural images that have a dominant information structure in the low frequency components.

Table 1. Largest and smallest singular values

No	Largest Singular Values(Top-10)	Smallest Singular Value (Bottom-10)
1	13.349.367.056.649	574.417.675
2	1.448.451.995.423	534.663.167
3	970.602.859.906	529.879.115
4	728.438.353.060	511.318.445
5	623.870.538.389	492.772.421
6	583.317.020.034	476.662.895
7	477.714.213.391	449.081.011
8	419.479.420.203	433.699.008
9	371.470.947.532	420.032.664
10	345.704.603.932	401.949.996

Image reconstruction is carried out by utilizing the main components of the SVD decomposition. The following visualization shows the relationship between matrices and the results of the successfully reconstructed image presented in Figure 6.

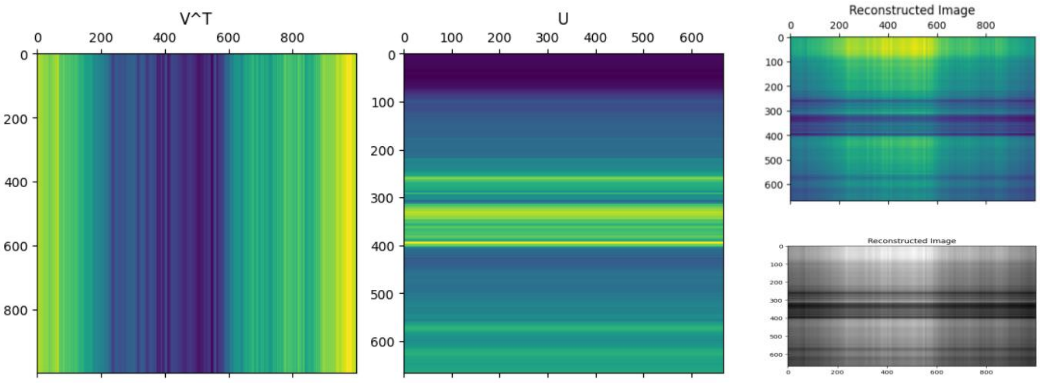


Fig 6. Reconstructed Image

4.3. dampaknya Image reconstruction with rank variation and its impact

Image reconstruction with varying rank (k) values shows how the number of retained principal components affects the quality of the compression result. At very small k values, such as k = 1 or k = 5, the image appears blurry and loses much detail because only the global structure is retained. When k increases to moderate values, such as k = 15 or k = 20, the principal details begin to appear clearer and the image quality improves while the file size remains more efficient. At larger k values, such as k = 60 or k = 80, the reconstruction results almost closely resemble the original image because most of the important information has been restored. This finding confirms the trade-off between visual quality and storage efficiency: the larger the k value, the better the image quality, but the storage load also increases.

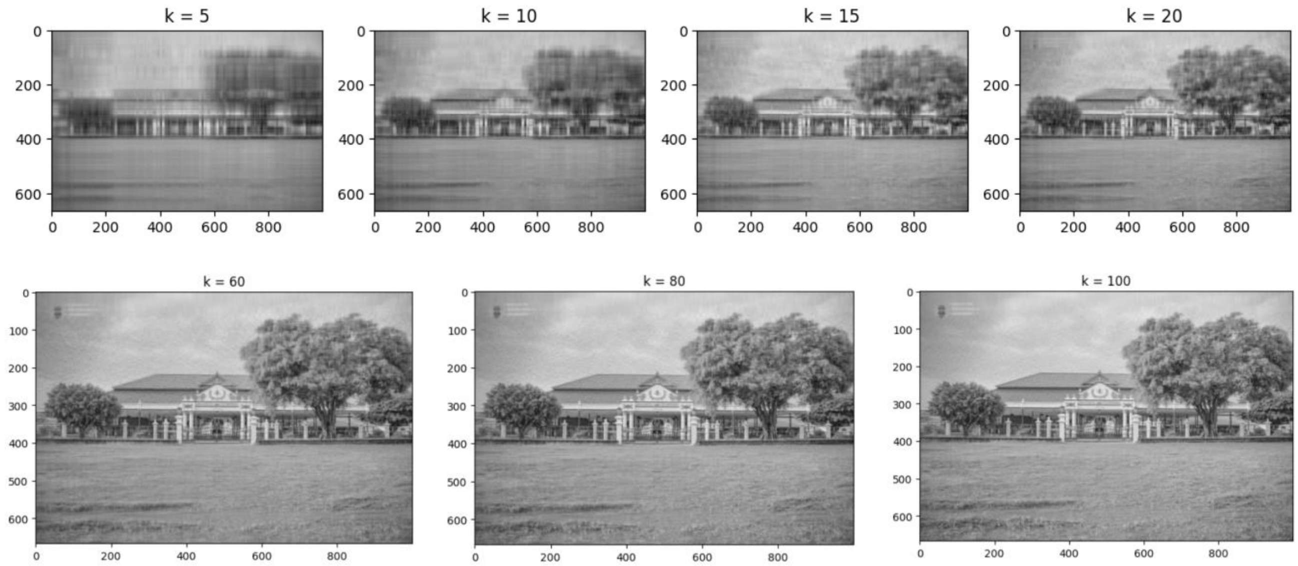


Fig 7. Image Reconstruction with Rank (k) Variation

4.4. RGB image compression using per-channel SVD

In RGB image compression, each color channel R, G, and B is processed separately using SVD to obtain reconstructions in the form of R_compressed, G_compressed, and B_compressed. The visualization results show how each channel experiences information reduction according to the preserved singular values. The R channel generally has the highest singular value and therefore carries the most dominant information, while the G and B channels have a smoother singular distribution pattern. After the three channels are reconstructed and recombined, the compressed RGB image still looks natural, indicating that even though minor information is reduced, the color structure and overall appearance of the image are still well maintained. Comparing experiments with k = 5 and k = 60 are presented in Figure 8.

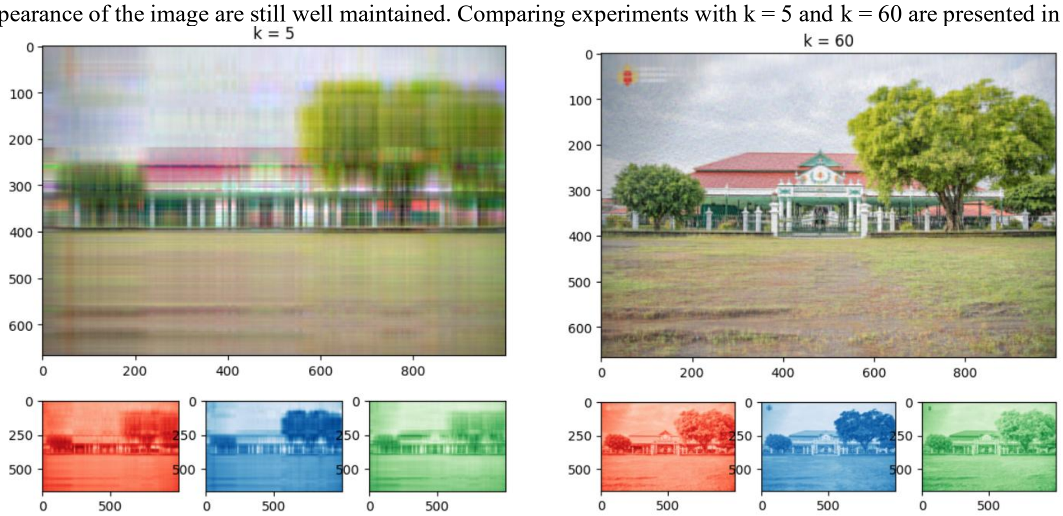


Fig 8. 60 RGB image compression using SVD Channel 5 and Channel 60

RGB image compression experiments were conducted using two different rank values, namely k = 5 and k = 60, to observe the difference in reconstruction quality at low and high compression levels. With k = 5, the compression is very strong so that only a few singular values are retained, while at k = 60 more structural and color information is retained so that the reconstructed image is closer to the original. Testing these two values provides a clear picture of the impact of rank selection on the visual quality of RGB images after compression.

To understand how image information is distributed during compression using SVD, singular value graphs are displayed on both a linear and logarithmic scale. This visualization helps show how quickly singular values decay, identify values that carry key information, and determine the optimal rank threshold that can be used for compression without significant quality loss. These graphs serve as the basis for analysis in selecting an effective compression level.

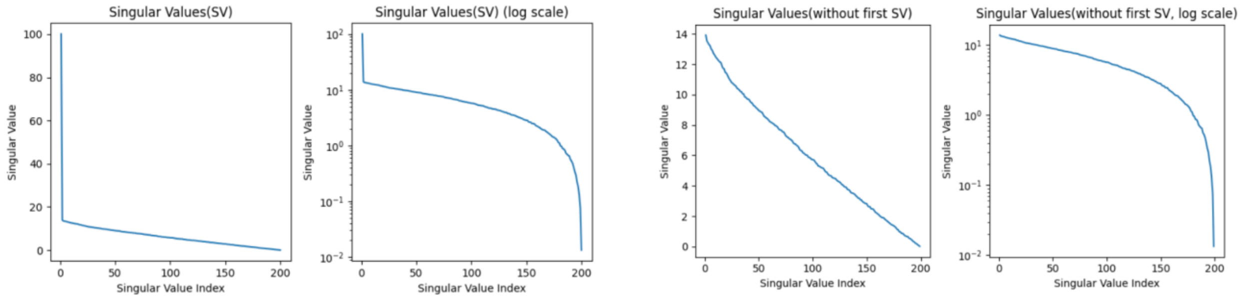


Fig 9. Singular Values Graph

The singular value graph on a linear scale shows that only the first few singular values have very large magnitudes, while subsequent values decrease sharply towards zero. This indicates that most of the image's important information is concentrated in the early components. Meanwhile, the graph on a logarithmic scale clarifies the exponential decrease pattern, showing that after a certain index, the singular values become very small and contribute only to minor details or noise. This pattern confirms that images can be significantly compressed by retaining only a small number of major singular values, without drastically losing visual quality. This graph serves as an important reference in determining the optimal rank for image compression.

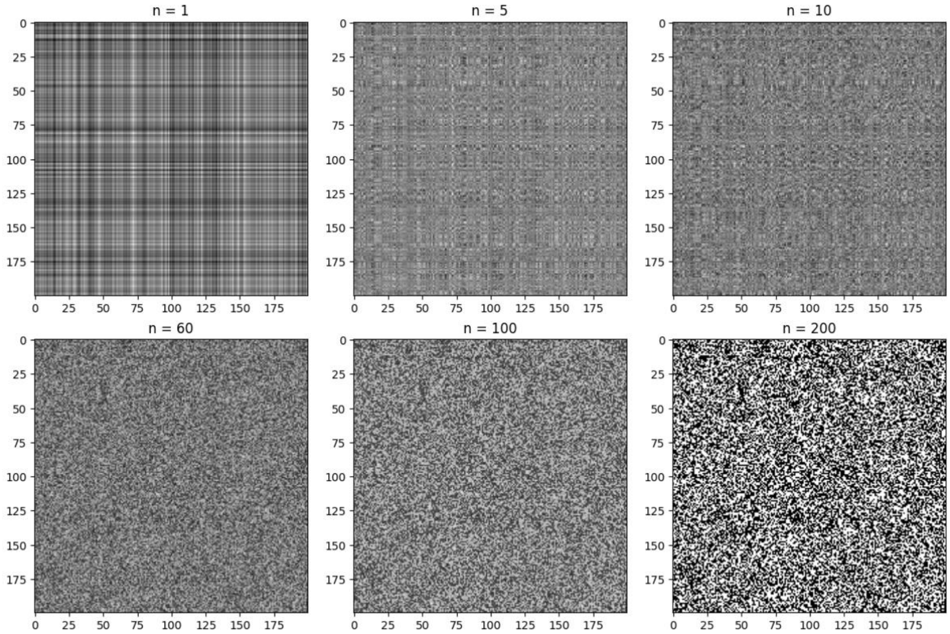


Fig 10. Plotting the compressed noise for different values of k

In Figure 10, to understand how SVD works on images that lack visual structure, an experiment was conducted using a random noisy image of size 200×200. Each reconstruction is displayed with varying rank values (n), ranging from n = 1 to n = 200. This visualization aims to show how SVD tries to reconstruct the noise pattern based on the number of singular components retained. Thus, these results provide an overview of the differences in SVD behavior between structured and random images, and show how increasing rank affects the quality of noise reconstruction.

To understand how image energy or information is distributed during the decomposition process using SVD, the resulting singular values are analyzed. The largest singular values indicate the main components that contain the most significant structure and information in the image, while the smallest singular values describe fine details or even noise that contribute very little to visual quality. By displaying a row of the 10 largest and 10 smallest singular values in a single table, this analysis provides a clearer picture of the proportion of image energy and which components can be retained or discarded during the compression process. Table 2 below presents this comparison in a structured manner for easy interpretation.

Table 2. Largest and smallest singular values

No	Largest Singular Value	Meaning / Explanation	Smallest Singular Value	Meaning / Explanation
1	10.013.995.076	The largest energy component, forming the main structure of the image.	0.52705213	Small details; low energy contribution.
2	1.391.310.945	Major contribution to the main pattern; high level of detail.	0.47866155	Very fine detail; tends to be noisy.
3	1.353.817.089	Large and important details in the image.	0.40899112	Minor information; not critical.

4	1.341.200.651	Determines the contours and main shape of the object.	0.33967294	Fine detail; often lost during compression.
5	1.329.860.163	The important structures are still dominant.	0.29717016	Very small details; low impact.
6	1.320.722.486	Significant intermediate details.	0.22466117	Low level information; almost invisible.
7	1.299.767.481	Medium texture; still quite important.	0.18454010	Small noise or micro details.
8	1.291.561.789	Large texture on the image.	0.13176074	It has almost no effect on the visual appearance.
9	1.272.645.399	Intermediate details; visual transition areas.	0.07501907	Micro details; can be removed without major visual impact.
10	1.262.234.687	Intermediate details that are still relevant.	0.01336529	Very small contribution; usually considered noise.

4.5. Image Quality Comparison Results

The results of image quality comparison to assess the effectiveness of image compression using the Singular Value Decomposition (SVD) method, a comparison was made between the original image and the compressed image at two different rank values, namely k = 5 and k = 60. Quality evaluation was carried out using four main metrics, namely Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and compression efficiency through Compression Ratio (CR). These measurements provide a comprehensive overview of the level of distortion, visual fidelity, similarity of image structure, and storage efficiency resulting from the compression process are presented in table 3.

Table 3. Largest and smallest singular values

Parameter	k = 5	k = 60
MSE	514.67	72.87
PSNR (dB)	21.03	29.51
SSIM	0.664	0.925
Compression Ratio (CR)	50.19×	4.35×

The comparison of the quality of the original image with the compressed image using SVD at rank k = 5 and k = 60 shows a very significant difference in both visual quality and compression efficiency. At k = 5, a very large MSE value indicates a high reconstruction error, while a low PSNR indicates a high level of noise in the compressed image. An SSIM value of only around 0.66 indicates that much of the image structure and detail are lost, resulting in the image appearing very blurry and losing important information. However, compression at k = 5 produces very high efficiency with a Compression Ratio (CR) reaching 50×, resulting in a much smaller file size but with the consequence of poor quality. Conversely, using k = 60 produces much better results. A smaller MSE value indicates a low reconstruction error, a PSNR approaching 30 dB indicates good image quality, and an SSIM of 0.925 indicates that the compressed image remains very similar to the original image, with almost all visual details retained. Although the compression efficiency decreases to a CR of approximately 4.35×, this compression level remains effective and provides an optimal balance between file size savings and visual quality. Thus, k = 60 can be considered a more ideal rank choice for image compression of the Yogyakarta Cosmological Axis in the context of digital learning.

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

In an additional evaluation phase, the study compared the performance of SVD on two types of data: natural and noisy images. The results show that noisy images have very slow-decreasing singular values, making the compression process ineffective because almost all singular components are needed to maintain the original shape. In contrast, the Yogyakarta Cosmological Axis image shows a rapid decrease in singular values, indicating that most of the image information is concentrated in a few main components, making it easier and more efficient to compress. Furthermore, visualization of the YCbCr color space compared to RGB demonstrates the importance of the luminance (Y) channel, which carries the majority of the image's structural information. This finding is in line with modern compression methods such as JPEG and HEVC, which utilize luminance–chrominance separation to improve efficiency. Thus, this analysis confirms that SVD is highly suitable for application to natural images and has strong relevance to the concept of color space-based compression.

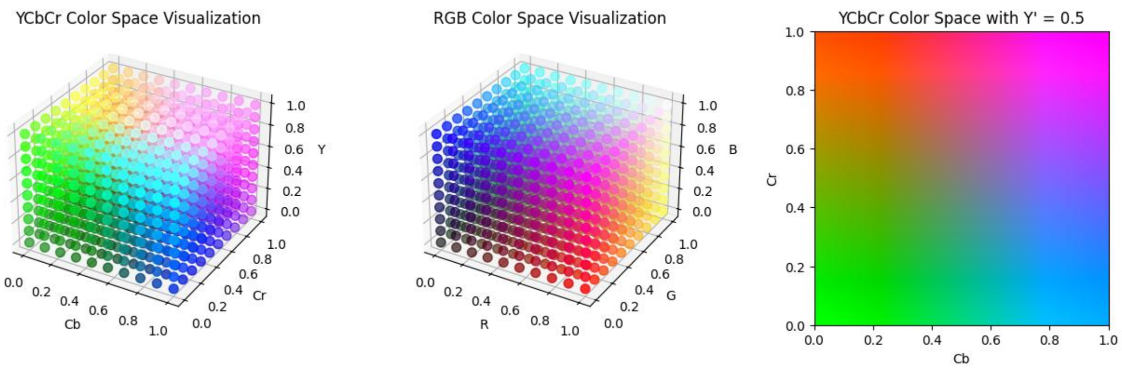


Fig 11. Color Space YCbCr and RGB Visualization

In the first 3D graph, the YCbCr color space is plotted using the Cb, Cr, and Y axes, showing that the luminance (Y) component is separated from the chrominance (Cb and Cr) components. This emphasizes why compression systems like JPEG utilize the Y channel as the primary focus, as it conveys the structure and detail of the image. The second 3D graph shows the RGB color space, which maps colors based on a direct combination of R, G, and B. Meanwhile, the visualization of the Cb–Cr plane with a fixed Y (Y'=0.5) illustrates how changes in chrominance produce color variations without changing the luminance level. This overall visualization clarifies the fundamental differences between the two color spaces and demonstrates their relevance to compression techniques based on luminance–chrominance separation.

5. Conclusion

This study demonstrates that the application of the Singular Value Decomposition (SVD) method can improve image compression efficiency in the context of digital learning in vocational education without significantly sacrificing visual quality. Experimental results at various k values show that the larger the singular component used, the better the image reconstruction quality is indicated by an increase in PSNR and SSIM values and a decrease in MSE. Meanwhile, a smaller k value provides a higher compression ratio, so that SVD provides flexibility to adjust the needs between quality and storage efficiency. The novelty of this study lies in the structured application of SVD in a vocational context, especially as part of the development of digital learning media that demands a balance between file size and the preservation of visual details. These findings confirm that SVD can be an easy-to-implement, adaptive, and relevant image compression alternative to support the transformation of digital learning in vocational education environments. As a follow-up to this study, it is recommended that the development of image compression using SVD be tested on a wider variety of image types, including complex textured images and high-resolution color images, to obtain a more comprehensive picture of its performance. Furthermore, further research could compare SVD with modern compression methods such as Principal Component Analysis (PCA), Discrete Cosine Transform (DCT), or deep learning-based techniques to assess their relative advantages in the context of vocational education. Implementing SVD in the form of an application or interactive learning module is also recommended to enable students to understand the mathematical concepts behind image compression more practically. Integrating user experience evaluation and testing on devices with limited memory and computing resources would further strengthen this research's contribution to the development of digital learning media.

Acknowledgement

The authors express their deepest appreciation and gratitude to the Department of Technology and Vocational Education, Yogyakarta State University, Yogyakarta, Indonesia, for the academic support and research facilities provided during the completion of this study. The authors also express their gratitude to the Institute of Visual Informatics, Universiti Kebangsaan Malaysia, Selangor, Malaysia, for their valuable contributions, collaboration, and insights that have enriched the quality of this research.

References

[1] A. H. Bentbib, K. Kreit and I. Labaali, "Randomized Tensor Singular Value Decomposition for Multidimensional Data Compression," 2022 11th International Symposium on Signal, Image, Video and Communications (ISIVC), El Jadida, Morocco, 2022, pp. 1-6, doi: 10.1109/ISIVC54825.2022.9800729.

[2] Britant and A. Tiwari, "Quantum Variational Singular Value Decomposition: A new hybrid approach towards quantum image compression," 2025 17th International Conference on COMmunication Systems and NETworks (COMSNETS), Bengaluru, India, 2025, pp. 1068-1073, doi: 10.1109/COMSNETS63942.2025.10885679.

[3] C. Liu, Z. Zhi, W. Zhao and Z. He, "Research on Fingerprint Image Differential Privacy Protection Publishing Method Based on Wavelet Transform and Singular Value Decomposition Technology," in IEEE Access, vol. 12, pp. 28417-28436, 2024, doi: 10.1109/ACCESS.2024.3367996.

[4] D. Mishra, A. Kumar, V. S. Rathor, H. S. Pal and G. K. Singh, "Color Crop Image Compression Technique using Singular Vector Sparse Reconstruction," 2023 IEEE 7th Conference on Information and Communication Technology (CICT), Jabalpur, India, 2023, pp. 1-5, doi: 10.1109/CICT59886.2023.10455585.

[5] E. M. Oanta, "Application of Singular Value Decomposition for Low Rank Representation of Images," 2024 Advanced Topics on Measurement and Simulation (ATOMS), Constanta, Romania, 2024, pp. 216-219, doi: 10.1109/ATOMS60779.2024.10921614.

[6] G. Gonzalez-Sahagun, S. E. Conant-Pablos, J. Carlos Ortiz-Bayliss and J. M. Cruz-Duarte, "A Generalist Reinforcement Learning Agent for Compressing Multiple Convolutional Networks Using Singular Value Decomposition," in IEEE Access, vol. 12, pp. 136131-136147, 2024, doi: 10.1109/ACCESS.2024.3457863.

[7] H. Sharma and A. K. Sharma, "Var-HR: Noncontact Heart Rate Measurement Using an RGB Camera Based on Adaptive Region Selection With Singular Value Decomposition," in IEEE Sensors Letters, vol. 8, no. 4, pp. 1-4, April 2024, Art no. 7002104, doi: 10.1109/LSENS.2024.3375892.

[8] H. Zhang, "Data Processing Integrating Singular Value Decomposition Algorithm and Tensor Chain Decomposition Algorithm," in IEEE Access, vol. 13, pp. 38964-38978, 2025, doi: 10.1109/ACCESS.2025.3546029.

[9] H. Zhao and L. Ma, "Power Distribution System Stream Data Compression Based on Incremental Tensor Decomposition," in IEEE Transactions on Industrial Informatics, vol. 16, no. 4, pp. 2469-2476, April 2020, doi: 10.1109/TII.2019.2934766.

[10] J. Davies and C. S. Wright, "Using the Singular Value Decomposition to Generate Composite NFTs," 2023 IEEE International Conference on Omni-layer Intelligent Systems (COINS), Berlin, Germany, 2023, pp. 1-6, doi: 10.1109/COINS57856.2023.10189323.

[11] J. Qian and D. Liu, "Segmented Adaptive Singular Value Decomposition for Data Compression of IGBT," 2022 IEEE 11th Data Driven Control and Learning Systems Conference (DDCLS), Chengdu, China, 2022, pp. 431-436, doi: 10.1109/DDCLS55054.2022.9858350.

[12] J. Wen, S. Wang, K. Xie, J. Tian and Y. Wang, "Efficient and Adaptive CUR Matrix Decomposition for Flexible Compression of Network Monitoring Data," in IEEE Transactions on Network Science and Engineering, vol. 12, no. 3, pp. 2231-2242, May-June 2025, doi: 10.1109/TNSE.2025.3546687.

[13] K. R. Žalik and M. Žalik, "Comparison of K-Means, K-Means++, X-Means and Single Value Decomposition for Image Compression," 2023 27th International Conference on Circuits, Systems, Communications and Computers (CSCC), Rhodes (Rodos) Island, Greece, 2023, pp. 295-301, doi: 10.1109/CSCC58962.2023.00055.

[14] L. Jiang, Z. Huang, Y. Xi and J. Liu, "Sound Field Reconstruction of Plate Using Compressed Singular Value Decomposition Equivalent Source Method Combined with Generalized Inverse of Matrix," 2024 OES China Ocean Acoustics (COA), Harbin, China, 2024, pp. 1-5, doi: 10.1109/COA58979.2024.10723574.

[15] M. Farzaneh and R. M. Toroghi, "Robust Audio Watermarking Using Graph-based Transform and Singular Value Decomposition," 2020 10th International Symposium onTelecommunications (IST), Tehran, Iran, 2020, pp. 137-141, doi: 10.1109/IST50524.2020.9345876.

[16] M. Thoma et al., "Flar-SVD: Fast and Latency-Aware Singular Value Decomposition for Model Compression," 2025 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Nashville, TN, USA, 2025, pp. 1889-1898, doi: 10.1109/CVPRW67362.2025.00178.

[17] 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.

[18] 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.

[19] R. Ballester-Ripoll, P. Lindstrom and R. Pajarola, "TTHRESH: Tensor Compression for Multidimensional Visual Data," in IEEE Transactions on Visualization and Computer Graphics, vol. 26, no. 9, pp. 2891-2903, 1 Sept. 2020, doi: 10.1109/TVCG.2019.2904063.

[20] R. Nuca, M. Parsani and G. Turkiyyah, "An Adaptive Two-Stage Algorithm for Error-Bounded Scientific Data Compression," 2025 IEEE International Parallel and Distributed Processing Symposium (IPDPS), Milano, Italy, 2025, pp. 987-997, doi: 10.1109/IPDPS64566.2025.00092.

[21] R. Pourramezan, R. Hassani, H. Karimi, M. Paolone and J. Mahseredjian, "A Real-Time Synchrophasor Data Compression Method Using Singular Value Decomposition," in IEEE Transactions on Smart Grid, vol. 13, no. 1, pp. 564-575, Jan. 2022, doi: 10.1109/TSG.2021.3114585.

[22] R. Ranjan, P. Kumar, K. Naik and V. K. Singh, "The HAAR-the JPEG based image compression technique using singular values decomposition," 2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET), Patna, India, 2022, pp. 1-6, doi: 10.1109/ICEFEET51821.2022.9848400.

[23] R. Xiao, Z. Zong and L. Yang, "Clutter Suppression Based on Singular Value Decomposition and Fast Wavelet Algorithm," IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 2024, pp. 9490-9494, doi: 10.1109/IGARSS53475.2024.10642147.

[24] S. J. Li, H. Pang, P. Y. Li, Y. N. Li and Z. X. Liu, "Image compression based on SVD algorithm," 2021 International Conference on Computer Information Science and Artificial Intelligence (CISAI), Kunming, China, 2021, pp. 306-309, doi: 10.1109/CISAI54367.2021.00065.

[25] S. N. Hashemipour et al., "Big Data Compression in Smart Grids via Optimal Singular Value Decomposition," 2020 IEEE Industry Applications Society Annual Meeting, Detroit, MI, USA, 2020, pp. 1-8, doi: 10.1109/IAS44978.2020.9334900.

[26] W. Wang, C. Chen, W. Yao, K. Sun, W. Qiu and Y. Liu, "Synchrophasor Data Compression Under Disturbance Conditions via Cross-Entropy-Based Singular Value Decomposition," in IEEE Transactions on Industrial Informatics, vol. 17, no. 4, pp. 2716-2726, April 2021, doi: 10.1109/TII.2020.3005414.

[27] X. He, L. Zhang and F. Ding, "Singular Value Decomposition Representation of Color Image Based on Quaternion Equivalent Complex Matrix," 2023 IEEE 3rd International Conference on Electronic Technology, Communication and Information (ICETCI), Changchun, China, 2023, pp. 193-196, doi: 10.1109/ICETCI57876.2023.10176429.

[28] Y. Jaradat, M. Masoud, I. Jannoud, A. Manasrah and M. Alia, "A Tutorial on Singular Value Decomposition with Applications on Image Compression and Dimensionality Reduction," 2021 International Conference on Information Technology (ICIT), Amman, Jordan, 2021, pp. 769-772, doi: 10.1109/ICIT52682.2021.9491732.

[29] R. Pourramezan, R. Hassani, H. Karimi, M. Paolone and J. Mahseredjian, "A Real-Time Synchrophasor Data Compression Method Using Singular Value Decomposition," in IEEE Transactions on Smart Grid, vol. 13, no. 1, pp. 564-575, Jan. 2022, doi: 10.1109/TSG.2021.3114585.

[30] A. Mai, L. Tran, L. Tran and N. Trinh, "VGG deep neural network compression via SVD and CUR decomposition techniques," *2020 7th NAFOSTED Conference on Information and Computer Science (NICS)*, Ho Chi Minh City, Vietnam, 2020, pp. 118-123, doi: 10.1109/NICS51282.2020.9335842.

[31] 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.

[32] H. Zhang, "Data Processing Integrating Singular Value Decomposition Algorithm and Tensor Chain Decomposition Algorithm," in *IEEE Access*, vol. 13, pp. 38964-38978, 2025, doi: 10.1109/ACCESS.2025.3546029.

[33] N. T. Hai and T. M. Thanh, "Robust Image Watermarking Algorithm Integrating QR and Singular Value Decomposition in the Discrete Wavelet Transform Domain," *2025 2nd International Conference On Cryptography And Information Security (VCRIS)*, Hanoi, Vietnam, 2025, pp. 1-6, doi: 10.1109/VCRIS68011.2025.11250561.

[34] B. D. Kurniadi, “Traditionalising of Yogyakarta’s urban landscape: The return of the cosmological axis,” *Urban Studies*, Nov. 2025, doi: 10.1177/00420980251365478.

[35] N. C. Kresnanto, W. H. Putri, R. Raharti, and D. N. Luthfiana, “Sustainable mobility as a climate adaptation response in protected world heritage areas using Perception of Outstanding Universal Value: The Case of Cosmological Axis of Yogyakarta Indonesia,” *BIO Web Conf*, vol. 155, p. 07004, Jan. 2025, doi: 10.1051/bioconf/202515507004.

[36] D. Ayudya, W. Nuryanti, and M. S. Roychansyah, “The morphology of urban tourism space (case: Malioboro Main Street as cosmological Axis of Yogyakarta city, Indonesia),” *International Journal of Tourism Cities*, vol. 10, no. 4, pp. 1266–1290, Nov. 2024, doi: 10.1108/IJTC-12-2023-0261.

[37] Y. Li and J. Wang, “Game Creation as a Pedagogical Model for SDG Education: A Project-Based Approach in Vocational Learning,” *Eur J Educ*, vol. 60, no. 4, Dec. 2025, doi: 10.1111/ejed.70333.

[38] K. Asha, S. V. K. S. Pratyusha, and P. S. Murty, “A Secure Hybrid Watermarking Framework using DWT, SVD and Elliptic Curve Cryptography,” *in 2025 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE)*, IEEE, Apr. 2025, pp. 1–7. doi: 10.1109/AMATHE65477.2025.11081383.

[39] J. W. Boardman, "Inversion Of Imaging Spectrometry Data Using Singular Value Decomposition," *12th Canadian Symposium on Remote Sensing Geoscience and Remote Sensing Symposium*,, Vancouver, BC, Canada, 1989, pp. 2069-2072, doi: 10.1109/IGARSS.1989.577779.

[40] 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.