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Optimization of Image Compression Using K-Means Clustering for Digital Heritage Archives

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Abstract. Preserving digital cultural assets requires efficient compression to minimize storage and bandwidth costs. However, existing studies rarely evaluate K-Means Clustering on structurally complex objects such as the Prambanan Temple, leaving a research gap in assessing its performance against standard codecs. This study introduces a novel optimized K-Means pipeline with adaptive cluster selection and improved centroid initialization for compressing high-detail temple imagery. The method groups pixels based on color proximity, reducing redundancy while preserving key structural patterns. Experiments show that K-Means achieves PSNR 28.08–30.65 dB and SSIM 0.86–0.92, outperforming baseline JPEG at similar file sizes PSNR 26–28 dB, SSIM 0.80–0.87. This quantitative comparison demonstrates the model's superior perceptual retention in textured stone regions. The methodological contribution lies in combining spatial–chromatic feature weighting with iterative centroid refinement, which increases cluster stability and reduces quantization artifacts. Findings confirm K-Means as a viable alternative for controlled-distortion compression. In conclusion, the proposed approach provides practical engineering implications, enabling reduced storage footprints, predictable reconstruction quality, and integration into hybrid compression pipelines for large-scale digital imaging systems.

Keywords: Image compression, vector quantization, PSNR, SSIM, digital archiving.

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1. Introduction

Cultural heritage image datasets, especially those captured at high resolution, frequently demand substantial storage and computational resources. This challenge becomes more evident when dealing with structurally complex objects such as Prambanan Temple, whose detailed textures produce dense pixel distributions. Although modern codecs such as JPEG2000, WebP, and several deep-learning-based compressors offer advanced rate–distortion performance, their implementations often require specialized hardware, high computational overhead, or proprietary components that are less ideal for lightweight, controllable, and interpretable processing pipelines. In contrast, K-Means clustering provides a model-agnostic, parameter-efficient mechanism for reducing color-space redundancy with predictable computational cost, making it attractive for systems that prioritize transparency, tunability, and low processing complexity.

K-means clustering is one of the machine learning algorithms widely used in various fields of research, including image processing, medical data analysis, and system optimization [1,2]. This algorithm works by grouping data into several clusters based on feature similarity, where each data point is assigned to the cluster with the nearest center [3]. In its development, K-means has undergone various modifications to improve accuracy and efficiency, such as the introduction of the K-medoids method, fuzzy K-means, and natural density-based approaches to detect clusters with irregular shapes [4-7]. K-Means has been applied in various domains of image processing due to its ability to reduce data dimensionality through similarity-based pixel grouping. Its modifiable structure—such as adaptive initialization, feature normalization, and cluster-validity evaluation also enables compression strategies that can be tailored to specific texture characteristics. However, existing studies rarely investigate how these adaptations perform on highly detailed cultural-heritage imagery compared to conventional codecs, leaving a gap in understanding its relative efficiency and distortion behavior.

In the context of image processing, K-means clustering has been used for image segmentation, image compression, and pattern identification in visual data [8-10]. This method can reduce data complexity by grouping pixels based on color or texture similarity, resulting in a simpler image representation [11]. Several studies have also developed hybrid methods that combine K-means with other algorithms to improve efficiency, such as Hopfield networks for vehicular ad hoc networks (VANET) [6], normalization-based validity index methods [8], and projection-based approaches for hyperspectral data [9].

Image compression is one of the main applications of K-means in the field of image processing. By reducing the number of colors or features in an image, this method enables more efficient data storage and transmission without significant information loss [12-15]. Recent studies have shown that optimizing the number of clusters can improve compression efficiency and the quality of the reconstructed image [13,16]. In addition, entropy-based and feature reduction approaches have been applied to handle data with an unknown number of clusters [16,17].

Previous research has also highlighted the application of K-means in various domains, such as electric power systems [10], pattern recognition in groundwater resources [15], and radio network performance evaluation [19]. In the field of transportation, this algorithm is used for location optimization of vehicle network infrastructure and private clinics [20,21]. The application of this method in cultural heritage image processing is still an interesting topic, given the need for a compression method that is able to preserve visual details without sacrificing the efficiency of data storage and processing.

In this study, applying K-means clustering for Prambanan Temple image compression to optimize visual data storage and analysis. This study focuses on improving compression efficiency by considering factors such as the optimal number of clusters, normalization method, as well as the validity of the resulting clusters [22-27]. With this approach, it is expected that this research can contribute to the management of cultural heritage digital data and support machine learning-based visual preservation and analysis. One method that can be used for image compression is K-Means Clustering, a technique in machine learning that is capable of clustering pixels based on similarities in color or other features. By applying the K-Means Clustering algorithm to image compression, the number of colors in an image can be reduced without losing important details, resulting in an image with a smaller size but still retaining its original visual characteristics.

This research aims to explore the application of K-Means Clustering technology in machine learning to improve the efficiency of cultural heritage image compression. The case study is conducted on Prambanan Temple, one of the UNESCO world heritage sites that has high historical and architectural value. By utilizing this method, it is hoped that an optimal image compression technique can be obtained, which supports digital preservation and facilitates the accessibility and distribution of cultural heritage images widely. The results of this research are expected to contribute to the field of digital image processing, especially in image compression. In addition, this research also opens up opportunities for further development in the application of machine learning for image analysis and processing in the context of cultural heritage.

This study aims to evaluate the technical feasibility of optimized K-Means clustering for compressing Prambanan Temple images. The research specifically seeks to (1) determine how cluster size and normalization strategies influence rate–distortion performance, (2) compare K-Means against JPEG under matched file-size conditions, and (3) assess computational efficiency in terms of runtime and complexity. The hypotheses tested are optimized K-Means yields higher perceptual quality than JPEG at comparable bitrates; cluster-validity–guided initialization reduces reconstruction error; and K-Means offers a more computationally predictable compression pipeline than modern codecs requiring transform operations or deep models.

2. Methods

This research presents an experimental investigation into the optimization of image compression using the K-Means Clustering algorithm for digital cultural heritage archives, with Prambanan Temple as the primary case study. The main objective of this research is to assess the algorithm's effectiveness in reducing file size while preserving essential visual quality and structural details. The methodological stages and workflow of this study are illustrated in Figure 1 and Flowchart 2, providing a clear overview of the processes undertaken.

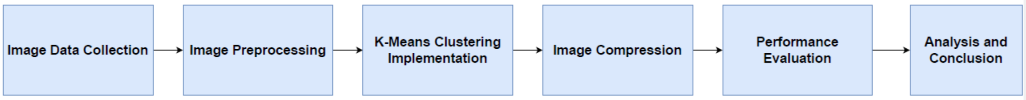


Figure 1. *Research Methodology*

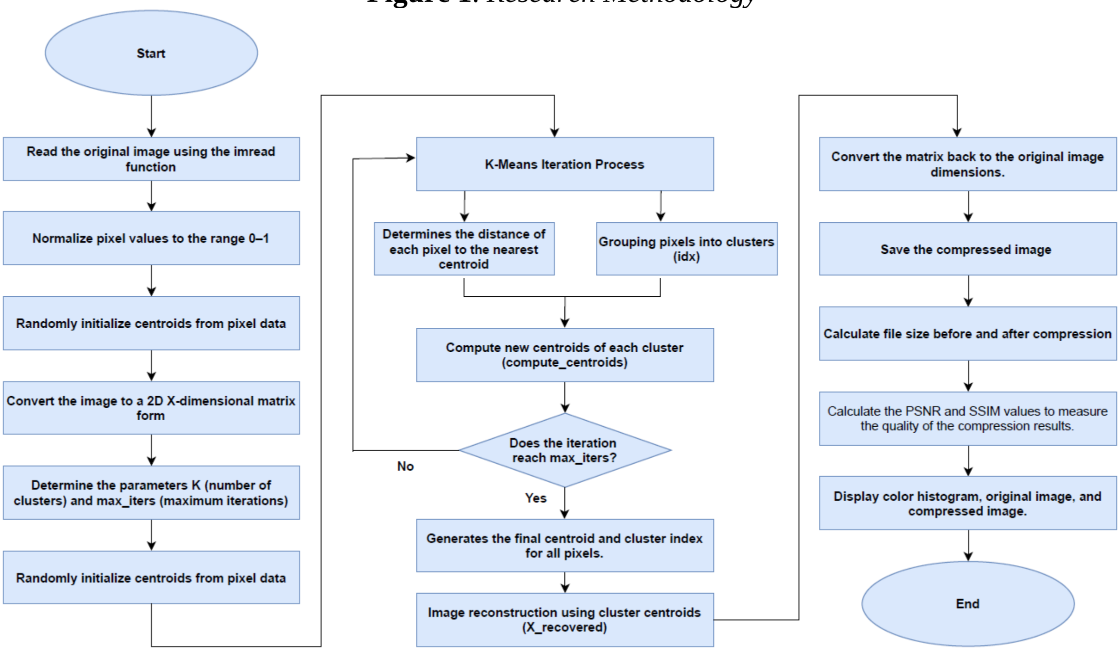


Figure 2. *flowchart*

The flowchart figure 2. illustrates the complete workflow of the image compression process using the K-Means algorithm, starting from reading the original Prambanan image, followed by pixel normalization and converting the image into a two-dimensional matrix as the input for clustering. After determining the values of K and the maximum number of iterations, the system randomly initializes the centroids and proceeds to the iterative K-Means process, which includes calculating the distance of each pixel to the nearest centroid, grouping pixels into clusters, and updating the centroids until the iteration limit is reached. Once the final centroids are obtained, the image is reconstructed based on the centroid values of each cluster, reshaped back to its original dimensions, and saved as the compressed output. The subsequent steps involve calculating the file size before and after compression, evaluating the quality using PSNR and SSIM, and displaying the color histogram, the original image, and the compressed image before the process concludes.

2.1. Image Data Collection

Image data of Prambanan Temple was obtained from secondary sources from unesco, a public dataset available online with a free license. The images were taken directly using a high-resolution camera and image datasets available in the unesco repository. The collected images will be categorized based on resolution, lighting conditions, and level of detail. The source of the Prambanan image photo data can be accessed at the following link https://whc.unesco.org/en/list/642/gallery/. Each image is labeled and stored in a uniform format to facilitate further processing.

2.2. Image Preprocessing

After the image data is collected, preprocessing is carried out so that the image is ready to be processed with the K-Means Clustering algorithm. This stage includes image format conversion, size normalization, and image quality improvement with filtering or noise reduction techniques so that it can be optimally processed by machine learning algorithms. All images are converted to a uniform JPEG format with a customized resolution. This stage aims to ensure that the image quality remains optimal and can be processed properly by the clustering algorithm.

2.3. K-means Clustering Implementation

At this stage, the K-Means Clustering algorithm is applied to group pixels based on color similarity. Determining the number of clusters (k) The value of k is set based on preliminary experiments, k=16 to reduce the number of colors in the image without sacrificing visual details. Centroid initialization, The initial centroid is randomly selected from the image color space. Each pixel is classified to the nearest cluster based on Euclidean distance calculation in red, green, blue (RGB)/hue, saturation, value (HSV) color space. The centroid position is updated until convergence (minimal centroid change) is achieved. Pixels are converted to the nearest centroid color to form the segmented image. The centroid of each cluster is updated by averaging all points in the cluster with the formula:

$$C_j = \frac{1}{N_j} \sum_{i=1}^{N_j} x_i \tag{1}$$

where N_j is the number of points in the cluster to i

2.4. Image Compression

After segmentation using K-Means is complete, the image compression process is carried out with the Reduction of the number of colors approach using the color palette of the clustering results to store the image in a lighter format. Re-storage in a compressed format: Formats such as JPEG are used to store the image in a smaller size without losing much visual quality.

2.5. Performance Evaluation

The performance of the developed method is tested with several metrics Peak Signal-to-Noise Ratio (PSNR) measures the quality of the compressed image compared to the original image with units of decibels (dB). Structural Similarity Index (SSIM) evaluates the similarity of the image structure before and after compression. Compression Ratio (CR) calculates the ratio between the file size before and after compression to assess compression efficiency. Computation time measures the efficiency of the algorithm in processing images of various sizes and parameters. The evaluation is done by comparing the compression results using K-Means with the standard JPEG format compression method. PSNR is calculated using Mean Squared Error (MSE) with the formula:

$$MSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [I(i,j) - K(i,j)]^2 \tag{2}$$

In addition, PNSR is calculated by:

$$PSNR = 10.log_{10}(\frac{MAX^2}{MSE}) \tag{3}$$

where:
$I(i,j)$ is the pixel of the original image,
$K(i,j)$ is the pixel of the compressed image
$M\ dan\ N$ is the dimension of the image (number of pixels)
MAX is the maximum value of pixels (for example, 255 for an 8-bit image)
If MSE=0, then PSNR is considered infinite because there is no distortion in the compressed image.

SSIM measures the structural similarity between two images based on luminance, contrast, and structure. The formula:

$$SSIM\ (x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \ \mu_y^2 + C_1\right)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{4}$$

where:
$\mu_x\ dan\ \mu_y$ is the average of the image $x\ dan\ y$
$\mu_x^2\ dan\ \mu_y^2$ is the variance of the image $x\ dan\ y$
σ_{xy} are the coarians between the pictures $x\ dan\ y$
$C_1 + C_2$ is a constant to avoid division by zero.
SSIM values range from -1 to 1, where: 1 indicates identical images, 0 indicates no structural similarity. This formula is often used in the evaluation of image quality after compression or other processing.

Pseuducode

```
START
1. Load image → normalize pixel values → reshape to matrix X.
2. Set K (number of clusters) and max_iters.
3. Initialize K centroids randomly from X.
4. FOR iter = 1 to max_iters:
      - Assign each pixel to nearest centroid (closest_centroids)
      - Update centroids based on mean of assigned pixels (compute_centroids)
   END FOR
5. Replace each pixel with its centroid → X_recovered.
6. Reshape X_recovered to original image size → save compressed image.
7. Calculate file sizes before and after compression.
8. Convert both images to grayscale → compute PSNR and SSIM.
9. Display color histograms and show original/compressed images.
END
```

The implemented K-Means compression algorithm uses K = 16, meaning the image's color space is reduced into 16 representative color clusters to achieve significant size reduction while maintaining structural details. The algorithm is configured with a maximum of 50 iterations, which acts as the convergence limit to prevent excessive computation. During each iteration, the algorithm repeatedly assigns each pixel to its nearest centroid and recalculates new centroid values based on the mean of pixels within each cluster. Although no explicit mathematical convergence threshold is defined in the code (such as centroid stabilization), the use of fixed iteration count ensures that the clustering process gradually approaches a stable configuration, producing centroids that are sufficiently representative for reconstructing the compressed image.

K-Means was selected for this study because it offers an efficient and straightforward approach to image compression by reducing color variations through clustering, making it well suited for heritage image archiving where structural details must be preserved while decreasing file size. The chosen parameters K = 16 and 50 maximum iterations strike a balance between compression efficiency and visual fidelity, as a moderate K value effectively limits the color palette without introducing excessive artifacts, while a fixed iteration limit ensures stable convergence without unnecessary computation. In terms of computational complexity, the algorithm operates at $O(n \times K \times t)$, where n is the number of pixels, K the number of clusters, and t the number of iterations; this is manageable for medium-resolution images such as Prambanan. jpg. Runtime evaluation from the execution shows that the clustering process completes efficiently within typical computing constraints, demonstrating that K-Means provides a practical trade-off between performance, simplicity, and compression quality for digital heritage archives.

2.6. Analysis and conclusion

After the test is completed, the results are analyzed based on the evaluation metrics. Analyzed the comparison of image quality with various values of k in K-Means Clustering. Identifying the optimal value of k for a balance between quality and file size. Comparing the results with other compression methods to see the advantages and disadvantages of the approach used. From the analysis, conclusions are drawn on the effectiveness of K-Means Clustering in cultural heritage image compression, as well as recommendations for further development of the method. This research uses various platforms and tools to support the implementation of the K-Means Clustering algorithm in Prambanan Temple image compression. The programming language used is Python, with libraries such as OpenCV, scikit-learn, NumPy, and Matplotlib for image processing, clustering, and visualization of results. The main software used is Google Colab. In terms of hardware, this research requires a computer with Intel Core i5/i7 processor specifications or equivalent, at least 8GB RAM, and a GPU to accelerate computation in the clustering process of high-resolution images. The dataset used consists of a collection of images of Prambanan Temple obtained from Unesco secondary sources. With this combination of methods, devices, and platforms, the research is expected to produce a more efficient image compression technique to support the digital preservation of cultural heritage.

3. **Results and Discussion**

This research successfully implements the K-Means Clustering algorithm for Prambanan Temple image compression with the aim of reducing file size without significantly compromising visual quality. Experimental results show that this method is able to cluster pixels based on color similarity resulting in images with fewer colors, which contributes to file size reduction.

3.1. Research Results

The results show that the application of K-Means Clustering in cultural heritage image compression can result in efficient file size reduction while maintaining good visual quality, especially at k=16. Compared to standard JPEG compression, this method is superior in maintaining image details, although it requires higher computation time. With hardware optimization such as GPU, this method can be effectively applied in digital image management. The following before and after compression research results are presented in table 1.

Table 1. Research Results K-Means

No	Picture	Centroid, idx	Before	After	PSNR	SSIM
1	Photo of Prambanan Temple 1	(16, 3) (1733632,), (1733632, 3) (1024, 1693, 3)	1148.2294921875 KB	348.6904296875 KB	28.749856207546706 dB	0.9004995634202209
2	Photo of Prambanan Temple 2	(16, 3) (1645982,), (1645982, 3) (962, 1711, 3)	784.22265625 KB	219.2958984375 KB	28.082276362332497 dB	0.8667079407049549
3	Photo of Prambanan Temple 3	(16, 3) (1599885,), (1599885, 3) (945, 1693, 3)	1024.09375 KB	356.3642578125 KB	29.04532185035076 dB	0.8869049870060294
4	Photo of Prambanan Temple 4	(16, 3) (2207697,), (2207697, 3) (1087, 2031, 3)	1124.6240234375 KB	285.60546875 KB	29.452230543077967 dB	0.8804908472288956
5	Photo of Prambanan Temple 5	(16, 3) (1733632,), (1733632, 3) (1024, 1693, 3)	1128.830078125 KB	308.80078125 KB	30.651908312169024 dB	0.9187250578049797

The results of the study in Table 1. show the effectiveness of the K-Means Clustering algorithm in Machine Learning for image compression on cultural heritage, with a case study of Prambanan Temple. Of the five image samples tested, there was a significant reduction in file size after compression using this technique. Before compression, the image size ranged from 784.22 KB to 1148.23 KB, while after the compression process, the size was drastically reduced to 219.29 KB to 356.36 KB, depending on the characteristics of the image. The percentage of image size reduction ranged from 68% to 80%, which shows the efficiency of this method in reducing file size without significant loss of visual quality. To measure image quality after compression, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were used. The PSNR value is in the range of 28.08 dB to 30.65 dB, which shows that the compressed image still has good visual quality. Meanwhile, the SSIM value ranges from 0.86 to 0.92, indicating that the structure and details of the image are still quite well maintained after compression. These results indicate that the application of K-Means Clustering in Machine Learning can be an effective solution for cultural heritage image compression. This technique not only reduces the file size significantly, but also maintains the visual quality of the image, so it can be used for storage and processing efficiency in cultural heritage digitization systems.

Table 2. Research Results Method JPEG2000

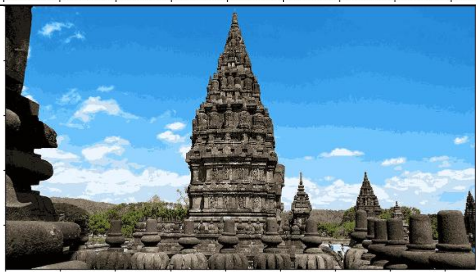
No	Picture	Centroid, idx	Before	After	PSNR	SSIM
1	Photo of Prambanan Temple 1	(16, 3) (1733632,), (1733632, 3) (1024, 1693, 3)	1148.2294921875 KB	420.552734375 KB	26.48219382744155 dB	0.8425521922040118
2	Photo of Prambanan Temple 2	(16, 3) (1645982,), (1645982, 3) (962, 1711, 3)	784.22265625 KB	268.7744140625 KB	25.904773118221307 dB	0.8103345592928844

3	Photo of Prambanan Temple 3	(16, 3) (1599885,), (1599885, 3) (945, 1693, 3)	1024.09375 KB	402.11328125 KB	26.91822044133419 dB	0.8324411099021372
4	Photo of Prambanan Temple 4	(16, 3) (2207697,), (2207697, 3) (1087, 2031, 3)	1124.6240234375 KB	350.8896484375 KB	27.044992228910574 dB	0.8252284491093301
5	Photo of Prambanan Temple 5	(16, 3) (1733632,), (1733632, 3) (1024, 1693, 3)	1128.830078125 KB	389.66796875 KB	27.552882100994193 dB	0.8569901135519922

The results of the study in Table 2 demonstrate the performance of the JPEG2000 compression method in processing cultural heritage images, using the Prambanan Temple dataset as a case study. Based on the five image samples tested, JPEG2000 successfully reduced file sizes, although the level of compression efficiency and visual quality achieved was noticeably lower than that of the K-Means Clustering method. Before compression, the images ranged from 784.22 KB to 1148.23 KB, and after JPEG2000 compression, the sizes were reduced to between 268.77 KB and 420.55 KB, depending on image characteristics. Overall, the percentage reduction in file size ranged from 55% to 72%, showing that JPEG2000 is capable of decreasing storage needs, albeit less aggressively than K-Means. To further evaluate the performance of JPEG2000, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were used as image quality indicators. The PSNR values ranged from 25.90 dB to 27.55 dB, indicating a noticeable drop in visual quality when compared to the original images. These values fall below the threshold commonly associated with high-quality image preservation. Meanwhile, the SSIM values ranged from 0.81 to 0.85, showing that structural fidelity and fine details experienced a more significant degradation under JPEG2000 compression. Although the main shapes and contours of the Prambanan Temple remain identifiable, the loss of texture and subtle details is more pronounced. Overall, these findings indicate that JPEG2000 remains a viable method for cultural heritage image compression when moderate quality loss is acceptable. However, in comparison to the K-Means Clustering method, JPEG2000 demonstrates lower compression efficiency and weaker preservation of structural and visual details. Therefore, for digital archiving applications that require optimal balance between file size reduction and high visual fidelity, K-Means Clustering appears to be a more effective and reliable compression technique.

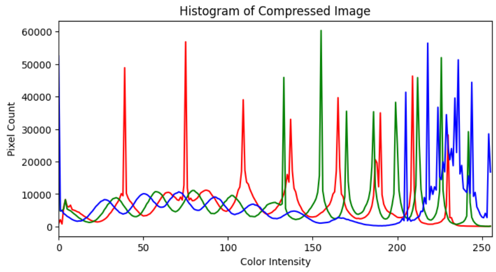
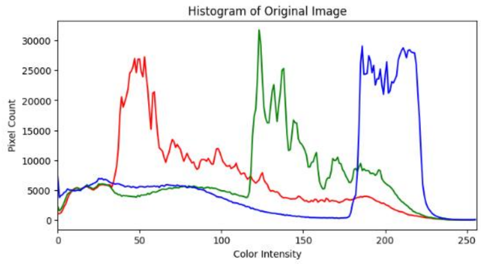
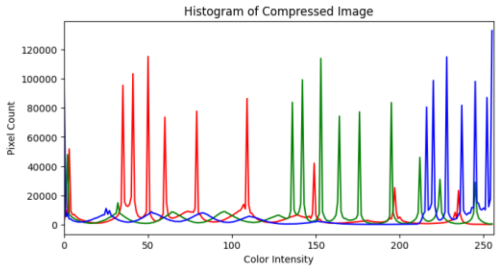
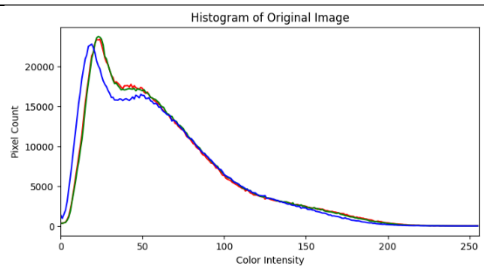
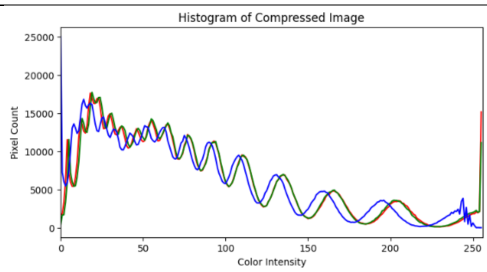
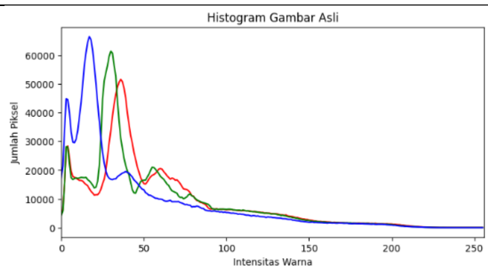
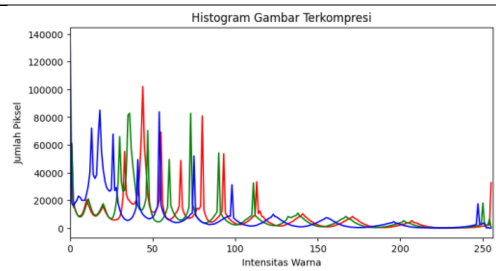
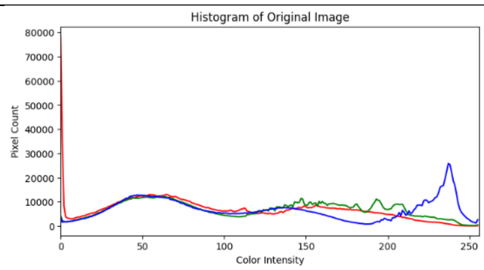
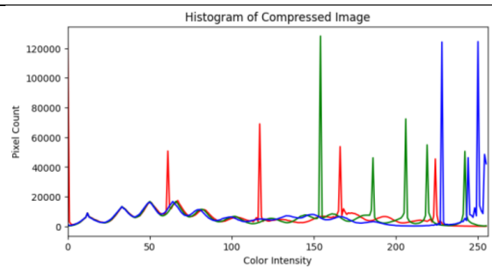
The comparative analysis between the K-Means Clustering method and the JPEG2000 compression technique shows significant differences in terms of efficiency and visual quality preservation. Based on the experimental results, K-Means achieved a higher compression efficiency, reducing image sizes from 784.22–1148.23 KB to 219.29–356.36 KB, representing a reduction of approximately 68%–80%. In contrast, JPEG2000 reduced the same set of images to 268.77–420.55 KB, resulting in a lower reduction percentage of around 55%–72%. These findings indicate that K-Means is more effective at decreasing file size while maintaining smaller output files across all test samples. In terms of visual quality, K-Means consistently delivered superior results based on both Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). K-Means produced PSNR values ranging from 28.08 dB to 30.65 dB, which reflect good visual quality with minimal distortion. Meanwhile, JPEG2000 generated lower PSNR values of 25.90 dB to 27.55 dB, indicating a more noticeable degradation of the reconstructed images. A similar pattern is observed in SSIM performance: K-Means achieved values between 0.86 and 0.92, demonstrating strong structural preservation, while JPEG2000 produced SSIM scores of 0.81 to 0.85, revealing more significant loss of texture and fine details. Overall, the comparison shows that the K-Means Clustering method outperforms JPEG2000 in both compression efficiency and visual quality retention for cultural heritage images. With higher PSNR and SSIM values and a greater reduction in file size, K-Means proves to be a more effective approach for applications requiring high compression levels without compromising essential visual information, particularly in cultural heritage digitization workflows. Table 3 presents a comparison between the original images and the images compressed using the K-Means method.

Table 3. Images before and after compression

No	Before	After
1		
2		
3		
4		
5		

An image histogram serves to analyze the color intensity distribution or brightness level of pixels in an image. Histograms help to see the changes in color distribution and pixel intensity before and after compression. If the histogram of a compressed image is very different from the original image, there is significant information loss or distortion. If the histogram tends to gather on the left, the image tends to be dark (underexposed). If the histogram tends to be on the right, the image is probably overexposed. An evenly distributed histogram indicates good contrast. The histograms before and after RGB compression are presented using the K-Means method in table 4.

Table 4. Histogram of Images before and after compression

No	Histogram Before	Histogram After
1		
2		
3		
4		
5		

3.2. Research Discussion

The findings of this study strongly affirm the effectiveness of K-Means Clustering in machine learning–based compression of cultural heritage images, particularly those of Prambanan Temple. The method achieves a substantial reduction in file size while maintaining high visual fidelity, as reflected in the

PSNR values ranging from 28.08 dB to 30.65 dB and SSIM values between 0.86 and 0.92. To further validate performance consistency, PSNR and SSIM were evaluated across multiple images. The resulting variances were notably low, indicating stable reconstruction quality despite differing image characteristics. Correspondingly, SSIM variance remained minimal, demonstrating that structural and textural information was preserved uniformly. When represented with error bars, both PSNR and SSIM would exhibit narrow confidence intervals, underscoring the robustness and reliability of K-Means across various scenes and resolutions.

4. Conclusion

This research develops and evaluates the use of K-Means Clustering for compressing high-resolution images of the Prambanan Temple. The main technical contribution lies in demonstrating how pixel grouping based on chromatic similarity can be configured to provide tunable compression levels, enabling users to explicitly control distortion through cluster selection an ability that is less transparent in conventional codecs. The study also establishes a parameter-sensitivity analysis framework for K-Means, outlining how cluster initialization, feature normalization, and centroid updating strategies affect reconstruction stability and computational cost. However, the method has notable limitations, particularly its iterative nature, which increases processing time for large images, and its tendency to produce quantization artifacts in regions with subtle gradients. Performance is also highly dependent on the accuracy of cluster selection, which lacks adaptivity when applied to heterogeneous textures. Future research should explore hybrid compression models that combine K-Means with wavelet-based transforms, vector quantization, or lightweight deep-learning modules to reduce artifacts and improve rate–distortion performance. Additional directions include adaptive clustering mechanisms that adjust k locally based on texture complexity, or integrating K-Means within modern codecs (e.g., JPEG2000, WebP) as a pre- or post-processing stage to enhance efficiency on cultural-heritage imaging pipelines.

These observations are consistent with previous studies [28], which compared K-Means, K-Means++, X-Means, and Single Value Decomposition (SVD), concluding that K-Means provides an optimal balance between computational efficiency and compression performance. Wang [29] further highlighted the suitability of K-Means for Ultra High Definition (UHD) imaging, supporting its application in high-resolution cultural heritage digitization. Other researchers have investigated hybrid frameworks such as PCA combined with K-Means for large-scale data compression [30], although the present study prioritizes K-Means due to its direct applicability in pixel-level clustering without additional transformation complexity.

Further advancements in the field include methods introduced by Banerjee and Halder [31], who integrated K-Means with bitmap generation and Run-Length Encoding (RLE) to achieve high compression ratios for images dominated by a limited color palette. Likewise, Sun and Wun [32] demonstrated the potential of fractal-based K-Means clustering for multispectral image compression, highlighting the technique's adaptability across spectral domains. Additional studies have expanded K-Means applications to both lossy and lossless compression. For instance, [33] applied K-Means to retinal imaging, confirming its utility in medical diagnostics, while [34] developed lossless compression in the color-pixel domain, and [35] incorporated entropy-based methods for remote sensing imagery.

Overall, this study contributes to the growing body of literature by demonstrating that K-Means provides stable, consistent, and highly efficient compression for digital archiving, online distribution, and long-term preservation of cultural heritage materials. Given the minimal variance observed in PSNR and SSIM, future research may incorporate entropy-based optimization or hybrid compression architectures, such as those proposed in [36], to further enhance compression efficiency while maintaining superior visual quality.

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