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Segmentation of Aerial Images Using Different Clustering Techniques

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Abstract

The segmentation of aerial images using different clustering techniques offers valuable insights into interpreting and analyzing such images. By partitioning the images into meaningful regions, clustering techniques help identify and differentiate various objects and areas of interest, facilitating various applications, including urban planning, environmental monitoring, and disaster management. This paper aims to segment color aerial images to provide a means of organizing and understanding the visual information contained within the image for various applications and research purposes. It is also important to look into and compare the basic workings of three popular clustering algorithms: K-Medoids, Fuzzy C-Mean (FCM), and Gaussian Mixture Model (GMM). This will help find the best way to separate colors in aerial images. According to a thorough comparative study, PSNR and correlation metrics show that K-Medoids outperform other clustering techniques in terms of segmentation quality. Also, the effect of changing the number of clusters on the image quality was studied; when the number of clusters increases, the image quality increases. It was found that when K-Medoids were used, the PSNR and correlation were 35.57 and 0.99, respectively. When FCM and GMM were used, they were 35.54, 0.99, 31.67, and 0.97, respectively, when the number of clusters was 12.

Keywords: K-Medoids, FCM, GMM, PSNR, Correlation.

تجزئة الصور الجوية باستعمال تقنيات التجميع المختلفة

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الخلاصة

توفر تجزئة الصور الجوية باستعمال تقنيات التجميع المختلفة رؤى قيمة في تفسير هذه الصور وتحليلها. ومن خلال تقسيم الصور إلى مناطق ذات معنى، تساعد تقنيات التجميع في تحديد وتمييز مختلف الأشياء والمناطق ذات الاهتمام، مما يسهل التطبيقات المختلفة، بما في ذلك التخطيط الحضري والرصد البيئي وإدارة الكوارث. تهدف هذه الورقة إلى تقسيم الصور الجوية الملونة لتوفير وسيلة لتنظيم وفهم المعلومات المرئية

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الموجودة داخل الصورة لمختلف التطبيقات والأغراض البحثية، وكذلك للتحقيق ومقارنة تحليل خوارزميات التجميع المستعملة على نطاق واسع، وهي K–Medoids وFuzzy C–Mean (FCM)، و Gaussian Mixture Model (GMM)، فيما يتعلق بمنهاجياتهما الأساسية لتحديد النهج الأكثر فعالية لتجزئة الصور الجوية الملونة. من خلال دراسة مقارنة شاملة، تبين أن K–Medoids تتفوق على تقنيات التجميع الأخرى من حيث جودة التجزئة، كما تم قياسها بواسطة PSNR ومقاييس الارتباط. كما تمت دراسة تأثير تغيير عدد العناقيد على جودة الصورة، فعندما يزداد عدد العناقيد تزداد جودة الصورة. تشير نتائج الاختبار إلى أن أعلى نسبة PSNR وارتباط هي 35.57 و 0.99 على التوالي عند استخدام K–Medoids، بينما في حالة استعمال FCM و GMM فإن PSNR والارتباط هما 35.54 و 0.99 و 31.67 و 0.97 على التوالي عندما عدد العناقيد يساوي 12 .

1. Introduction

In applications for data analysis and data mining, clustering is crucial. It involves arranging a collection of things into groups based on how much they resemble one another rather than the members of other groups. The components of a cluster have recognizable traits. Finding commonalities between data based on their shared qualities and clustering related data objects together is how cluster analysis is performed. An effective clustering technique will yield high-superiority clusters with high intra-class similarity and low inter-class similarity [1], [2]. Image segmentation is the most important technique of image processing, which is the automatic or semi-automatic process used to separate the region of interest (ROI). Image segmentation is defined as trying to find homogenous limits inside an image and then classifying them. It also allows images to be divided into pertinent areas by homogeneity or heterogeneity criteria [3], [4]. Many clustering methods are used in this paper to segment the images into several segments, such as K-Medoids, Fuzzy C-mean (FCM), and Gaussian Mixture Model (GMM), and compare them to find the best technique for segmenting the images in terms of maintaining the quality of the images. These techniques are highly sought-after and valuable due to their ability to retain a larger amount of image information, their ease and speed of implementation, and the consistently good results they yield [5], [6].

The article is organized as follows: Section 2 offers the related work. Section 3 discusses the existing image clustering methods. In Section 4, the layout of the proposed image clustering system is described. Section 5 covers the findings and discussion. Section 6 covers the comparison with previous related work. This article's conclusions are given in Section 7.

2. Related Works

This section offers a comprehensive review of relevant literature that will be utilized in this investigation. It includes an overview of various methods, like K-medoids, FCM, and GMM.

Rajni et al. [7] provided a method that involves segmenting color images by employing the feature-based fuzzy C-means-extreme learning machine (FBFCMELM) algorithm. This algorithm utilizes entropy, intensity, and edge features for classification, ensuring that the intensity values are updated to preserve local characteristics while still clearly delineating image boundaries. Pixel values within each cluster are assigned to the peak value of the cluster's sub-histogram. Feature extraction using FBFCM provides reliable samples for training the extreme learning machine (ELM). The trained ELM classifier is then used to obtain segmented pixels for uncertain classification. Experimental results on various images demonstrate that the proposed method produces better-segmented RGB images with enhanced details and edges. The test result indicates the PSNR value is equal to 25.46.

Hang et al. [8] proposed a local fuzzy clustering segmentation approach based on leveraging a feature selection Gaussian mixture model. Initially, spatial distance constraints were incorporated into the local information function to refine the membership degree. Integrating feature saliency subsequently improved the objective function. Through the application of the Lagrange multiplier method, the optimal form of the objective function was determined. It was possible to make the process even better while making it easier to choose local features by adding neighborhood weighting data to the iteration expression of the classification membership degree. The efficacy of this approach was evaluated by applying it to Gaussian noise, salt-and-pepper noise, multiplicative noise, and mixed noise interference images, utilizing both the improved FLICM algorithm, the fuzzy C-means with spatial constraints (FCM_S) algorithm, and the original FLICM algorithm for clustering and segmentation. A comparative analysis of segmentation results, based on peak signal-to-noise ratio and error rate, was conducted across the different algorithms. The outcomes of this study indicate that the PSNR value is equal to 15.95.

In 2022, Nookala [9] proposed a way to separate color images that uses peak-and-valley filtering to get rid of noise and Gaussian kernel-based fuzzy c-means (PVFCM) for color image separation. Initially, the image undergoes denoising through peak-and-valley filtering. Subsequently, segmentation employing Gaussian kernel-based fuzzy c-means is applied to the denoised image. The OASIS-MRI image dataset is used to test how well this method works. Metrics like PSNR, score, number of iterations (NI), and execution time (TM) are measured at different levels of Gaussian noise. The results demonstrate a marked enhancement over existing methods in terms of PSNR, Score, NI, and TM, affirming the effectiveness of the proposed technique. The outcomes of this study indicate that the PSNR value is equal to 34.23.

Xuefeng et al. [10] proposed an innovative approach for image segmentation by combining rough set theory with a GMM. The resulting segmentation algorithm exhibits enhanced robustness and immunity compared to conventional methods. This algorithm prioritizes information preservation and effectively retains finer image details. Consequently, it is capable of capturing multiple image layers. A new adaptive fractional-order differential mask in the Fourier domain was created to improve the segmentation process even more. This mask is used after preprocessing. This addition serves to improve the segmentation layers. The test results indicate the best PSNR value obtained from all datasets is 29.83.

3. Materials and Methods

This section explains the database used in the experiments conducted as well as the clustering methods that are used in the research.

3.1 USC-SIPI Image Database

We use the University of Southern California Signal and Image Processing Institute's (USC-SIPI) image database "Aerials," which was released in 1977 and contains 37 colors and one monochrome high-altitude aerial photograph, whose sizes are twelve 512 x 512, twenty-five 1024 x 1024, and one 2250 x 2250, to test the effectiveness of clustering techniques. It is available at https://sipi.usc.edu/database/database.php?volume=aerials.

In contrast to other types of images, aerial images have several distinctive features:

1) Aerial photographs offer a distinctive top-down or oblique viewpoint of the scene, providing a wide picture of the surroundings or things from above. Ground-level photographs taken with handheld cameras have a different angle and vision from those taken from this vantage point.

2) Aerial pictures frequently encompass vast areas, such as landscapes, cities, or regions, allowing for a broad spatial context. Other photographs, on the other hand, might concentrate on particular things, people, or scenes that were taken up close.
3) Environmental elements, including the weather, atmospheric effects, and time of day, have an impact on aerial photographs. These variables may have an impact on the clarity, visibility, and interpretation of the photographs, causing a distinct analysis of aerial images from other forms of images.
4) Aerial images can capture fine details and provide high-resolution imagery, especially when obtained from satellites or specialized aerial platforms. This level of detail allows for the identification and analysis of smaller objects or features that may not be discernible in other types of images.

3.2 K-Medoids Algorithm

The main role of the k-medoids strategy is to find k clusters in n objects by selecting medoids randomly for each cluster. The remaining objects are grouped with the medoids that are similar to them. It used medoids as a reference point instead of calculating the average value for all cluster elements [11], [12]. The k-medoids algorithm is explained in the following steps [13]:

1) Select k data items randomly to represent the initial medoids.
2) The closest medoid has been used to assign the remaining data points to a cluster.
3) Arbitrarily choose a non-medoid data point and calculate the total cost of replacing the previous medoid data point with the non-medoid data point currently chosen.
4) When the entire cost of replacement is less than zero, the replacement process is performed to construct the new set of k-medoids.
5) Steps 2, 3, and 4 are repeated until the medoids are stable in their positions.

Algorithm 1 explains the steps of the K-Medoids algorithm.

Algorithm 1 summarizes the K-Medoids steps.

Input: Ky: the number of clusters, Dy: a data set containing n objects.
Output: A set of ky clusters.
Algorithm:

- Randomly select ky as the Medoids for n data points.
- Find the closest Medoids by calculating the distance between data points n and Medoids k and map data objects to that.
- For each Medoids m and each data point o associated to m do the following:

  Swap m and o to compute the total cost of the configuration than
  Select the Medoids o with the lowest cost of the configuration.
- If there is no change in the assignments repeat steps 2 and 3 alternatively.

3.3 Fuzzy C-mean Algorithm (FCM)

Fuzzy C-Means (FCM) is a clustering methodology that achieves excellent results in a wide range of applications in the fields of engineering, economics, psychology, and many more. It maps each data point to two or more clusters. Consider $X = \{x_1, x_2, ...x_i, …. x_n\}$ be the n data points, and $V = \{v_1 ,v_2 ,…...v_j ,......v_c\}$ be the set of c cluster centers. The goal of FCM is to divide the data points into c groups so that the data points within a group share comparable features to the data points inside the other groups based on minimizing the objective function, as in the following equation [14–16].

$$J = \sum_{j=1}^{n} \sum_{i=1}^{c} \mu_{ij}^{m} \left\| x_j - v_i \right\|^2 \quad (1)$$

In the FCM algorithm, where m represents the fuzzifier value, v_i denotes the center of the i^{th} cluster, $\mu_{ij} \in [0,1]$ represents the membership of data point x_j to the v_i cluster center, and $(\|.\|)$ is the distance measure used to calculate the distance between the data point (x_j) and the cluster center (v_i). The FCM algorithm is iterative and updates the membership (μ_{ij}) and cluster centers using the following equations:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\left\| \frac{x_j - v_i}{x_j - v_k} \right\| \right)^{\frac{1}{m-1}}} \quad (2)$$

$$v_i = \frac{\sum_{j=1}^{n} \mu_{ij}^{m} x_j}{\sum_{j=1}^{n} \mu_{ij}^{m}} \quad (3)$$

The initial cluster centers for the FCM procedure are chosen at random from the c number of data points. Additionally, equation 2 is used to calculate the membership value depending on the separation between the data point x_j and the cluster center Vi. The objective function value is then calculated using Equation 1 based on previously assessed membership values. Equation 3 is then used to update the cluster centers based on the membership values of each data point. When the difference between subsequent iterations' objective function values is smaller than the user-specified stopping criterion value, the iterative process is terminated. Although FCM is a crucial tool for image processing since it produces excellent results, it has several drawbacks, such as noise sensitivity and a lack of knowledge about the neighborhood [14–16].

3.4 Gaussian Mixture Model (GMM)

GMM is a supervised method for presenting multivariate probability distribution areas. The weighted Gaussian component densities calculated using iterative Expectation-Maximization (EM) optimization are added together to form the parametric graphical model, which is represented by the following equation [17–19].

$$p(x|\lambda) = \sum_{i=1}^{k} w_i \, g\left(x \middle| \mu_i, \textstyle\sum_i \right) \quad (4)$$

The component density for k labels/components is determined by the mean vector, μ_i, and covariance matrix, $\sum_i$, which are derived from the targeted mixing proportions vector, x. This relationship can be expressed through the following equation:

$$g\left(x \middle| \mu, \textstyle\sum_i \right) = \frac{1}{(2\pi)^{D/2} \left| \sum_i \right|^{1/2}} exp\left\{ -\frac{1}{2} (x - \mu_i) \textstyle\sum_i^{1} (x - \mu_i) \right\} \quad (5)$$

It should be noted that the covariance matrix, $\sum_i$, can be either full rank (with a rank ($\sum_i$) equal to the minimum value between M and k) or diagonal. Additionally, the total weighted density is constrained to be equal to 1.

$\sum_{i=1}^{M} w_i = 1.$

4. Proposed System

The proposed aerial image segmentation system consists of five main consecutive stages: (1) color aerial image loading, (2) reshaping the image, (3) performing clustering, (4) image segmentation to N clusters, and (5) clustered image. Figure 1 illustrates the structure of the proposed aerial image segmentation system as described below:

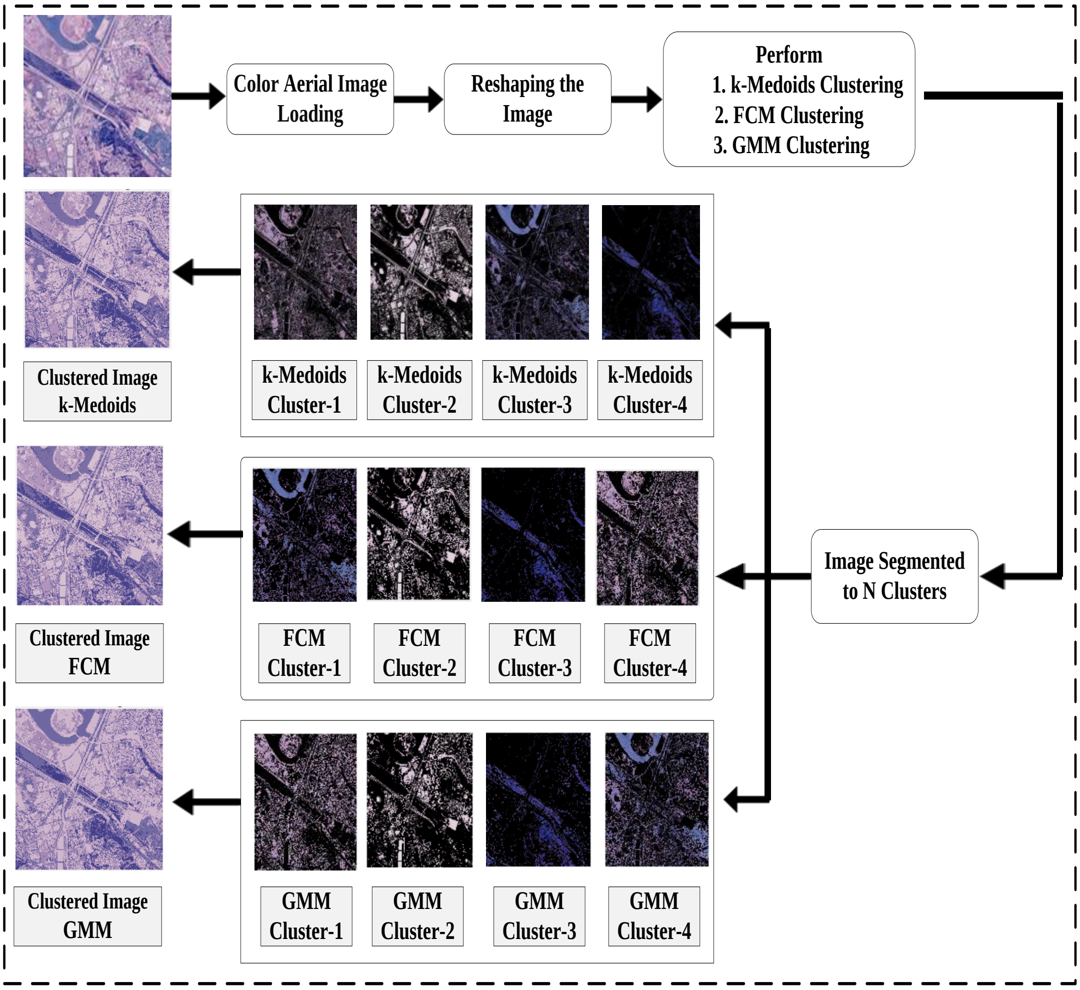

Figure 1: The proposed aerial image segmentation layout

4.1 Color Aerial Image Loading

This step loads the color aerial image from the file.

4.2 Reshaping the Image

Reshaping an image refers to the process of changing its dimensions or altering its structure while preserving its content and overall appearance. When we talk about reshaping an image, we typically refer to two aspects: the size (dimensions) of the image and the arrangement of its pixels. Thus, reshape the image into a 2D matrix (pixels as rows, RGB channels as columns). The size of the original image is 512 x 512 x 512 (RGB) and consists of three bands; then, this image is reshaped into a 512 x 512 2D matrix where pixels are rows but RGB channels are columns.

4.3 Performing Clustering

Clustering algorithms strive to organize comparable data points into cohesive groups while ensuring that dissimilar points remain separate. In the context of image segmentation, individual pixels or clusters of pixels are treated as data points. The clustering algorithm then categorizes each pixel into a distinct segment or cluster based on its similarity to neighboring pixels. This process essentially partitions the image into meaningful regions or segments, facilitating tasks such as object detection, feature extraction, and image understanding. In this paper, three clustering algorithms are applied, as described in Section 3.

4.4 Image Segmented to N Clusters

The objective of this step is to partition the image into multiple clusters based on the color image values. When there are more clusters, the division will be more accurate in terms of how the image's color values converge, as shown in Figure 2. Figure 2 shows an example of splitting an image into four clusters using three different clustering algorithms, namely K-medoids, FCM, and GMM.

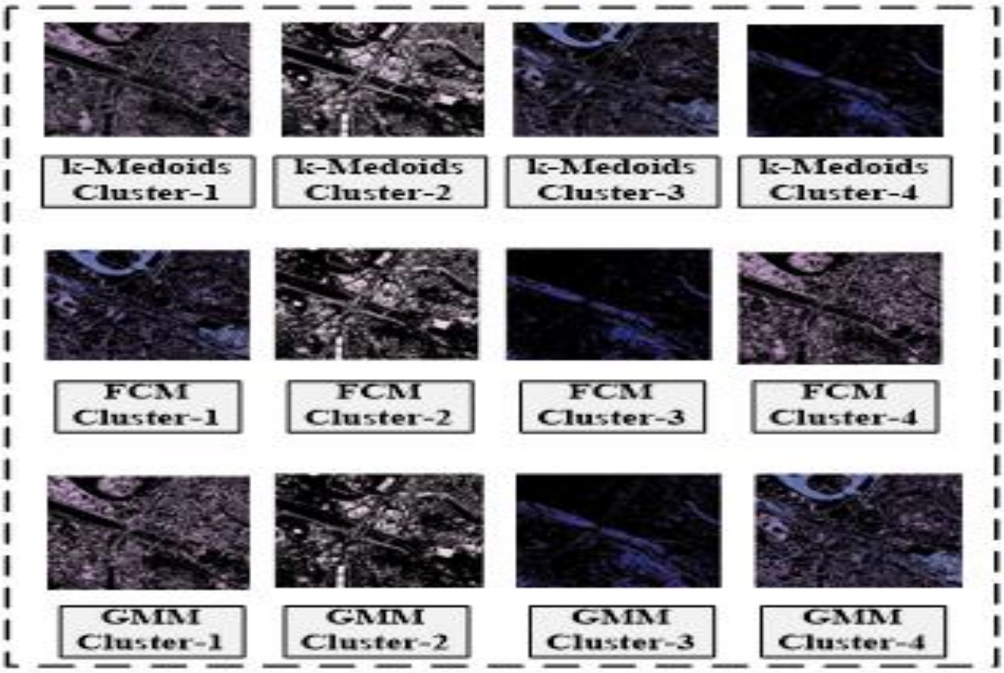

Figure 2: Segmenting the image into four clusters

4.5 Clustered Image

A clustered image refers to an image that has undergone a clustering algorithm for segmentation or grouping of pixels into distinct clusters or regions based on their similarity. In a clustered image, each pixel is assigned to a specific cluster or segment, as shown in Figure 3, which explains the clustered image obtained from the cluster of four clusters shown in Figure 2.

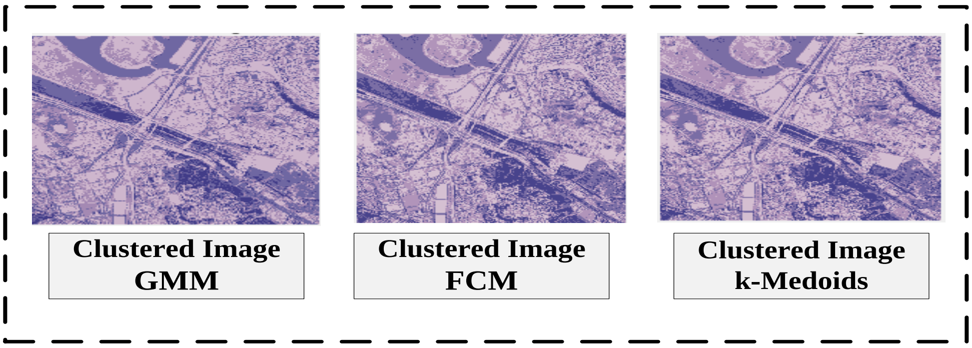

Figure 3: Clustered image

5. Results and Discussion

Two metrics, namely correlation and peak signal-to-noise ratio (PSNR), are employed to assess the effectiveness of the proposed system. The correlation coefficient is a metric used in statistics to quantify the connection between two variables. It establishes the degree and nature of the linear relationship between the variables. The correlation coefficient is denoted by the symbol "C" and ranges between -1 and 1 [20], [21]. PSNR is a measure used to quantify the quality of a reconstructed or clustered image compared to the original reference image. PSNR is calculated by comparing the mean squared error (MSE) between the original and clustered images. The correlation and PSNR are described in the following equations [22–25].

$$C = \frac{\sum_{i=1}^{N}(a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_{i=1}^{N}(a_i - \bar{a})^2}\sqrt{\sum_{i=1}^{N}(b_i - \bar{b})^2}} \quad (6)$$

$$PSNR = 10.log_{10}\left[\frac{(255)^2}{\frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{M-1}[\hat{I}(i,j) - I(i,j)]^2}\right] \quad (7)$$

Let N be the number of samples, a_i and b_i be the data values of the ith sample, and $\bar{a}$ and $\bar{b}$ be the average values.

The proposed system's effectiveness is assessed by utilizing the database outlined in Section 3.1. The database consists of 37 color images. The proposed system was tested on all databases, but only the results of four images are shown in Figure 4. The proposed system's performance was assessed by passing each image to the proposed system by applying the three clustering algorithms. Table 1 displays the outcomes of the correlation and PSNR when the number of clusters is equal to 4, while Tables 2 and 3 show the results when the number of clusters is equal to 7 and 12, respectively. From these results, we conclude that when the number of clusters increases, the PSNR value increases and the correlation coefficient value also increases, which indicates obtaining the best quality of the clustered image when compared to the original image. These three images (Figure 5, Figure 6, and Figure 7) show the results of the clustered image after using K-Medoids, FCM, and GMM on all of the images that were tested, with cluster numbers of 4, 7, and 12.

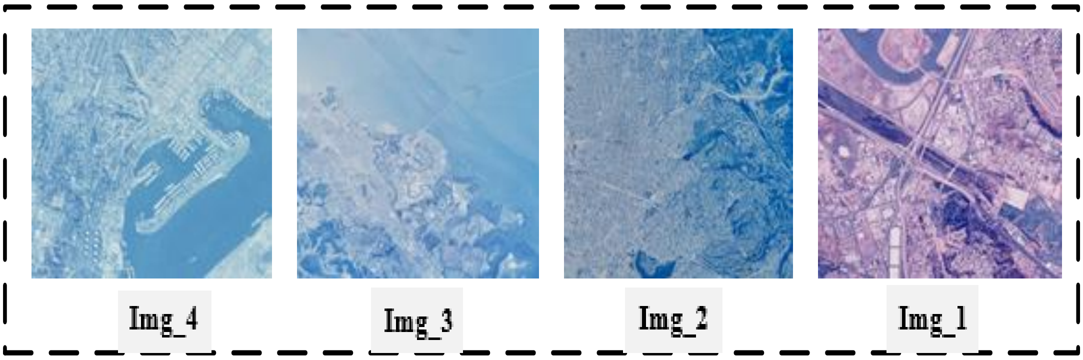

Figure 4: Original tested image

Table 1: The results of clustering algorithms when cluster number = 4

Image Name	k-Medoids Clusters no.=4		FCM Clusters no.=4		GMM Clusters no.=4	
	PSNR	**Corr.**	**PSNR**	**Corr.**	**PSNR**	**Corr.**
Img_1	25.69	0.95	25.68	0.95	24.96	0.93
Img_2	28.18	0.95	28.17	0.95	26.35	0.91
Img_3	30.11	0.93	30.11	0.93	27.89	0.88
Img_4	30.84	0.96	30.83	0.96	26.28	0.89

Table 2: The results of clustering algorithms when cluster number = 7

Image Name	k-Medoids Clusters no.=7		FCM Clusters no.=7		GMM Clusters no.=7	
	PSNR	**Corr.**	**PSNR**	**Corr.**	**PSNR**	**Corr.**
Img_1	28.90	0.98	28.89	0.98	26.42	0.95
Img_2	31.13	0.98	31.13	0.98	26.76	0.92
Img_3	32.82	0.97	32.80	0.97	28.11	0.89
Img_4	33.59	0.98	33.57	0.98	25.58	0.87

Table 3: The results of clustering algorithms when cluster number = 12

Image Name	k-Medoids Clusters no.=12		FCM Clusters no.=12		GMM Clusters no.=12	
	PSNR	**Corr.**	**PSNR**	**Corr.**	**PSNR**	**Corr.**
Img_1	31.12	0.99	31.11	0.99	27.19	0.96
Img_2	33.04	0.98	32.99	0.99	28.43	0.95
Img_3	34.96	0.98	34.80	0.98	29.44	0.93
Img_4	35.57	0.99	35.54	0.99	31.67	0.97

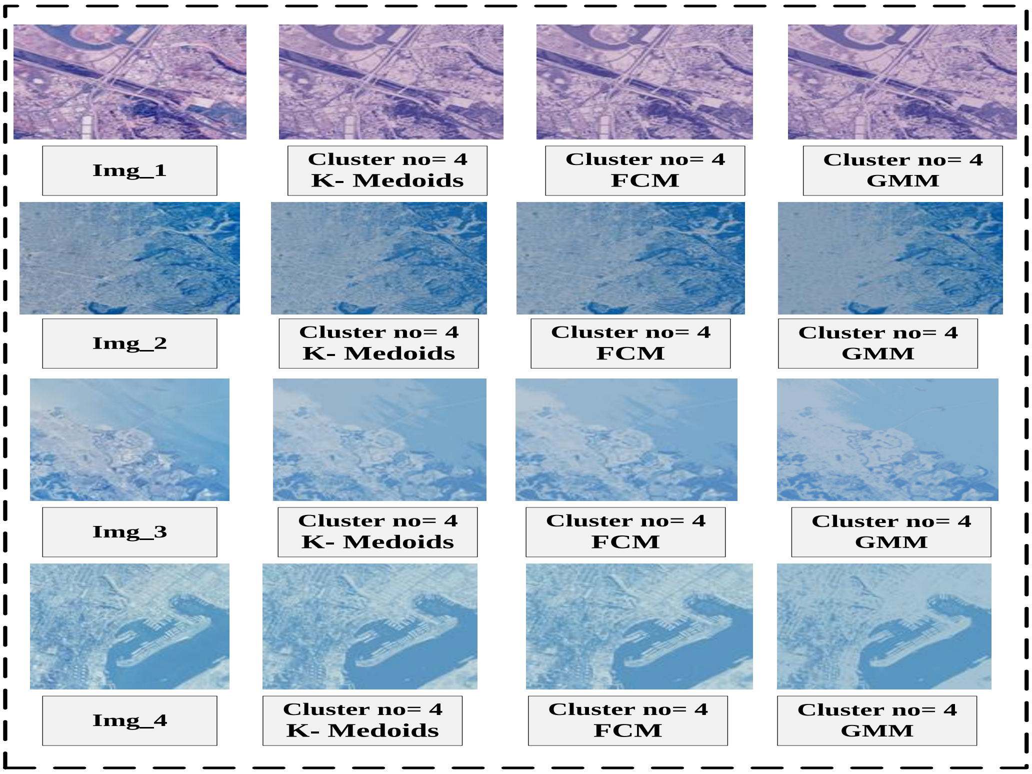

Figure 5: Clustered image using three clustering algorithms when cluster no = 4

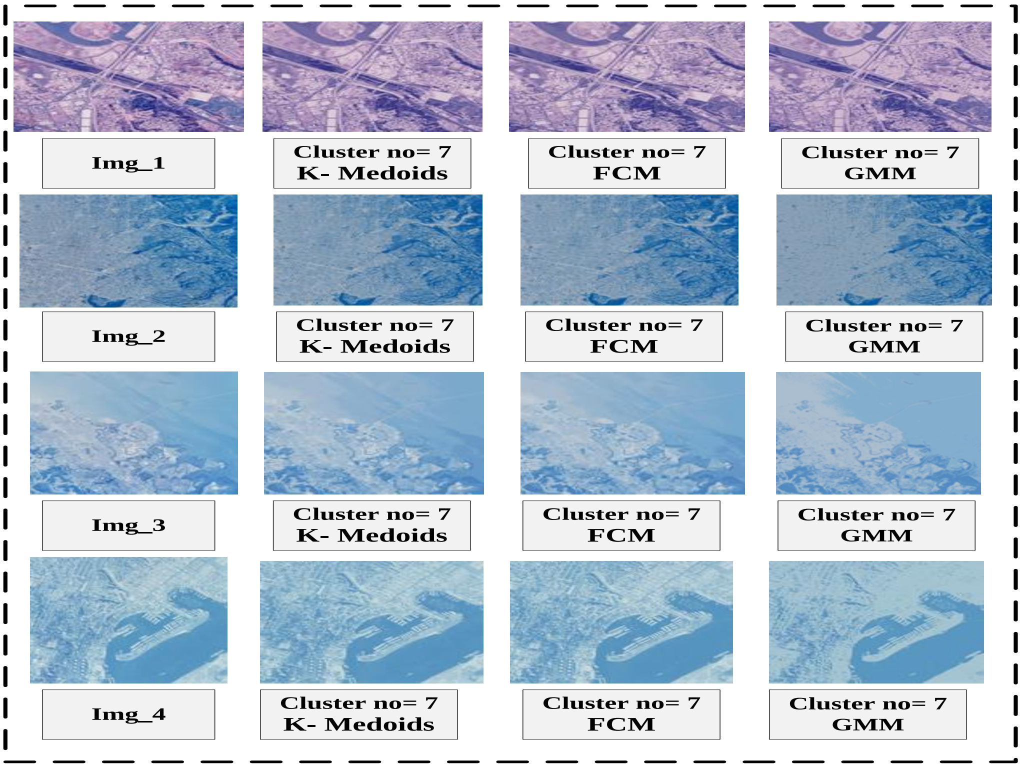

Figure 6: Clustered image using three clustering algorithms when cluster no = 7

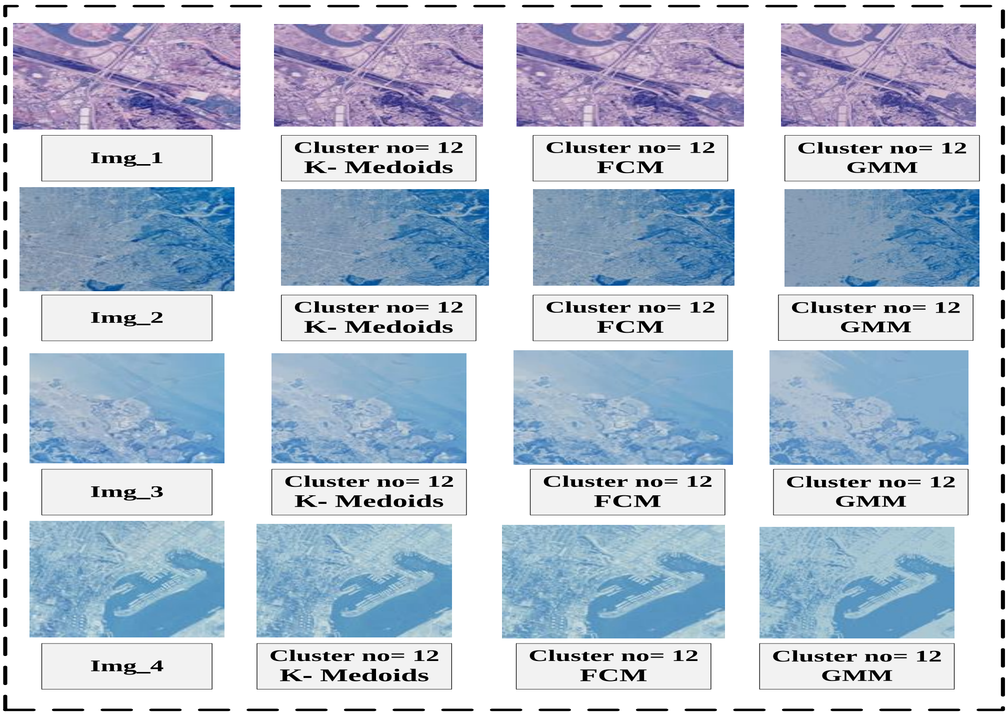

Figure 7: Clustered image using three clustering algorithms when cluster no = 12

Our tests show that when K-Medoids are used, the highest PSNR value is 35.57 and the highest correlation coefficient value is 0.99. When FCM and GMM are used, the highest PSNR value is 35.54 and the highest correlation coefficient value is 31.67. They are also the highest when the number of clusters is 12. Therefore, K-Medoids are the best clustering technique for segmenting images and maintaining image quality compared to the techniques used in this research.

6. Comparison with Related Works

To assess the effectiveness of the suggested approach and demonstrate that it produces superior findings to those of other published studies, the PSNR and correlation values from the proposed research are compared with those from earlier published studies. According to the results shown in Table 4, our method greatly outperforms the other research in terms of PSNR and correlation values.

Table 4: Compared results with previous experiments

Reference	PSNR	Corr.
[7]	25.46	-
[8]	15.95	-
[9]	34.23	-
[10]	29.83	-
proposed approach with k-Medoids	35.57	0.99
proposed approach with FCM	35.54	0.99
proposed approach with GMM	31.67	0.97

7. Conclusion

In conclusion, the segmentation of aerial photographs using various clustering approaches offers a powerful way of extracting relevant information and comprehending the spatial distribution of objects and features within these images. With increased research and development in this field, aerial picture analysis may become more precise and efficient, improving decision-making processes across a variety of disciplines. This paper aims to divide pixels or image patches into discrete clusters that share comparable qualities, such as color, texture, or intensity. Several clustering techniques, such as K-medoids, FCM, and GMM, have been used to segment aerial photos; however, K-medoids are more successful than other algorithms in maintaining image quality.

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