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Proposing an Applied, Simple, and Accurate Framework for the Image Processing Mission of Iran CanSat Competition

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ABSTRACT

CanSat is an educational competition where students design miniature satellite systems integrated into soda-can-sized containers. Iran CanSat is a competition at the student level that is held each year. In the Remote Sensing-Communication class of the competition, an image processing mission is designed. Target detection and area estimation are the main missions of this competition. In this paper, a simple, applied, and accurate framework based on clustering algorithms is proposed to find targets and areas within them. K-means, fuzzy c-means, and genetic algorithm (GA) K-means algorithms are employed in this study. The proposed framework was applied to a simulated image and an image captured by a CanSat. Results show that the clustering algorithms are appropriate for detecting targets in the image. Experimental results demonstrated identical performance between K-means and GA-optimized K-means clustering, with both methods estimating target areas within 8 m² of ground-truth measurements. Notably, fuzzy c-means (FCM) clustering outperformed these approaches, achieving an accurate area estimation of 661.63 m² – closely approximating field measurements. This precision validates the proposed framework's efficacy for CanSat image processing missions, particularly in target detection and area quantification tasks under competition constraints.

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1. INTRODUCTION

CanSat stands for Soda Can-size Satellite. The CanSat competition is held every year by the Khayyam Research Institute, affiliated with the Ministry of Science, Research and Technology (MSRT) of Iran. The CanSat competition is held in two classes: remote sensing communication and scientific exploration. In its 9th International Competition, a target detection mission is defined for Participating teams. In this mission, the software and hardware of the system must detect ground targets from a height of 200 to 300 meters using images captured from CanSat and calculate the area within the targets. This mission is a remote sensing task that should be done using image processing tools and techniques.

In recent years, CanSats have emerged as a low-cost alternative to CubeSats, enabling atmospheric and near-space experiments for education, research, and technology testing [1, 2]. Their compact, cylindrical design allows for rapid deployment, making them ideal for high-risk experiments and hardware validation before orbital missions. Studies highlight their applications in Earth observation, aeronautics, and science, technology, engineering, and mathematics (STEM) education, providing accessible platforms for universities and small research teams. While limited to atmospheric operations, advancements in miniaturized electronics suggest potential future roles in space-bound testing. This review examines CanSat development, current uses, and their evolving impact on aerospace innovation [3].

Basu and Kavuluru presented a novel direct georeferencing method for Earth Observation (EO) using CanSats, eliminating the need for ground control points. By integrating MEMS-based IMU sensors, high-precision global navigation satellite system (GNSS) receivers, and OV2640 imaging systems, a framework for accurate image geolocation through coordinate transformations based on sensor geometry and flight trajectory data was developed. Experimental validation during the CanSat India competition demonstrates the system's capability to produce precisely georeferenced imagery [4].

Hasan et al. present the design and implementation of an advanced CanSat prototype for integrated meteorological monitoring and real-time object detection. The system combines an FPV camera with environmental sensors and utilizes YOLO v3/v4 models for artificial intelligence-based object recognition. Experimental results demonstrate 5-10% operational error in field tests, validating its dual capabilities for both environmental analysis and disaster response applications. The developed platform offers a cost-effective solution for air pollution monitoring and emergency situational awareness through its innovative sensor fusion approach [5].

Remote sensing is a science, technique, and technology of extracting information from images or data obtained from sensors like cameras [6]. For extracting information, different techniques like edge detection [7], clustering [8], segmentation [9], classification [10], target detection [11] and so on, are used.

From the perspective of training samples, image information extraction techniques can be divided into two groups: supervised and unsupervised. In the supervised techniques, training data, including pixels corresponding to targets, is used to estimate unknown parameters of the techniques. In unsupervised techniques, similarity features without training samples are utilized to detect targets [12].

In the clustering-based techniques, researchers used K-means, fuzzy C-means (FCM), ISOdata, meanshift, K-Medoids, Neural Networks-based clustering, Hierarchical Clustering, Graph Theory-Based Clustering, Optimization-based clustering, and so on. The mentioned techniques were used in different applications and can also be used for CanSat missions [13].

In the segmentation-based techniques, some researchers employed thresholding-based [14], edge-based [15], region-based [16], watershed-based [17], artificial intelligence-based, deep learning-based, and so on. In the segmentation-based approaches, a set of pixels in a spatial domain is assigned to a segment [18, 19].

In the classification-based techniques, random forest [20], support vector machine [21], artificial neural network [22], maximum likelihood [23], optimization-based approaches [24], fuzzy logic [25], deep learning-based [26], bagging, boosting, and so on are employed. In the classification-based techniques, targets are considered a class and can be identified from images.

In target detection techniques, the portion of a target in a pixel is estimated, and it is assigned to the target if its portion is higher than a threshold. The following techniques were used in the previous studies on remote sensing and can be employed in analyzing

CanSat images: hypothesis testing-based methods, spectral angle-based methods, signal decomposition-based methods, constrained energy minimization-based methods, kernel-based methods, sparse representation-based methods, and deep learning-based methods [27].

In the previous image processing missions of Iran CanSat, some teams proposed methods to do this task. However, there was no appropriate framework for this mission. In this paper, we proposed an applicable, simple, and accurate framework for the image processing section in future CanSat events.

2. MATERIAL & METHODS

2.1 Data used

In this study, two images, including a simulated one and an image captured by a CanSat, were employed to analyze the proposed framework. Figure 1 shows the two images used in this study. In the simulated image, four targets with different colors are available. In the real image, four targets are available in black. The area within the targets was measured by KOLIDA K5UFO, which is 666.04 m^2.

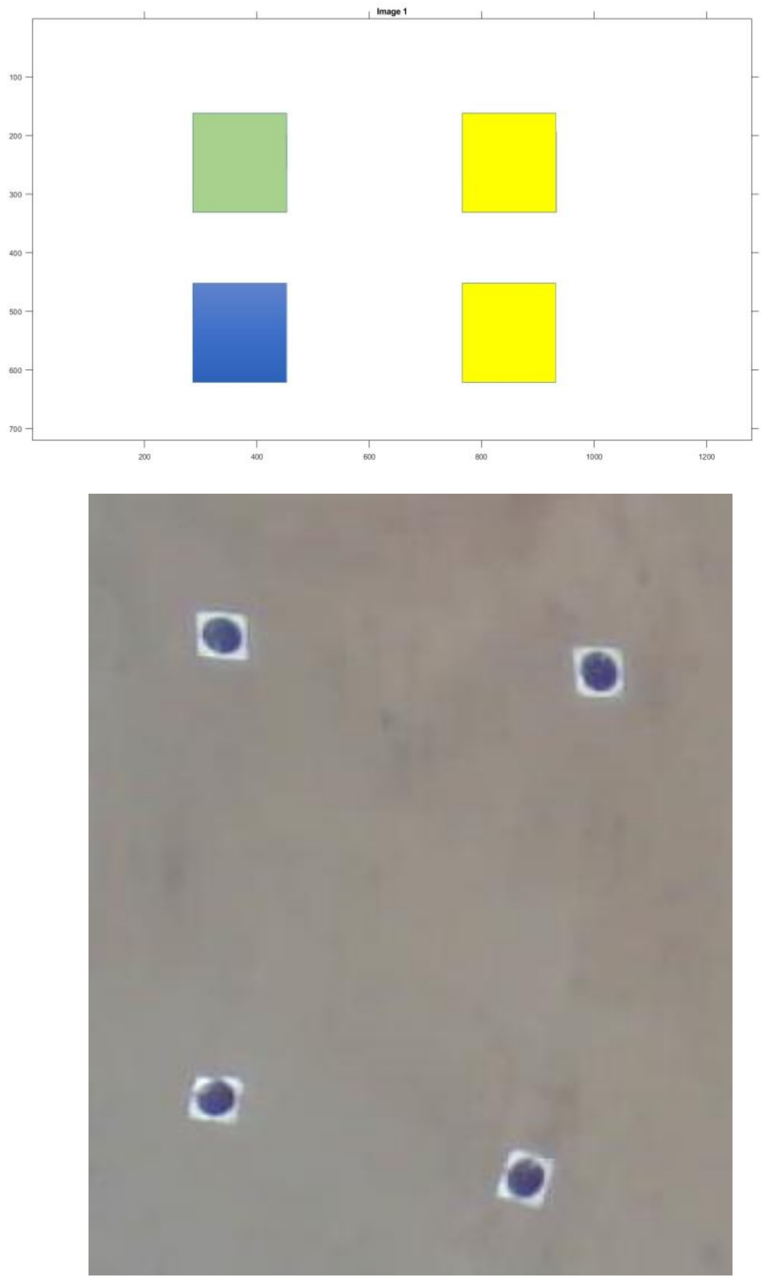


Fig. 1. The simulated image and real image captured by CanSat of the Electron team.

2.2 Methodology

According to Fig. 2, the image processing mission of the competition is to find an area between 4 targets using the image captured by CanSat.

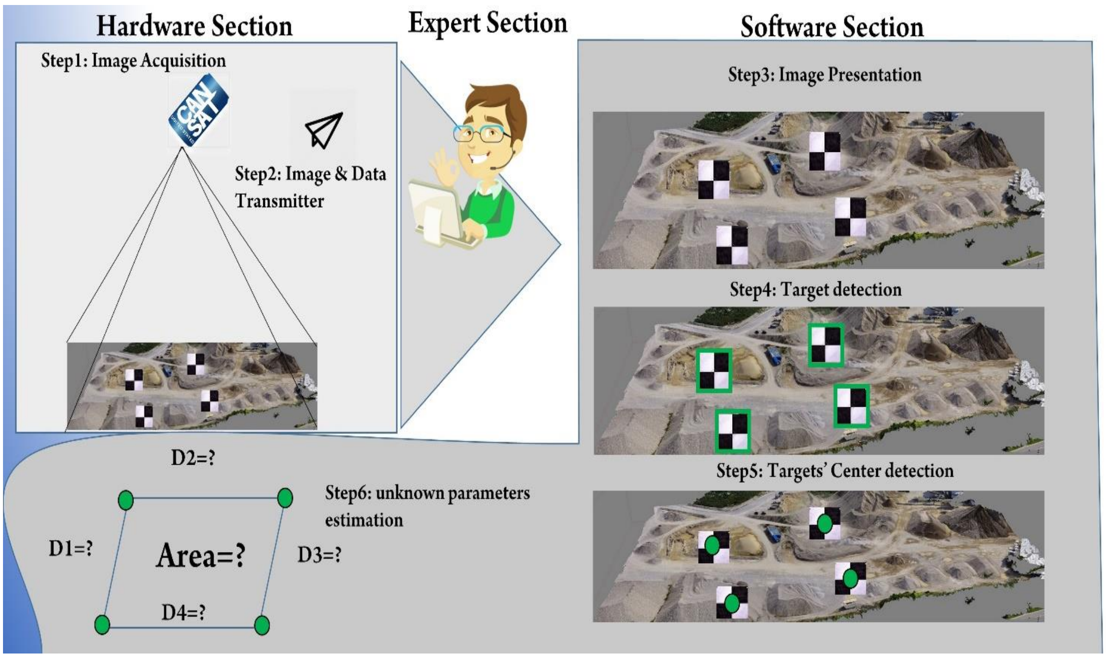


Fig. 2. The image processing mission of CanSat.

The proposed method is presented in Fig. 3. According to the figure, if the study area is in several scenes, it should be cropped. Then, the clustering image is obtained from the K-means clustering. Afterward, objects in the clustering image are identified. Then, the centers of objects are estimated. The area within the centers of objects is calculated. Finally, the calculated area is converted from image space to ground space. In the following, the proposed framework is presented in more detail.

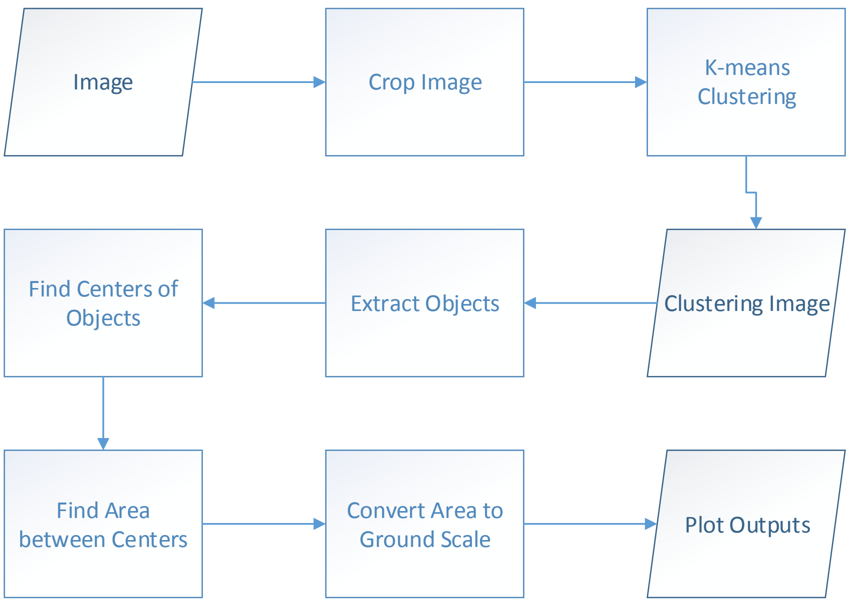


Fig. 3. The proposed workflow to do the image processing mission of CanSat.

The K-means is a useful and popular clustering method that can be used for detecting objects in an image [27]. In K-means clustering, the number of clusters that can be related to the number of targets should be defined by the user. Suppose k clusters are available. The steps of K-means clustering are:

- Step 1: cluster centers, i.e., are randomly selected.
- Step 2: Each pixel is assigned to the nearest center based on, e.g., Euclidean distance.
- Step 3: Calculate new cluster centers using the mean pixels of each cluster.
- Step 4: Run steps 2 and 3 to reach convergence.

Fuzzy C-means (FCM) is another useful clustering method that is used in this study [28]. Including the steps:

- Step 1: Define parameter m and the number of clusters (c)
- Step 2: Define the cluster's centers randomly.
- Step 3: Calculate the membership degree (u) of each pixel to each cluster based on the distance of the pixel to the center (d_{ik}) and fuzziness parameter (m).

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}} \tag{1}$$

- Step 4: Calculate the cluster's centers (v) using the membership degree and pixel value (x).

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}} \tag{2}$$

- Step 5: Perform steps 3 and 4 until convergence
- Step 6: Assign the cluster of each pixel based on its maximum membership degree.

The integration of the genetic algorithm and the K-means clustering method is another way to find targets for this study. The genetic algorithm (GA) is used to find optimum cluster centers [29]. The algorithm is applied according to the following steps:

- Step 1: Specify the number of clusters and GA parameters, including population, elitism rate, mutation rate, number of iterations, and crossover rate.
- Step 2: Define a fitness function in GA based on the distance of pixels and centers, like K-Means clustering.
- Step 3: Specify the cluster's centers randomly and calculate their fitness values.
- Step 4: Perform mutation, crossover, and elitism operators to find new cluster centers.
- Step 5: Calculate the fitness of the new cluster centers.
- Step 6: Run steps 4 and 5 to reach convergence.
- Step 7: Perform a K-means clustering algorithm based on the final centers.

After performing K-means clustering, the pixels of each cluster are detected. It is necessary to extract objects from pixels. In fact, in this step, we extract each object from pixels stuck to each other with a cluster. To this end, the bwlabel function in MATLAB is used. The bwlabel function is used for connected-component labeling in binary images. It identifies and labels disjoint regions (objects) in a binary matrix, assigning a unique integer to each connected group of foreground pixels (typically 1s). By default, it employs an 8-connected neighborhood (or optionally 4-connected) to determine connectivity. The output is a labeled matrix where all pixels belonging to the same object share the same label, enabling quantitative analysis of object properties.

For calculating the centers of each object ($\bar{x}, \bar{y}$) from its pixels, the following equations are used.

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n}$$
$$\bar{y} = \frac{y_1 + y_2 + \cdots + y_n}{n} \tag{3}$$

where, x_i and y_i are a position of pixel i in an object.

After finding the objects' center, Eq. 4 is employed to estimate the area within the centers of the objects (Area).

$$Area = \frac{1}{2}\left|\sum_{i=1}^{n} \bar{x}_i\,\bar{y}_{i+1} - \bar{x}_{i+1}\,\bar{y}_i\right| \tag{4}$$

To convert the area in the image (A_i) to area in the ground (A_g), Eq. 4 is used:

$$A_g = \frac{S_g^t}{S_i^t} * A_i \tag{5}$$

where, S_g^t and S_i^t are areas of a specific target in the ground and image, respectively. Four black-colored targets with regions known in the image were chosen as ground reference targets.

3. RESULTS AND DISCUSSION

All steps of the proposed method were implemented using MATLAB. Figure 4 shows the output of the proposed framework for the simulated image. According to this image, four targets and the background are detected and extracted accurately. Moreover, centers of targets are extracted precisely. The area within the targets is 138910 pixels. Since it is a simulated image, we cannot calculate the area on the ground.

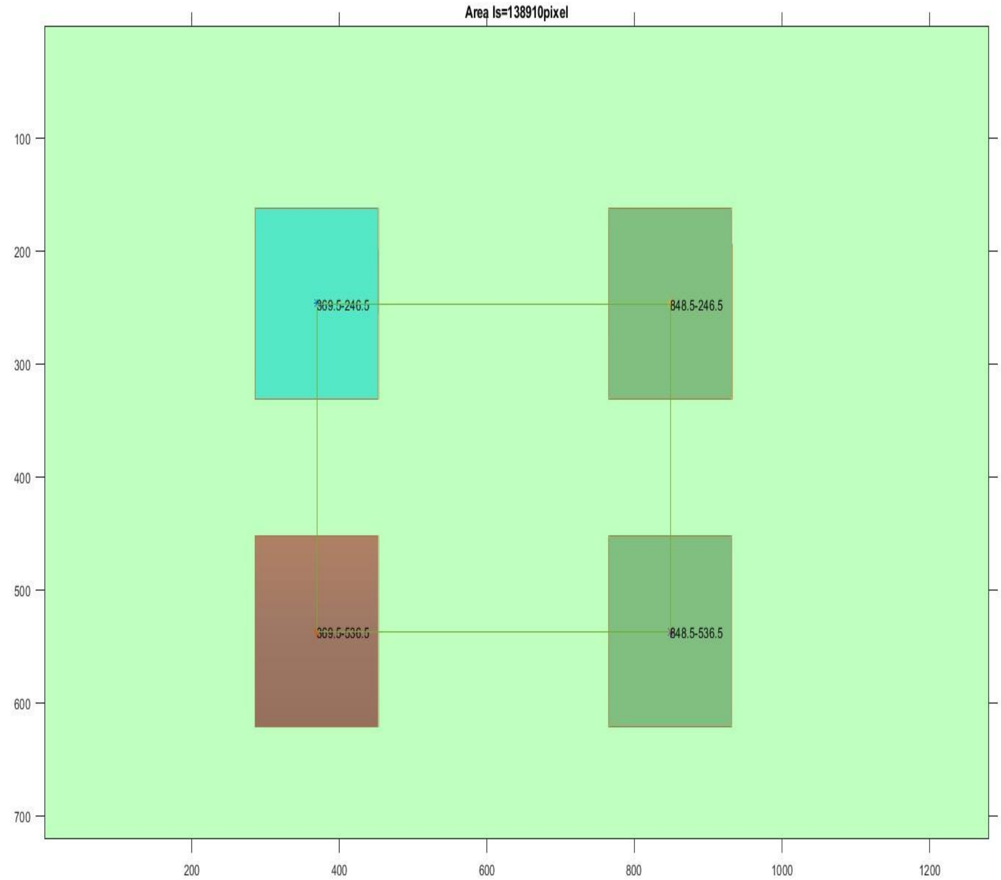


Fig. 4. Output of the proposed framework for the simulated image.

For the implementation of the K-means clustering method, MATLAB's default parameters were employed, with the number of clusters set to 6. This cluster count was determined empirically through trial and error after evaluating the results. The output of K-means clustering is presented in Figure 5. According to this figure, K-means clustering can precisely detect black targets in the image. The area within the targets in the image domain is 34708 pixels. The area estimated from K-means clustering is 673.77 m^2, and its difference with the real value is near 8 m^2. Accordingly, the relative error in area measurement is approximately one percent, which is deemed acceptable according to international standards and the National Cartographic Center's guidelines.

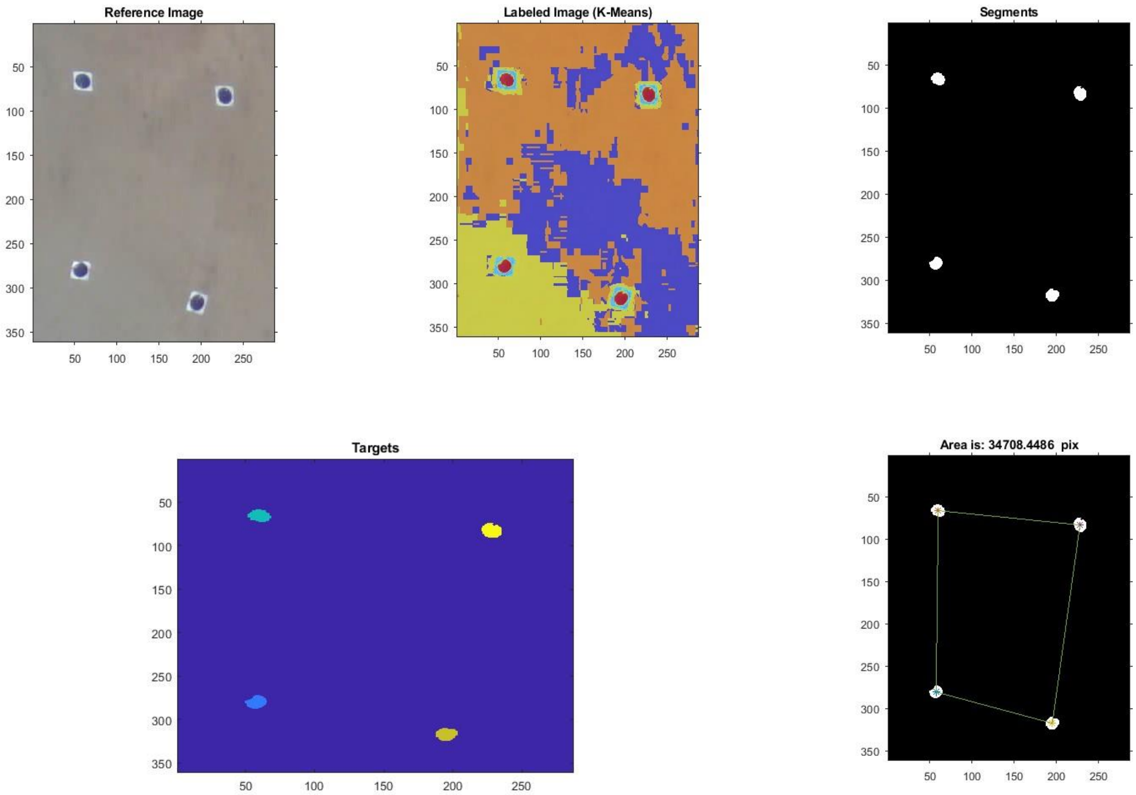
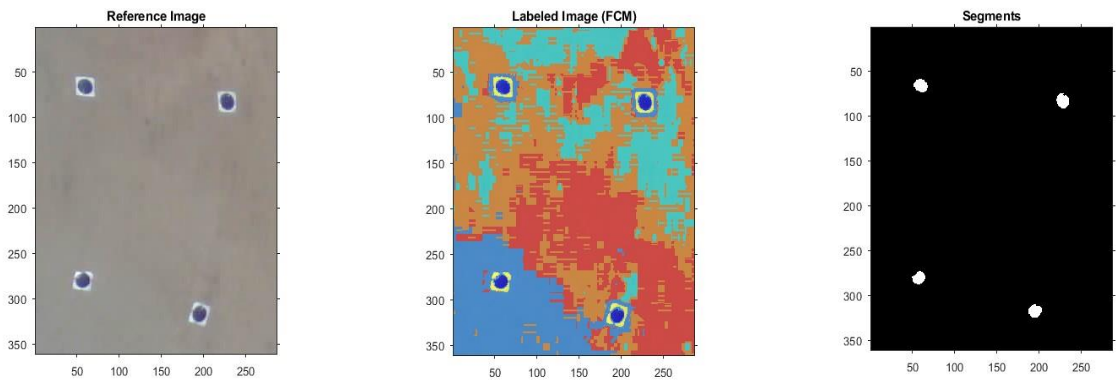


Fig. 5. Output of the proposed framework obtained from K-means clustering.

For the implementation of the FCM clustering method, the following parameters were used: number of clusters = 6, fuzziness exponent m = 1.2, maximum iterations = 100, and minimum improvement in the objective function = 0.001. The output of FCM clustering is presented in Figure 6. The FCM clustering is sensitive to m parameters to obtain highly accurate results. Through iterative grid-partitioning optimization of parameter m, the best clustering performance was achieved at m = 1.2. Like the K-means clustering, it can detect and extract targets from images. The center of the targets is changed in the FCM clustering. The area within the targets is 34796 pixels. The area on the ground scale is 661.63 m^2. Its error in estimating the area is about 5 m^2. The error in the FCM clustering is lower than the K-means one.



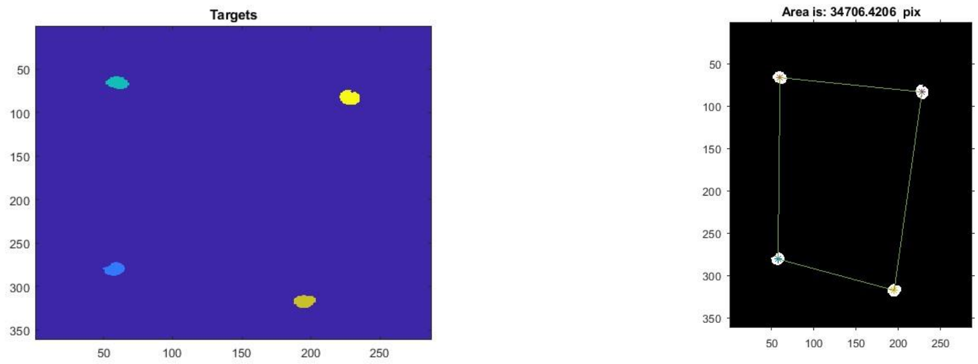


Fig. 6. Output of the proposed framework obtained from FCM clustering.

Like the K-means clustering, the outputs of GA-K-means clustering are acceptable. The outputs are presented in Fig. 7. The centers of targets and the area within them are the same as the results of K-means clustering. It shows that the results are acceptable. The configured parameters for the GA-K-means clustering approach are listed in Table 1. Figure 8 illustrates the convergence behavior of the genetic algorithm during the clustering process. As evident from the figure, the objective function exhibits a decreasing trend, demonstrating the algorithm's successful convergence. Furthermore, complete convergence is achieved around the 100^{th} iteration.

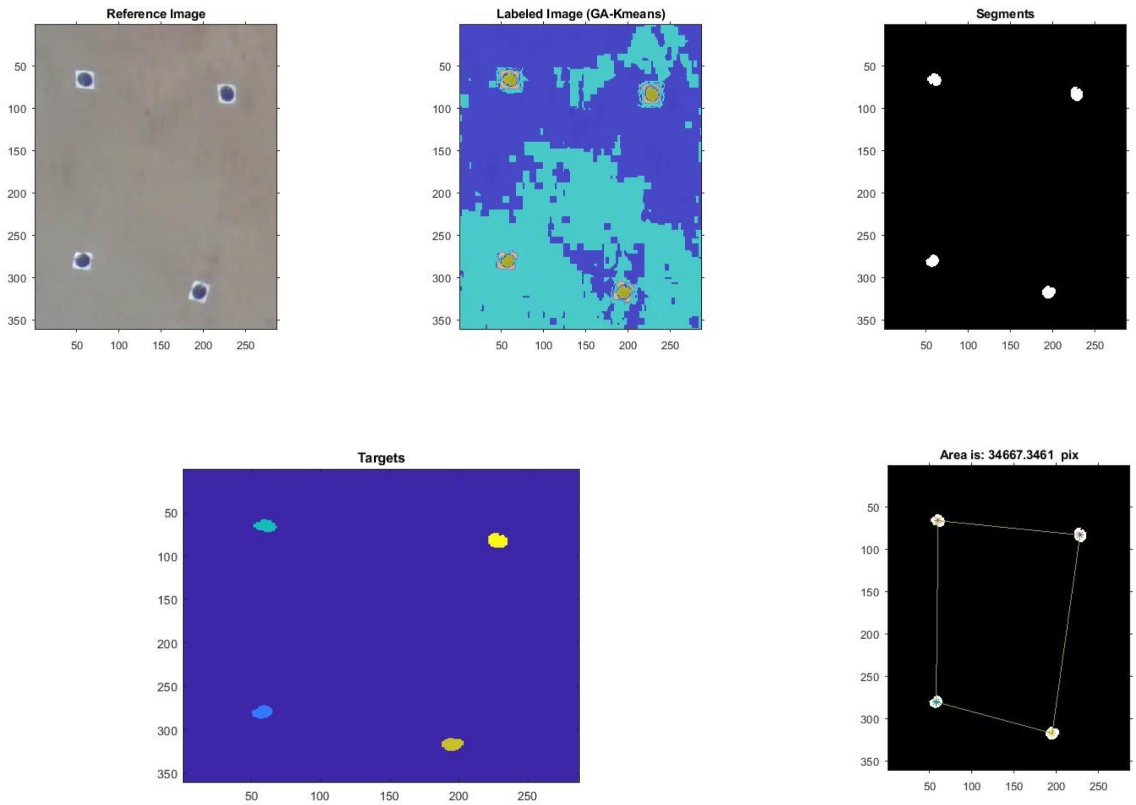


Fig. 7. Output of the proposed framework obtained from GA-K-means clustering.

Table 1. Configured parameters for the GA- K-means clustering approach.

Number of variables	5
Population Size	20
Population Type	Double vector
Crossover Rate	0.7

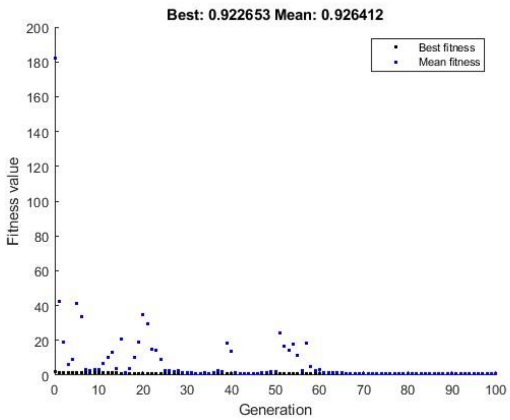


Fig. 8. Convergence diagram of GA for fitness function.

Table 2 presents the execution time of three clustering methods for area detection in images. According to the results, the K-means-based method achieved an execution time of 0.5626 seconds, while the FCM-based method required 1.15 seconds. The GA+K-means hybrid method showed the longest execution time at 2.14 seconds. These results demonstrate that the K-means approach has the lowest computational complexity, whereas the GA+K-means method exhibits significantly higher complexity. This difference can be attributed to the additional processing steps required by the hybrid method compared to standalone techniques. Notably, even the 2-second processing time remains acceptable for this category of image processing tasks and could prove practical for real-world applications.

Table 2. Execution time of three clustering methods.

Method	Run Speed (Second)
K-means	0.5626
Generation	100
EliteCount	2
Selection Function	Roulette wheel
Crossover Function	Crossoverarithmetic
Mutation Function	Mutationadaptfeasible

4. CONCLUSION

In this study, an image processing framework based on clustering algorithms was presented to find areas within the targets. Based on the results, the proposed framework is appropriate to find targets. Moreover, the outcomes of the proposed framework are acceptable for the CanSat image. K-means and GA-K-means clustering presented the same results. The area within the targets is estimated by a difference of about 8 m² of real area. The output of FCM clustering was better than the two mentioned clustering methods. By the FCM clustering, the area is estimated to be about 661.63 m2, which shows the proposed framework is suitable for the image processing mission of the CanSat competition.

While this framework is effective for this image and simulated imagery, its applicability may be limited in complex landscapes. The proposed framework in this study, while demonstrating promising results, faces limitations in handling challenging illumination conditions such as heavy shadows and low image contrast. These constraints arise from the inherent sensitivity of the current algorithm to variations in lighting intensity and distribution. To address these limitations, future research should investigate advanced techniques, including adaptive contrast enhancement, shadow-invariant feature extraction, and hybrid approaches that integrate deep learning with traditional computer vision methods to improve robustness in suboptimal lighting scenarios. Furthermore, the proposed method must be implemented and evaluated on a larger and more diverse set of image data in the future to confirm its reliability and generalizability thoroughly.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest

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