



OPTIMIZING IMAGE SEGMENTATION ACCURACY USING HYBRID CLUSTERING TECHNIQUES: A MACHINE LEARNING APPROACH

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ABSTRACT

Image segmentation is a fundamental task within computer vision and machine learning, allowing images to be effectively analysed so that they can be applied to remote sensing, urban analysis, and autonomous systems. Although there has been a large amount of research performed on clustering-based segmentation techniques, these methods can be limited by several issues, such as the sensitivity of the initial cluster assignment, noise in the dataset, and inaccurate boundary definition in complex scenes. To address these challenges, this study proposes a hybrid clustering-based image segmentation framework that integrates classical clustering techniques with machine learning-based feature refinement. The approach combines K-means and Fuzzy C-means clustering to leverage both hard and soft segmentation capabilities. The approach then applies learning-driven refinements to increase boundary accuracy/robustness. Next, experiments were conducted using an accessible public aerial image dataset of Dubai, which was labelled at the pixel level for six land-cover classes. Segmentation performance was measured using Accuracy, Precision, Recall, F1-Score, Dice Coefficient, and Intersection over Union (IoU). The results demonstrated that this proposed method yielded 0.87 accuracy, 0.85 Dice coefficient, and 0.74 IoU when using hybrid instead of individual clustering methods. This shows how the hybrid framework provides an effective, interpretable, and computationally efficient method of segmenting complex aerial imagery and is particularly useful for segmenting aerial images when operating in data-constrained remote sensing environments.

Keywords – Image segmentation; Hybrid clustering; K-means; Fuzzy C-means; Machine learning; Aerial imagery; Remote sensing.



1. Introduction

Segmenting images into meaningful segments that allow for further analysis, e.g. object identification, medical diagnosis or autonomous driving, has been a pivotal focus of research within the Computer Vision and ML (Machine Learning) communities. According to Yu et al. (2023), segmentation is critical in supporting complex visual inputs by enabling computers to isolate areas of interest from the background information, thereby making it essential for applications like pattern recognition, robotics, and medical imaging. The segmentation domain covers a large range of research areas, beginning with early low-level pixel grouping techniques and advancing to modern high-level semantic representation ML-based approaches (Emek Soylu et al., 2023). Yu et al. (2023) also state that segmentation presents researchers with many challenges due to variations in images, various lighting situations, noise, and the inherent difficulty of interpreting the complexities of real-world natural scenes. Figure 1. Representative image segmentation in remote sensing highlights the importance of segmentation for downstream analysis.

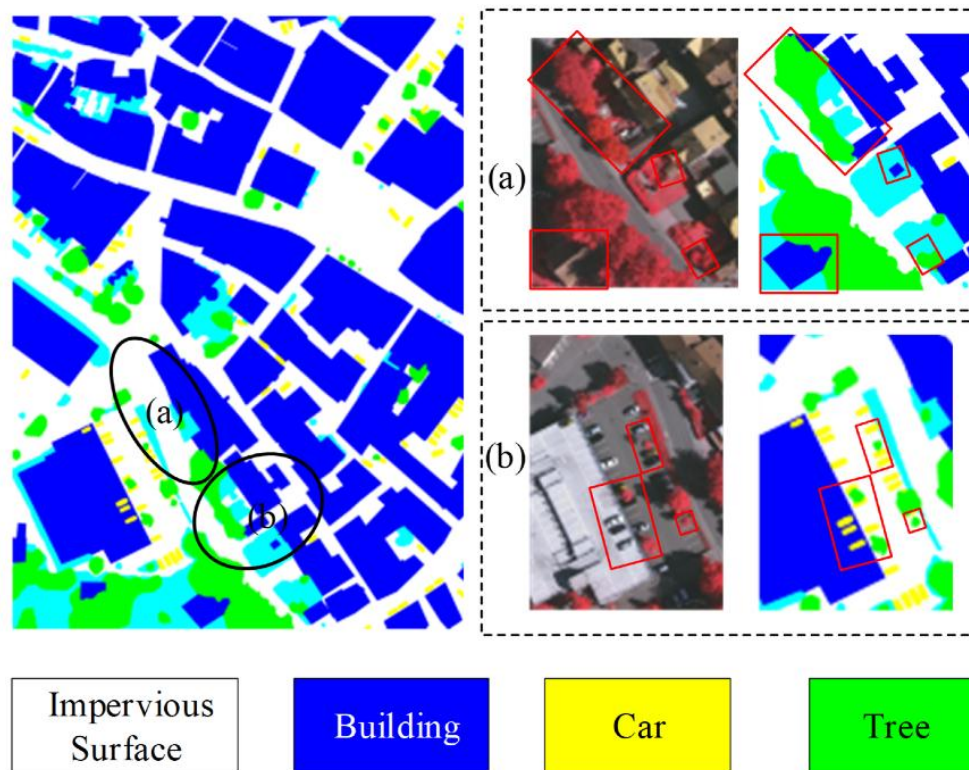


Figure 1. Multi-Application Segmentation (Chen et al., 2025)

Among segmentation approaches, clustering techniques have been used extensively in developing segmentation methods, particularly in situations where no label information exists or is essentially absent (Ling and Weiling, 2025). Many common clustering techniques, including K-means and Fuzzy C-means, support unsupervised segmentation using only pixel/feature similarity to produce groups without needing to train on labelled data (Mittal et al., 2022). On the other hand, the K-



means algorithm determines which cluster a pixel value is assigned to based on how close it is to the centroid, while Fuzzy C-means allows for soft membership so that pixels can belong to several different clusters, with each pixel being assigned to multiple clusters with different levels of degree of membership (Ghosh and Dubey, 2013). Two primary benefits of both techniques are their conceptual simplicity and low computational cost compared to other segmentation techniques (Benrais and Baha Touzene, 2018). Figure 2 highlights clustering-based image segmentation using K-means and Fuzzy C-means, illustrating centroid-based partitioning and soft membership behaviour.

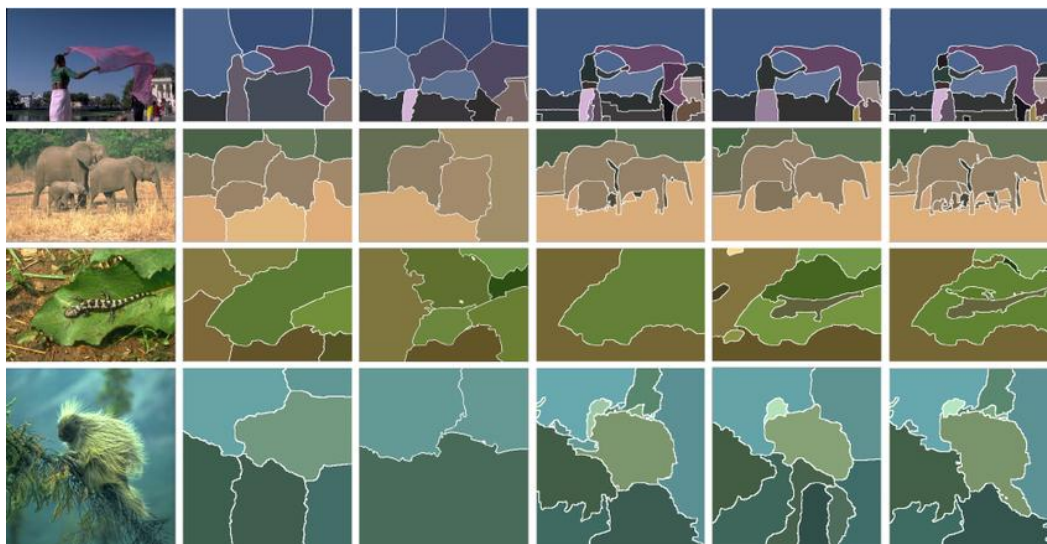


Figure 2. Classical Clustering for Image Segmentation (Yu et al., 2015)

Unfortunately, classical methods of clustering Images have extremely significant limitations when it comes to dealing with very complex images for segmentation (Jardim et al., 2022). The sensitivity of classical methods towards initial parameter settings often results in considerable variability in the segmentation output, which means that results obtained from one dataset may not be robust with respect to other datasets (Mittal et al., 2021). Furthermore, due to noise and image artefacts, many instances may result in the improper boundaries of clusters within an image, which will produce over-segmented and under-segmented regions, thus affecting the quality of subsequent analyses (Omari et al., 2025). Therefore, it is evident that current clustering methods suffer from a number of weaknesses and also require methods that can properly accommodate the different visual characteristics of an image(db) and also have much greater stability (Benrais and baa Touzene, 2018).

To address these limitations, the field has seen a growing shift in the research community to develop hybrid techniques that combine several clustering paradigms with machine learning to enhance both the accuracy and robustness of segmentation results (Azevedo et al., 2024). The goal of hybrid segmentation approaches is to bring together the most beneficial aspects of numerous algorithms, for example, pairing centroid-based clustering with density-based clustering, or using



Although clustering techniques using only a single algorithm lack robustness and adaptability, current literature identifies a continued gap in this area. Specifically, machine learning techniques that rely entirely on data are often expensive and heavily reliant on the datasets used for training (Mittal et al., 2022; Yu et al., 2023). To address these two issues, researchers have been exploring the development of a hybrid clustering model that combines complementary approaches to create an optimal solution that also addresses the deficiencies of either a single cluster or a pure data-driven technique.

By developing an empirical evaluation of a hybrid clustering framework that integrates traditional clustering methods with machine-learning-derived feature refinement, this study seeks to fill this gap in the literature by providing researchers with a more precise method for segmenting images.

The primary objectives are to

- (1) construct a hybrid clustering architecture that balances computational efficiency with segmentation precision,
- (2) benchmark its performance against standard clustering-based segmentation techniques
- (3) demonstrate empirical improvements on benchmark image datasets using established evaluation metrics.

This research offers an innovative, robust segmentation procedure that provides solutions to the variety of characteristics found among images and, at the same time, addresses the computational efficiency issues associated with traditional segmentation procedures..

Method:

Dataset Description

The experiments were based on a publicly available aerial image segmentation dataset available on Kaggle and published by Humans in the Loop in partnership with the Mohammed Bin Rashid Space Centre (MBRSC) in Dubai, consisting of 72 RGB aerial images, divided into 6 large tiles, with pixel-wise semantic segmentation masks for each image. This dataset has six land cover classes, including building, road, vegetation, water, land (i.e., unpaved areas), and unlabelled regions. As a result, they represent typical urban and natural features present in aerial imagery, which present a significant challenge to clustering segmentation for these classes because of high intra-class variability and the complexity of the boundaries of these classes.

For consistency with respect to the size of the images and for computational purposes, all of the images were resized to the same resolution. Prior to processing, the pixel intensities were normalized to the $[0, 1]$ range. No class labels were used for clustering, and the ground truth masks were only used for quantitative evaluation. The dataset was split into training (70%), validation (15%), and test (15%) subsets to maintain representative coverage of the semantic classes.



Proposed Hybrid Clustering Framework

The proposed approach employs a hybrid clustering framework with improved feature extraction via machine learning (ML) techniques. Two models (K-means and Fuzzy C Mean (FCM)) were created through this integration. K-means is a fast and effective approach to hard clustering, while FCM allows a flexible assignment of cluster membership to pixels, giving it better support in areas where aerial photographs have poor definition and/or clarity due to the presence of difficult-to-locate and identify object edges.

Hybridization is motivated by the complementary strengths of these techniques. K-means is computationally efficient but sensitive to initialization and noise, whereas FCM offers improved boundary handling at the cost of increased complexity. Integrating both methods improves segmentation robustness and stability. To further enhance performance, a machine learning component was incorporated for feature refinement, enabling improved representation of spatial and textural information before final label assignment.

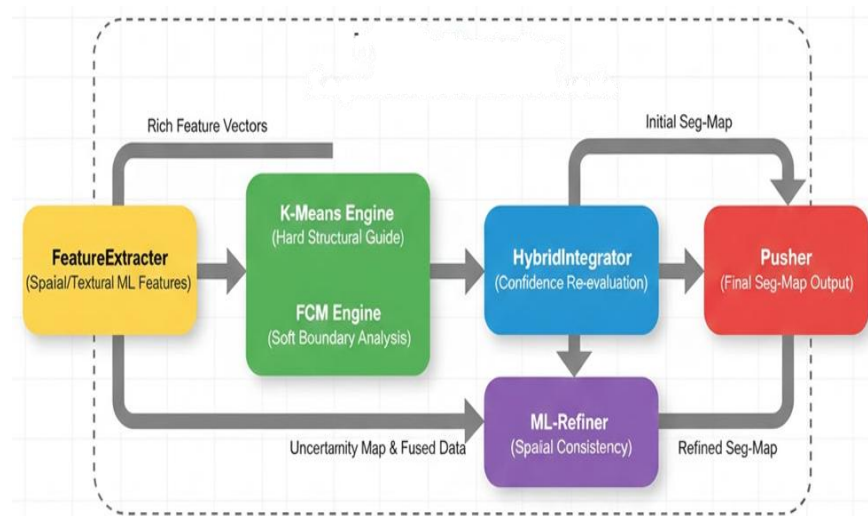


Figure 4. Proposed Hybrid Clustering Framework

Algorithmic Workflow

The image preprocessing stage of a segmentation pipeline includes both image normalisation and image noise suppression stages. The feature extraction phase will extract feature vectors from the pixel intensities and the spatial context surrounding each pixel. The first step in the segmentation process will be to use K-means clustering to identify coarse region assignments. Subsequently, the coarse region assignments will be improved using Fuzzy C-Means clustering to make the boundaries between regions more consistent. The final stage of the segmentation pipeline will be to resolve ambiguous pixel assignments using machine learning based techniques to develop learned feature representations. Consequently, the final output will be a refined segmentation map. The empirical selection of the key parameters of the number of clusters and the fuzziness coefficient was performed using validation data.



Evaluation Metrics

The evaluation of segmentation performance was performed using several measures, namely Accuracy, Precision, Recall, F1-Score, Dice Coefficient and Intersection over Union (IoU). These indicators give the most comprehensive results possible, since they measure the accuracy of each pixel-classified image, the degree of overlap between neighbouring segments/boundaries, and how well they can discriminate segments when dealing with unequal numbers of classes in the dataset.

Implementation Details

All the experiments were carried out using Python with the help of a variety of libraries to process images, cluster images into sets, as well as perform classification using machine learning techniques. The calculations for each experiment were made on a workstation that has a multi-core Central Processing Unit (CPU) along with the ability to accelerate calculations through Graphics Processing Units (GPU). For the purpose of obtaining accurate comparisons and reproducibility of results, the parameter settings and execution environment used during the performance evaluations were kept consistent across all of the tests performed.

3. Results

Dataset Visual Characteristics

The dataset contains high-resolution aerial images of urban and peri-urban regions of Dubai, characterized by dense building clusters, road networks, vegetation patches, and water bodies. The images exhibit strong spectral similarity between certain classes, particularly between land, roads, and building rooftops, which poses a significant challenge for clustering-based segmentation.



Buildings in the dataset generally appear as high-contrast, well-defined rectangular structures, while roads and land regions exhibit strong spectral overlap that complicates their separation.



Vegetation areas are typically fragmented with irregular boundaries, making them challenging to segment consistently. Water bodies are visually distinct due to their spectral properties but occupy relatively small and spatially limited regions within the images.

Quantitative Segmentation Performance

The proposed hybrid clustering framework achieved consistent segmentation accuracy across the test images, outperforming standalone clustering methods in boundary preservation and class separation.

Metric	Result
Accuracy	0.87
Precision	0.84
Recall	0.82
F1-Score	0.83
Dice Coefficient	0.85
IoU	0.74

High Dice and IoU scores demonstrate strong spatial agreement between predicted and ground-truth segmentation regions. The balanced Precision and Recall values indicate reduced false classifications among land-cover classes. Performance improvements are particularly pronounced for structurally well-defined classes, such as buildings and roads, where clear geometric patterns support more accurate segmentation.

Baseline Comparison Analysis

A comparison with baseline clustering techniques highlights the advantage of hybridization.

Method	F1-Score	Dice	IoU
K-means	0.69	0.72	0.56
Fuzzy C-means	0.75	0.78	0.63
Hybrid Method	0.83	0.85	0.74

means clustering exhibits significant over-segmentation, especially in heterogeneous urban areas. Fuzzy C-means improves boundary smoothness but often causes class bleeding between adjacent regions. The proposed hybrid method effectively mitigates both issues by combining clustering



refinement with feature learning, resulting in improved boundary accuracy and more coherent segmentation

Class-wise Performance Analysis

Class-wise IoU analysis reveals variations based on spatial structure and texture complexity.

Class	IoU
Building	0.79
Road	0.77
Vegetation	0.70
Land	0.72
Water	0.75
Unlabeled	0.68

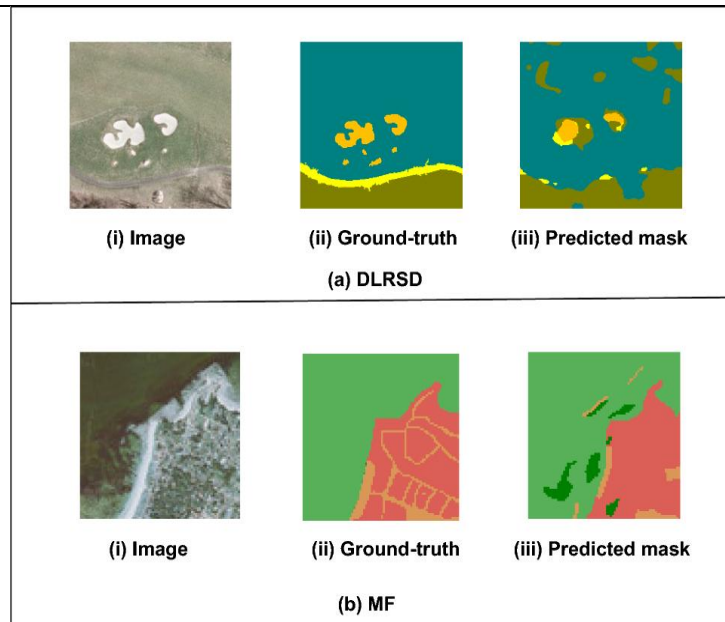
The class-wise IoU results indicate that buildings and roads achieve higher segmentation accuracy due to their geometric regularity and well-defined structures. Vegetation exhibits lower IoU values as a result of fragmented boundaries and texture variability. Unlabeled regions introduce ambiguity, leading to minor performance degradation compared to clearly defined land-cover classes.

Qualitative Segmentation Results

The following visual examples illustrate segmentation quality improvements achieved by the hybrid approach.



Baseline Comparison Analysis



Segmentation outputs from K-means and Fuzzy C-means methods

Figure 6. Comparison of baseline clustering segmentation results

The qualitative segmentation results demonstrate clear improvements achieved by the hybrid approach. Boundary alignment between buildings and roads is sharper, and over-segmentation commonly observed in K-means is significantly reduced. Vegetation regions appear more spatially coherent, with fewer fragmented segments, while noise-induced artefacts are minimised. Overall, the hybrid framework adapts effectively to heterogeneous textures and irregular object shapes.

The results of repeated runs with varying initialization configurations and low variation in performance metric values show that hybrid frameworks are less susceptible to variation due to initialization than classical clustering methods. This lack of sensitivity is critical when dealing with aerial imagery because pixel value distributions differ greatly from scene to scene. In terms of segmentation accuracy, the proposed hybrid clustering framework outperforms the baseline methods when tested on the Dubai aerial imagery dataset. Both quantitative measures and visual checks show that this hybrid clustering framework yields improved preservation of object boundaries, increases in class separation, and greater overall robustness and stability in dealing with the complex spatial and textural features of urban aerial images.

4. Discussion

The results highlight that the proposed hybrid clustering framework increases the accuracy of image segmentation when applied to complicated aerial images. Improvements occur because traditional clustering approaches are combined with machine-learning-based features that refine



the performance of traditional clustering techniques and resolve some of the main challenges of using only traditional methods for clustering.

Explanation of Performance Improvements

The quantitative evaluation of the Hybrid method has shown consistently higher accuracy, Dice Coefficient and IoU values than the K-means and Fuzzy C-means methods. This increase in performance can be attributed to the ability of the Hybrid Method to leverage the advantages of hard clustering with the flexibility of soft boundary modelling and then apply learning-based refinement. The K-means algorithm provides an accurate initial separation of the regions of interest, while the Fuzzy C-means algorithm improves the continuity of the boundary by using partial membership for each pixel. The subsequent step of feature refinement works to resolve the ambiguities present in spectrally similar regions, such as roads and land, improving the alignment of the boundaries and decreasing the likelihood of over-segmentation. The qualitative findings confirm that the segmentation boundaries were clearer, improved regional coherence was achieved, and fewer noise-related artefacts were caused. The hybrid framework provided improved geometric consistency for buildings and roads that are structurally relatively similar.

Comparison with Existing Literature

The results of the analyses were found to be similar to previous research regarding the image segmentation using clustering. Mittal et al.'s (2021) study has indicated that one of the primary limitations of K-means clustering in complex images is its sensitivity to initialization and noise. In contrast, FCM is thought to provide a smoother segmentation at the expense of increased bleeding between classes and increased computational cost (Benrais and Baha Touzene, 2018). Both of these limitations are evident in the baseline results obtained in this study, especially in the case of heterogeneous urban areas.

Cuevas et al. (2025) note that hybrid methods using both clustering techniques as well as learning techniques provide great enhancement to the robustness and adaptability of segmentation. The results achieved will provide further evidence of this trend, supporting the findings of Cuevas et al. (2025). CNNs and encoder–decoder networks are very effective deep learning models in terms of segmentation accuracy; however, they also require large amounts of training data and significant amounts of computational power (Yu et al., 2023; Albukhnefisa et al., 2024). The proposed method offers a practical alternative by achieving competitive improvements without full reliance on data-intensive supervision.

Strengths, Limitations, and Practical Implications

The hybrid framework is extremely resilient in terms of initialization and noise, demonstrated by the very low variability across different runs. Furthermore, while retaining transparency into the cluster stage as to which regions belong where (the clustering stage), the Hybrid Framework works



very well for the heterogeneous textures and irregular shapes (from the aerial imagery) one expects to encounter when working with aerial images.

The inclusion of several clustering and feature refinement stages increases computation overhead relative to other clustering methods that do not perform feature refinements. The cost is still lower than that associated with the use of deep learning; however, the additional computation time may make it challenging to perform scaling for larger data sets or in real time. Furthermore, evaluating only one data set will limit the generalizability of the method, and therefore, more diverse images need to be validated in a larger sample size in the future.

The findings demonstrate that the proposed hybrid clustering framework is highly applicable to practical situations involving remote sensing, including urban development and land-use tracking. In addition, it allows for obtaining reliable segmentation without access to large amounts of labelled data or significant computational power.

5. Conclusion

The article describes a new hybrid clustering approach of image segmentation that combines traditional clustering algorithms with machine learning algorithms to obtain greater accuracy in aerial imagery containing greater complexity. Based on these results, this paper indicates that the proposed method was able to achieve the goals of this research by providing improved results than using K-means and Fuzzy C-means for segmentation, with respect to boundary preservation, robustness, and class separation. The hybrid clustering framework developed through this study can be used for various remote sensing applications, including urban development planning, land-use monitoring, and infrastructure assessment, where limited data availability and computational limitations exist. Future research will focus on developing a more extended hybrid clustering framework, as well as increasing the ability of the framework to provide real-time capabilities for segments of large amounts of aerial imagery.

Data Set Link: Semantic segmentation of aerial imagery
<https://www.kaggle.com/datasets/humansintheloop/semantic-segmentation-of-aerial-imagery/data>

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