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Unsupervised Image Segmentation

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Abstract: Image segmentation involves partitioning of an image into distinct regions based on criteria such as color, texture, or shape, facilitating the focused analysis of relevant objects. Among the various approaches to image segmentation, clustering algorithms, particularly K-means, have gained prominence because of their efficacy in grouping similar pixels. However, these algorithms face challenges such as predetermining the number of regions and sensitivity to initial cluster centers. These issues often result in inconsistent segmentation. This paper proposes a novel color-based segmentation approach that utilizes density function mode detection to predict suitable cluster centroids, aiming to enhance the consistency and accuracy of segmentation results. As demonstrated by various tests, the proposed method has the potential to improve the analysis in numerous domains, including object detection, facial recognition, medical imaging and remote sensing.

Keywords: Image segmentation, Clustering, K-means, Kernel density estimation (KDE), Modes

Introduction

Image segmentation is a basic technique in computer vision and image processing that involves partitioning a digital image into several segments or regions, each representing a different object or part of the image (Lei & Nandi, 2023). This process aims to simplify the representation of an image, making it easier to analyze and understand its content. In essence, image segmentation groups together pixels with similar characteristics, such as color, texture, or intensity, making it possible to identify and isolate specific objects or areas of interest in the image.

Image segmentation is the basis for many applications that we encounter on a regular basis. In healthcare, for example, it facilitates medical imaging to diagnose diseases, detect tumors, or plan surgical interventions. In autonomous vehicles, image segmentation helps to recognize pedestrians, road signs, and other vehicles, contributing to safer navigation. In smartphone cameras, it enables portrait mode by separating the subject from the background. Security systems use it for facial recognition and object detection. Even in social media, image segmentation enables functions such as augmented reality filters and automatic tagging. These different applications show the versatility of image segmentation techniques, they are classified, by Siddiqui et al. (2022), into four general categories: thresholding, clustering, edge-based segmentation technique, and region-based segmentation as shown in Figure 1.

Each of these techniques has its own strengths that make them particularly suitable for certain contexts and different performance criteria. Among these different approaches, cluster-based methods stand out due to their popularity and versatility. One of the most widely used clustering techniques in image segmentation is the K-means algorithm (MacQueen, 1967) that consists in partitioning the image pixels into a set of clusters, where each pixel is assigned to the cluster with the closest center according to the algorithm 1.

- Selection and peer-review under responsibility of the Organizing Committee of the Conference

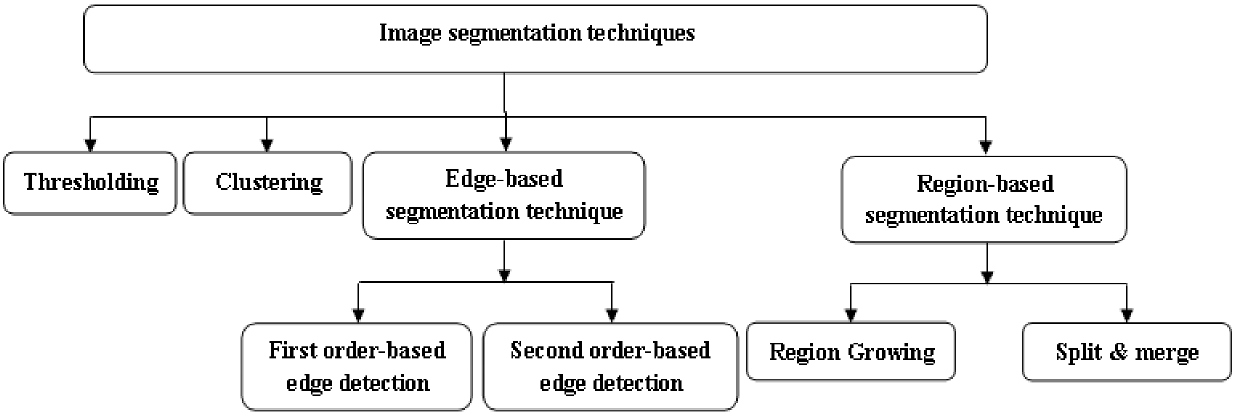


Figure 1. General classifications of the image segmentation technique(Siddiqui, 2022).

Algorithm 1. K-means Algorithm for Image Segmentation

Require:

- I : Image,
- K : number of clusters,
- *maxIter* :maximum iterations.

Ensure:

- Segmented image with K clusters

Initialize K cluster centers $\{c_1, c_2, ..., c_K\}$ randomly
$iter \leftarrow 0$
while not converged and $iter < maxIter$ **do for** each pixel p in I **do**
Assign p to nearest cluster center based on color or intensity
for $k \leftarrow 1$ to K **do**
Recalculate c_k as the mean of all pixels, p_i, in cluster k using
$iter \leftarrow iter + 1$

K-means algorithm is particularly effective for its simplicity and computational efficiency. These attributes, coupled with its ease of implementation, make it a preferred choice in many image segmentation applications, especially when combined with other prepossessing or post-processing techniques. However, the K-means algorithm also has limitations. It requires the number of clusters (K) to be specified in advance, which may not always be known. It is also sensitive to initial cluster center placement and may converge to local optima. Several variants of the K-means-based clustering algorithm have been tested to improve its performance and avoid these limitations, including integration with other techniques, improved initialization and convergence, and parallel and GPU-accelerated implementations. In this context, we propose a novel color-based segmentation approach that uses density function mode detection to predict the suitable initial cluster centroids for the K-means algorithm. After a review of related work in section 2, we introduce our novel color-based segmentation approach in section 3. We then analyze the results and discuss the implications of our findings in section 4. Finally, we conclude our study in section 5 by summarizing our findings and presenting our conclusive remarks.

Related Work

The effectiveness of the K-means algorithm in image segmentation has undergone significant enhancements through various innovations. Karbhari et al. (2018) proposed a GPU-accelerated parallel implementation of the K-means clustering algorithm for image segmentation, leveraging CUDA C on NVIDIA GPUs. This approach optimized performance by employing shared memory for efficient image data storage and constant memory for cluster data, reducing memory access latency and improving computational efficiency. This resulted in significant speedups in processing, with performance improvements ranging from $9x$ to $57x$ compared to the sequential version. Additionally, the approach scaled effectively as the number of clusters increased, further enhancing computational efficiency. Mashor(2000) introduced the moving k-means clustering algorithm, an innovative variant of the traditional k-means method that addresses several of its inherent limitations, including sensitivity to initial conditions and susceptibility to local optima.

While maintaining the core iterative process of assigning data points to the nearest centroid and updating centroids accordingly, the moving k-means algorithm introduces a key enhancement through its ”fitness” metric. This metric ensures that centroids are updated only if a cluster contains the minimum required number of data points, effectively reducing the algorithm’s vulnerability to poor initialization and local optima. As a result, the moving k-means algorithm becomes more robust to outliers and better at capturing complex data structures. These advantages make it particularly effective for segmenting microarray images, where spot sizes and intensities may vary against complex backgrounds, ensuring more accurate and reliable segmentation in challenging scenarios. The Optimized K-Means (OKM) algorithm (Siddiqui, 2012) introduced several important innovations to improve image segmentation. Unlike K-means, which assigns a pixel to the cluster with the highest variance when it is equidistant from multiple clusters, OKM assigns a pixel to a cluster with fewer members or a lower fitness value to improve cluster coherence. OKM also fixes the ”dead center” problem encountered in previous algorithms, such as moving K-means, which cannot distinguish between empty clusters and those with zero variance within clusters. By implementing these improvements, OKM avoids trapping cluster centers at local minima, a common pitfall of K-means, and thus improves the overall quality of clustering. Experimental evaluations show that OKM produces more homogeneous and accurate image segmentation, and thus represents a significant advance in K-means-based algorithms for image processing tasks.

Purohit et al. (2013) introduced another variant of K-means to enhance the initial centroid selection and the overall algorithm performance. This modified algorithm employs a systematic approach to select the initial centroids based on the Euclidean distance between the data points. By starting with the closest pairs and gradually forming sets, the algorithm improves the runtime efficiency and reduces the mean square error, demonstrating a particular efficacy with dense datasets. Additionally, Shunye (2013) proposed a novel clustering algorithm combining hierarchical clustering with k-means, leveraging a Huffman tree for initial centroid selection and the Manhattan distance for dissimilarity measurement. This method aims to improve cluster quality and stability compared with standard k-means, potentially avoiding local optima issues. Jose et al.(2014) introduced a tumor detection algorithm for MRI images that integrates k-means and fuzzy c-means clustering with machine learning classification. This hybrid approach enhances accuracy by segmenting distinct regions based on clustering, extracting features, and classifying tumor areas using classifiers, such as support vector machines or neural networks.

Adhikari et al.(2015) proposed an algorithm that combines K-means and subtractive clustering to enhance the image segmentation accuracy and efficiency. Their method integrated partial contrast stretching, initial K-means clustering, and iterative refinement using subtractive clustering, followed by thresholding for the final segmentation. Zheng et al.(2018) introduced an adaptive K-means image segmentation method based on LAB color space, enhancing segmentation robustness by adapting K-means clustering to color and texture features. Shah et al.(2021) introduce a method that integrates the Bar et al.(2011) model into the k-Means (KM) algorithm for image segmentation, addressing the limitations of standard k-Means, which often results in fragmented segments due to its focus solely on color quantization without considering pixel connectivity. The proposed Mumford–Shah k-Means (MS-KM) modifies the standard KM algorithm by incorporating a shape constraint derived from the Mumford–Shah model, optimizing both pixel similarity and segment shape using a modified distance measure. The method begins by selecting random cluster centroids and calculating image gradients. Each pixel is then assigned to a cluster based on a modified distance metric that accounts for both color similarity and boundary length, determined from the image gradient. Afterward, cluster centroids are recalculated by averaging the pixels in each segment. This process repeats until convergence, ensuring the optimization of both content similarity and segment shape. The approach effectively reduces fragmentation and produces smoother segment boundaries compared to standard k-Means while maintaining computational efficiency.

Wisaeng et al.(2022) proposed a breast cancer detection method combining K-means++ clustering with cuckoo search optimization, demonstrating superior accuracy in segmenting mammogram images into tumor and non-tumor regions. This approach enhances detection accuracy while reducing noise and improving the clarity of segmented regions. It starts with preprocessing techniques, including color normalization and noise reduction, to enhance image quality. Then, K-Means++ initializes cluster centroids for image segmentation, and CSO further optimizes these centroids by mimicking the behavior of cuckoo birds laying eggs in host nests. The segmentation process is refined using mathematical morphology and OTSU’s thresholding to highlight cancerous regions more effectively. Kalaipriya et al. (2023) presented a segmentation and classification approach for human lung cancer detection, incorporating optimization strategies. This method begins with the preprocessing of medical images, followed by a hybrid segmentation technique that combines an enhanced k-means clustering algorithm with random forest. For classification, an artificial neural network (ANN) is employed, improved through particle swarm optimization (PSO) to optimize parameters and refine feature selection.

The proposed method in Braik et al.(2023), involves optimizing the k-means clustering algorithm using the white shark optimizer (WSO) to address the weakness of k-Means algorithm, which is its susceptibility to random initialization of the initial center. The k-Means serves as the starting point for the WSO, which then optimizes the final position. The WSO-based k-Means approach was evaluated on publicly available MRI brain tumor datasets and compared with the standard k-Means algorithm, fuzzy c-means (FCM), and other meta-heuristics. The results showed that the WSO-based k-Means outperformed the other algorithms in clustering performance. Kaur(2023) proposed an innovative hybrid image segmentation technique that integrates K-means clustering with two bio-inspired optimization methods: Particle Swarm Optimization (PSO) and the Firefly Algorithm (FA). The approach processes plant images using three comparative methods: basic K-means, K-means with PSO, and K-means with the Firefly algorithm, with the latter proving to be the most effective.

The Firefly algorithm, inspired by the flashing behavior of fireflies and their attraction mechanisms, addresses K-means' tendency to get stuck in local optima by optimizing centroid positions and discovering global solutions through improved exploration. This hybrid method achieves up to 97% segmentation accuracy and superior correlation coefficients compared to traditional methods, making it highly valuable for applications in plant disease detection, medical imaging, and content-based image retrieval. Its success lies in combining the clustering efficiency of K-means with the global optimization strengths of the Firefly algorithm, leading to more reliable and precise image segmentation in various fields. Sabha et al.(2024) focused on determining the optimal value of K for K-means clustering in color segmentation. It utilizes the Gray Level Co-occurrence Matrix (GLCM) to retrieve correlated features and calculate the aggregate probability of their occurrence based on pixel pairings. The number K is identified as spikes in this correlation. The results show that this approach achieves high efficiency, with an accuracy of 98%. Khan et al. (2024) proposed a nonparametric K-means clustering approach (EAIS) designed to enhance image segmentation by automatically determining the number of clusters and their initialization.

Unlike traditional clustering methods, which struggle with predefined segment numbers, EAIS adapts by utilizing five modules: deep image reconstruction for smoothing and reducing color channel variance, intra-histogram peak level detection for understanding pixel distributions, inter-histogram peak level association for linking similar clusters, mutual consensus-oriented cluster seeds merging to reduce redundancy and determine the optimal number of clusters, and morphological reconstruction-driven spatial post-processing to enhance spatial consistency within segments. The method employs image histograms to determine optimal initialization conditions and dynamically merges cluster seeds. Experimental results on the BSDS500 benchmark show that EAIS performs comparably or better than state-of-the-art methods, offering both high segmentation quality and computational efficiency.

The k-means clustering algorithm remains one of the most widely used algorithms in the literature, and many authors have compared their new proposals to k-means during validation processes. In this section, we focus exclusively on work related to image segmentation. Ahmed et al.(2020) presented a structured and comprehensive review of the k-means algorithm, discussing its limitations and the latest advances aimed at improving its capabilities and applicability within the research community. In this paper, we present a novel approach based on density function mode detection to optimize and accurately determine the initial centroids for the k-means algorithm. By overcoming the challenges associated with the selection of the initial centroids, our method aims to improve the efficiency and accuracy of the k-means clustering algorithm. This improvement leads to the identification of optimal starting points, resulting in more precise and reliable segmentation results.

Method

Our proposed image segmentation method improves the standard K-means clustering approach by integrating density function mode detection to optimize the selection of initial centroids. The procedure is outlined as follows:

1. First, the image is loaded and converted into a numerical array, where the pixel values are separated into red, green, and blue (RGB) channels. For each channel, we estimate the pixel intensity

distribution using kernel density estimation (KDE), which is given by the equation 1:

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K(\frac{x - x_0}{n}) \quad (1)$$

where n is the number of data points (pixels), d is the dimensionality (3 for the RGB color space), h is the bandwidth parameter, x_i represents the data points, and K is the kernel function. Common kernel choices include the Gaussian kernel, Epanechnikov kernel, and others. In our method, we use the Gaussian kernel, defined by equation 2 due to its smoothness properties and its ability to model data distributions effectively.

$$K(x) = \frac{1}{(2\pi)^{\frac{d}{2}}} e^{-\frac{1}{2}\|x\|^2} \quad (2)$$

Ultimately, the choice of kernel should balance smoothness and computational efficiency based on the application. Another important parameter is the bandwidth(h), which controls the width of the kernel and thus the smoothness of the estimated density function. A small bandwidth leads to a more sensitive estimation, capturing finer details but potentially overfitting the data, while a large bandwidth results in a smoother estimate that may overlook subtle variations in the data. In practice, bandwidth selection is often done via cross-validation or heuristics such as Silverman's rule of thumb, which provides an optimal bandwidth for Gaussian kernels under certain assumptions. Our method uses Silverman's rule of thumb to determine the bandwidth, balancing sensitivity and generalization to avoid overfitting or underfitting the data.

The density function obtained from KDE helps us understand the distribution of colors in the image. This step is critical for identifying areas with higher data concentration, which correspond to regions with higher pixel intensity or feature density. The kernel function smooths the data distribution, providing a continuous estimate of the underlying structure. Proper selection of both the kernel function and bandwidth is essential for accurate density estimation, which in turn allows for more reliable detection of dense areas vital for selecting suitable initial centroids in the K-means algorithm.

After estimating the density function for each color channel, we identify the prominent peaks (modes) representing significant pixel intensity levels. These 1D modes from each channel are then combined into 3D modes, forming a set of RGB color combinations representing the dominant colors in the image

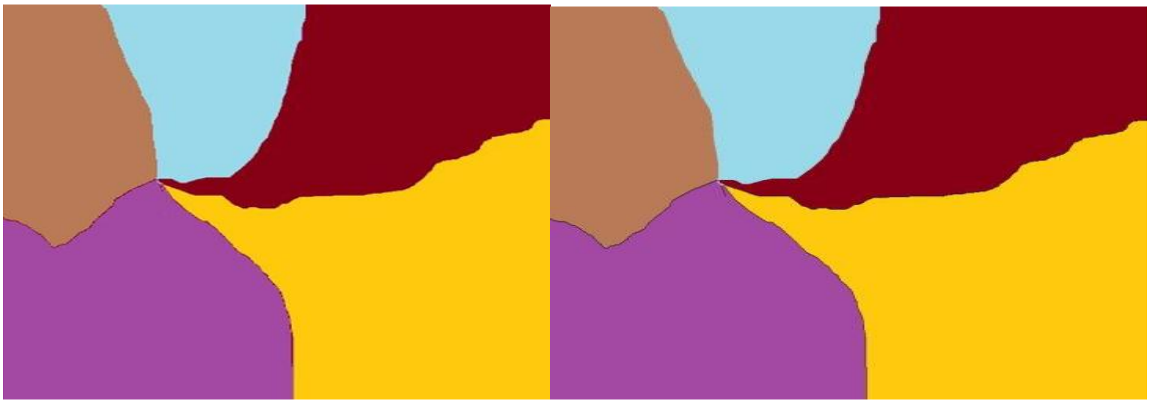
The identified 3D modes serve as the initial centroids for the K-means clustering algorithm. This step ensures that the algorithm selects the optimal initial centroids in a way that avoids local maxima and ensures a better distribution of centroids across the dataset, leading to more accurate and effective clustering.

2. The algorithm groups the image pixels based on color similarity. To ensure robustness, clusters with pixel counts below a computed threshold are discarded. This threshold is calculated using the interquartile range (IQR) method, ensuring that only significant clusters contribute to the final segmentation.

3. The remaining clusters' centroids are used for the final K-means clustering step. The result is a segmented image where each pixel is assigned the color of its respective cluster centroid. The method effectively prevents the algorithm from converging to local minima by initializing centroids based on data-driven mode estimation, improving the segmentation quality.

Results and Discussion

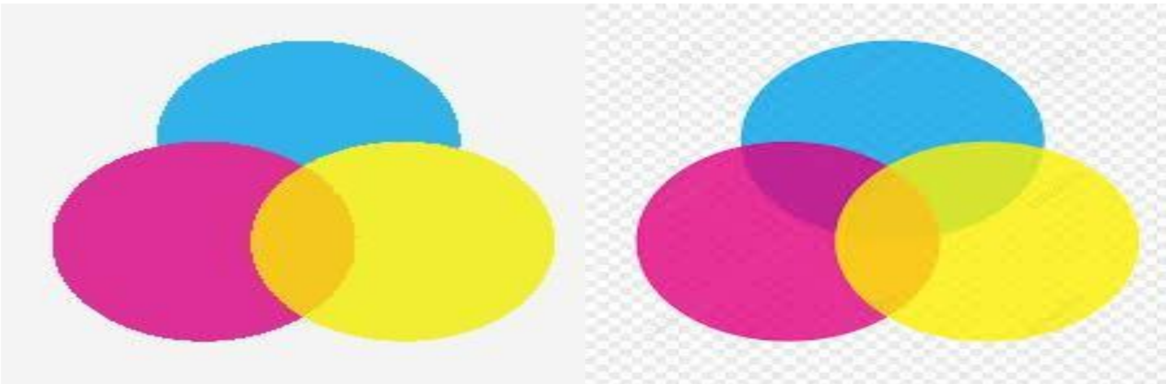
In order to verify the efficiency and feasibility of the proposed algorithm, we tested it on the image used in Chowdhury et al.(2016), shown in Figure 2a. This benchmark image allows an initial comparison with previously published approaches and a direct visual assessment of the segmentation quality between the original image and its segmented counterpart. In our experiment, the KDE–based initialization automatically selected five significant color clusters, which were then refined by K-means. Visual inspection of Figure 2b shows that the method faithfully preserves the main structures of the scene while producing compact and homogeneous regions. Most object boundaries are sharply delineated and the background is strongly simplified, confirming the ability of the proposed unsupervised algorithm to extract meaningful regions without any prior knowledge of the number or location of the segments



(a) Original picture (b) Segmented picture

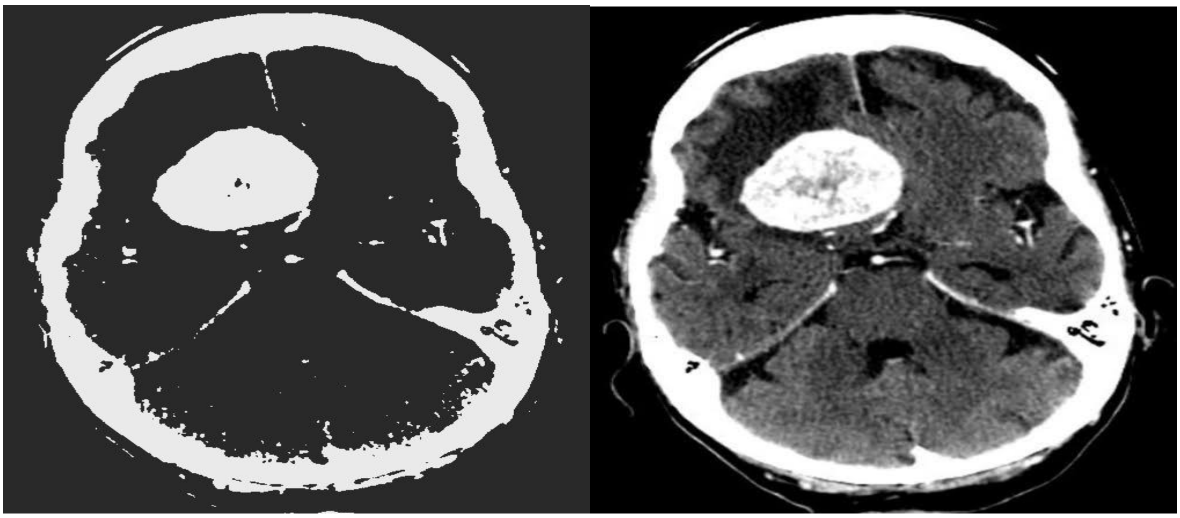
Figure 2. Image used in the experiments

As a second experiment, we considered the synthetic ”tricolor” image composed of three partially overlapping colored disks (Figure 3a). This image is interesting because it contains a small number of well–separated colors together with mixed regions created by the overlaps and a textured background. The proposed KDE–based procedure automatically selected five significant color clusters, which K-means then refined (Figure 3b).



(a) Original picture (b) Segmented picture

Figure 3. Tricolor image



(b) Original picture (b) Segmented picture

Figure 4. Pathological brain image

The resulting segmentation clearly separates the three primary disks, the orange overlap region, and the background. In particular, the transparency grid present in the original image is almost completely removed, and the contours of the disks remain smooth and well localized, illustrating the ability of the method to recover both pure and mixed regions from multimodal color distributions. We also evaluated the proposed approach on a pathological brain slice containing a bright intra-cranial lesion (Figure 4a). The global gray-level distribution is strongly skewed, with three main modes corresponding to the dark background, the normal brain parenchyma, and very bright structures (bone and hyperdense lesion). From the estimated density functions, the KDE–based initialization retained two dominant clusters, which were then refined by K-means.

As illustrated in Figure 4b, the resulting segmentation succeeds in isolating the high-intensity structures (skull and lesion) from the rest of the brain tissue, while still providing a coherent partition of the intracranial region. This experiment suggests that the method can enhance the visual contrast between normal and abnormal regions without requiring any prior information about the lesion

Conclusion

In this work, we proposed an unsupervised color-based segmentation method that exploits kernel density estimation to detect the dominant modes of the RGB distributions and uses these modes as data-driven initial centroids for the K-means algorithm, thereby reducing the sensitivity to initialization and discarding insignificant clusters. Experiments on a natural scene, a synthetic tricolor image and pathological brain slices show that the approach preserves the main structures while producing compact and homogeneous regions, accurately separates pure and mixed color areas in multimodal distributions and yields coherent partitions on low-contrast medical images, where high-intensity abnormalities are clearly emphasized. Future research will focus on extending the framework to other color spaces and multimodal data (e.g., RGB–depth or multispectral images), integrating spatial regularization to further suppress noise and small isolated regions, conducting large-scale comparisons with state-of-the-art, including deep learning–based segmentation models, and adapting the method to interactive or semi-supervised scenarios in which limited user input can guide the segmentation process.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPHELS journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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