Multimedia Tools and Applications (2023) 82:35493–35555
https://doi.org/10.1007/s11042-023-14861-9

A survey on the utilization of Superpixel image for clustering based image segmentation

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Received: 9 February 2022 / Revised: 22 June 2022 / Accepted: 6 February 2023 /
Published online: 8 March 2023

Abstract

Superpixel become increasingly popular in image segmentation field as it greatly helps image segmentation techniques to segment the region of interest accurately in noisy environment and also reduces the computation effort to a great extent. However, selection of proper superpixel generation techniques and superpixel image segmentation techniques play a very crucial role in the domain of different kinds of image segmentation. Clustering is a well-accepted image segmentation technique and proved their effective performance over various image segmentation field. Therefore, this study presents an up-to-date survey on the employment of superpixel image in combined with clustering techniques for the various image segmentation. The contribution of the survey has four parts namely (i) overview of superpixel image generation techniques, (ii) clustering techniques especially efficient partitional clustering techniques, their issues and overcoming strategies, (iii) Review of superpixel combined with clustering strategies exist in literature for various image segmentation, (iv) lastly, the comparative study among superpixel combined with partitional clustering techniques has been performed over oral pathology and leaf images to find out the efficacy of the combination of superpixel and partitional clustering approaches. Our evaluations and observation provide in-depth understanding of several superpixel generation strategies and how they apply to the partitional clustering method.

Keywords Superpixel · Clustering · Image segmentation · Optimization · Leaf images · Oral histopathology

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1 Introduction

Digital image processing is in high demand in a variety of fields, including computer vision [22], robotics [115], remote sensing [168], industrial inspection [51], and medical diagnostics [129]. Superpixels generation is a technique that is commonly employed as a pre-processing step in computer vision applications. Introduced by Ren et al. [122], superpixels are small image regions with a uniform appearance that are created when the original image is over-segmented. Superpixels can be define as groups of pixels with identical characteristics that can be utilised as mid-level units to reduce computing costs of many computer vision problems, such as image segmentation, saliency, tracking, classification, object detection, motion estimation, reconstruction. The superpixel representation considerably decreases the amount of image primitives and hence enhances the representational efficiency when compared to the regular pixel representation in images. In contrast to pixel, superpixel can greatly reduce the size of the object to be processed as well as the complexity of subsequent processing [3, 149, 150]. Because of these advantages superpixel approaches are commonly employed as a pre-processing step for a variety of tasks [3, 84, 149, 150].

Good superpixels techniques can increase the performance of computer vision applications [145]. There are several methods for producing superpixels, each with its own set of benefits and downsides that may be better suited to a certain application. If the speed of the algorithm is critical, the SEEDS [138] algorithm may be a better option. If superpixels are utilised to form a graph, the Normalized Cuts (NC) [126] algorithm may be the best option, as it generates more regular superpixels with a more attractive appearance. If superpixels are utilised as a pre-processing step in segmentation algorithms, a method that considerably improves segmentation algorithm performance, such as SLIC [5], is likely a viable choice. While defining an optimal method for all applications is challenging, the following characteristics are generally desirable: (a) Superpixel boundaries should correspond strongly to object boundaries, allowing as many pixels on the object boundaries to be recalled as feasible. (b) Superpixels should be quick to compute, memory efficient, and simple to use when employed to minimise computational complexity as a pre-processing step. (c) Superpixels should improve both the speed and the quality of results when utilized for segmentation purpose.

Image segmentation can be accomplished by a variety of clustering algorithms. However, there is no agreed-upon definition of a cluster, and the many methods of clustering have each developed their own strategies for grouping the data. Therefore, the clustering techniques can be roughly divided into two groups depending on the cluster formation: hierarchical clustering and partitional clustering. Figure 4 displays a taxonomy of the clustering techniques. Because of its superior computational efficiency, partitional clustering has gained a significant amount of popularity in recent years and is now widely considered to be superior to hierarchical clustering. This is especially true for larger datasets. In this paper we use clustering algorithms, specially the partitional clustering, for image segmentation. The selected partitional clustering algorithms are: the K-means, the Fuzzy c-Means (FCM).

The paper provided here is much more focused on the fundamentals; it is based on a comparison of several clustering techniques, both with and without superpixel pre-processing, using the same dataset containing 100 different Rosette Plant images and 100 different Oral histopathology images. As SLIC algorithm is mostly used among others superpixel generation technique for image pre-processing, we use this algorithm for superpixel generation. The images are segmented using K-Means (KM), Fuzzy C-Means (FCM), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) Algorithms. We also compare the above methods with Multiscale Superpixel based Fast Fuzzy C-Means Clustering (SFFCM) method. The images are segmented and their binary forms are compared to the Ground Truth Image, with the determining factor being the average value of all the algorithms.

Research questions

1) In a wide variety of computer vision applications, superpixel segmentation proved to be an effective step in the pre-processing task. The goal of superpixel is to decrease image redundancy and boost efficiency from the perspective of the next processing task. There are numerous methods for creating superpixels, each with advantages and disadvantages that may be better suited for a specific purpose. So, choosing the right superpixel algorithm for a particular application is a major research topic. In superpixel based segmentation the following characteristics are often favoured: (i) The boundaries of an image should be well-adhered by superpixels. (ii) Superpixels should be fast, memory-efficient, and easy to utilise while reducing computational complexity.
2) Which specific superpixel generation technique has to be chosen for a specific image type?
3) Which superpixel generation algorithm is computationally effective?
4) How to identify what no of superpixel is best for a specific image type?
5) There are mainly two types of clustering techniques: Partitional clustering and Hierarchical clustering. Partitional clustering has grown significantly in popularity in recent years and is currently seen as being superior to hierarchical clustering due to its higher processing efficiency. But it has three major drawbacks, i) Higher computational time ii) Local optima trapping and iii) Sensitive to noise. Therefore, finding the strategies to overcome the said drawback will be an important task.
6) How the noise robustness can be incorporated into the partitional clustering algorithms?
7) How to overcome the local optima trapping problem of partitional clustering algorithms?
8) How the computational efficiency can be improved for partitional clustering algorithms?
9) In the literature, it is noticed that the use of superpixel as a pre-processing task greatly reduces the computational time. It also performs well for noisy image segmentation. So, the incorporation of superpixel image as the input of the partitional clustering algorithms might overcome the problems of higher computational time and sensitivity to noise. But finding the optimal combination of superpixel generation techniques and partitional clustering algorithms is an important task.
10) Which combination of superpixel generation techniques and partitional clustering algorithms is optimal for image segmentation?

The paper is organized as follows: Section 2 presents the literature survey and datasets part. Section 3 demonstrates the superpixel generation technique, Section 4 represents clustering methodologies. Section 5 represents the experimental results. The paper is concluded in Section 6.

2 Literature survey and datasets

This segment provides the current image segmentation and various superpixel generation techniques with their corresponding datasets, as shown in Tables 1 and 2, respectively. Superpixel based image clustering is a method of partition an image into multiple

Table 1 Summary of the Previous Works

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
Zhang et al. 2017 [165]	SLIC	Density-based spatial clustering of applications with noise (DBSCAN)	Lung nodule image	RG, PCNN, KM, FCM, PSO-SGNN and FEGD	**Pros:** 1) The overall computation time is reduced because the clustering algorithm uses superpixels, instead of pixels. 2) It is not necessary to specify the number of clusters in advance. 3) Robust in terms of the detection of outliers (noise) 4) The DBSCAN algorithm has the ability to locate clusters of arbitrary size and shape. **Cons:** 1) When cluster density varies, the DBSCAN algorithm fails. 2) When dealing with high-dimensional data, this method does not function effectively. 3) If the density varies or the dataset is too sparse, the algorithm fails to identify cluster.
Xiang et al. 2017 [151]	SLIC	Local iterative clustering	Polarimetric Synthetic Aperture Radar (PolSAR) images	Qin's method Liu's method	**Pros:** 1) Use of superpixels improves segmentation performance. 2) In terms of performance and ability to balance over and under segmentation, this technique surpasses other methods. **Cons:** 1) It is necessary to have the number of clusters determined in advance. 2) The result varies when there is an outlier (noise) present.
Li et al. 2017 [89]	SLIC	fast interactive foreground extraction method (SFAT).	Natural colour image	Growcut, LazyNap, One-cut, Grabcut	**Pros:** 1) The proposed SFAT outperformed interactive algorithms in terms of vision and the three requirements of MSE, SAD, and E-time. 2) Use of superpixel make this method robust in terms of the detection of outliers (noise). **Cons:** 1) FATs are difficult to apply to construct trimaps in a few types of photos,

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					for example, some images include small interior holes.
Wang et al. 2017 [144]	SLIC	superpixel clustering and sparse representation (SC-SR) algorithm.	10 standard benchmark images	NLM, K-SVD BM3D, EPLL	**Pros:** 1) The proposed methodology not only effectively reduced noise, but it also restored spatial content and edge region techniques more effectively than competing algorithms. 2) The algorithm produced fewer visual artefacts overall. 3) The proposed method outperformed the competition in terms of image denoising, especially in terms of preserving image edges and fine structure. **Cons:** 1) Due to the fact that image denoising is often a poorly-posed problem, its solution may not be unique.
Zhang et al. 2017 [166]	SLIC	Laplacian sparse subspace clustering (LSSC) and unified low-rank repre-sentation (ULRR) (LSSC-ULRR)	Colour image	LRMR based and clustering-based methods, including SR_RPCA, LRR, ULR and LSSC_BS	**Pros:** 1) LSSC_ULRR outperforms standard LR_MR and clustering-based approaches, and is on par with several contemporary state-of-the-art techniques. 2) In most circumstances, it can totally detect the entire prominent item with a huge size in an image. 3) When the backgrounds of the input images comprise numerous diverse textures, the method efficiently suppresses background noise. **Cons:** 1) The proposed method failed to achieve high performance on the images with complex structure.
Zhou et al. 2017 [169]	SLIC	Superpixel Multi-Feature Classification (SMFC)	Retinal image	Other state-of-the-art approach	**Pros:** 1) Using superpixels instead of pixels as the basic image representation helps detect exudates, which decreases image processing

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					complexity and enhances stability and robustness. 2) The proposed method is able to consider the global image information and the relationships of candidate lesions with their neighbouring superpixels within the retinal images. 3) In terms of sensitivity, specificity, and AUC, this method is more efficient than the others. **Cons:** 1) The proposed approach achieve less performance when there is a diversity of brightness and different size of images. 2) The proposed method may not be able to detect all exudates in retinal images if there are only a few or small exudate lesions.
George et al. 2017 [53]	SLIC	K-Means	Colour images of psoriasis	Other state-of-the-art method	**Pros:** 1) The SLIC technique produced efficient superpixels while also cutting down on overall computing time. 2) For psoriasis images with both erythema and scales, the approach produces verifiable and accurate results. 3) It works effectively with images of psoriasis with varying clarity, lesions of diverse sizes, severity scores and forms, as well as dense hairy images. **Cons:** 1) The k-means algorithm is vulnerable to outliers because an object with a very large value might significantly alter the data distribution. 2) Due to the existence of extreme points in the final clusters, the distribution is not optimum.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					3) There is no optimal technique to determine the number of clusters.
Lei et al. 2018 [84]	Multiscale morphological gradient recon-struction operation and watershed transform (MMGR-WT)	Superpixel based Fast Fuzzy C-Means clustering (SFFCM)	Colour image	FCM, FGFCM, HMRF-FCM, FLICM, NWFCM, KWFLICM, NDFCM, Liu's algorithm, FRFCM.	**Pros:** 1) Because the number of various colours is efficiently reduced by superpixel and colour histogram, SFFCM is highly quick for colour image segmentation. 2) SFFCM achieves good results for colour image segmentation because it incorporates both adaptive local spatial information and a global colour feature into the objective function. 3) Because the superpixel image formed by MMGR-WT is convergent, SFFCM is unaffected by parameter changes. **Cons:** 1) FCM algorithm have long computational time 2) There is no optimal technique to determine the number of clusters. 3) To obtain the best segmentation result for an image, the proposed method needs to be executed for several times.
Cong et al. 2018 [24]	SLIC	Spectral segmentation algorithm	Colour image	Ncut algorithm, Meanshift_Ncut	**Pros:** 1) Use of SLIC superpixel as pre-processing technique considerably reduces the overall computational time and reducing the storage burden on the computer. 2) The proposed algorithm is more sensitive to noise, it will affect the accuracy and the desired effect of the final image segmentation **Cons:** 1) Computationally Expensive for large, dense dataset.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					2) Before beginning the operation, the number of clusters must be determined.
Mittal & Saraswat 2018 [100]	SLIC	logarithmic kbest gravitational search algorithm based superpixel clustering (LKGSA-SC).	Colour image	RGA, MPSO, GOA, IGWO, MVO, GSA. Kmeans_SC	**Pros:** 1) LKGSA performed better than others nature-inspired algorithm. 2) Addition of SLIC technique in LKGSA (proposed LKGSA_SC) gave better result both numerically and visually compared to Kmeans_SC. 3) The proposed method to obtain better optimal cluster centroids. Cons: 1) The computational time is slightly high. 2) A priori specification of the number of clusters.
Zhang et al. 2018 [167]	SLIC	K-Means	Plant leaf image	KSNNC, SIFT, IRT	**Pros:** 1) The SLIC technique produced efficient superpixels while also cutting down on overall computing time. 2) The proposed method is more robust than the other algorithms and improve plant disease recognition accuracy. **Cons:** 1) The k-means algorithm is vulnerable to outliers because an object with a very large value might significantly alter the data distribution. 2) Due to the existence of extreme points in the final clusters, the distribution is not optimum. 3) There is no optimal technique to determine the number of clusters.
Wei et al. 2018 [145]	SLIC	super hierarchy (SH) algorithm	Colour image	FH, ERS, SEEDS, LSC	**Pros:** 1) The proposed method was a robust hierarchy superpixel segmentation technique

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					that can be applied to a wide range of computer vision problems. 2) Extensive testing demonstrates that the proposed method is reliable and convenient in producing a hierarchical system of superpixels that can be used for a wide range of activities. **Cons:** 1) The computational time is slightly high which need to be improved.
Fu et al. 2018 [49]	SLIC	multiscale and multifeatured hierarchical image segmentation (MMHS).	polarimetric synthetic aperture radar (PolSAR) image	watershed transform segmentation (WTS) method, the mean shift (MS) method, the multiresolution segmentation (MRS)	**Pros:** 1) The proposed algorithm have high segmentation accuracy and low computational time. 2) The algorithm can be used to analyse HSR remote sensing data and might be used as a basis for real-time processing. **Cons:** 1) There should be an adjustable multifeatured integration strategy to handle all situations. 2) Find the best combination index in the segmentation results is also a hard task.
Angulakshmi et al. 2018 [97]	The superpixels are computed using the central tendency values of blocks of the image conventional.	Spectral Clustering	Brain tumour MRI image	Fuzzy-C-Means (FCM), Gaussian Mixture Model (GMM), K-means	**Pros:** 1) In comparison to existing ways, the proposed method takes less time to execute. 2) Spectral clustering gave better sensitivity and specificity compared to other method. 3) Use of superpixels improves segmentation performance. Cons: 1) The algorithm have low Dice score for real patient images 2) The proposed method is unable to extracting multiple features from ROI (Region of Interest).

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
Yuan et al. 2018 [159]	Modified Density-based Spatial Clustering of Application with Noise (MDBSCAN)	Ng-Jordan-Weiss (NJW) based Spectral Clustering	Colour image	NC, STSC, SAS	**Pros:** 1) The MDBSCAN method was used to create several high-quality superpixels with good boundary adherence. 2) The suggested method (MDBSCAN_SC) combines the benefits of both the MDBSCAN and NJW-based spectral clustering methods. 3) The proposed method has a decreased computing cost and greatly better segmentation accuracy. **Cons:** 1) There is no optimal technique to determine the number of clusters. 2) The number of superpixel is to set in advance.
Mittal& Saraswat, 2019 [102]	SLIC	Intelligent gravitational search algorithm based superpixel clustering (IGSA-SC)	H&E-stained estrogen receptor positive (ER+) breast cancer images	SDE, MPSO, GSA, OGSA, PGSA, GGSA, MGSA	**Pros:** 1) The proposed method determined the best cluster centroids. 2) It would be useful for quickly segmenting nuclei in histology images with a reasonable amount of time. 3) The proposed algorithm keeps the convergence rate and moves exactly toward the global optimum. **Cons:** 1) The proposed method is unable to handle the large histology datasets. 2) The algorithm has slow convergence and the tendency to become trapped in local minima.
Albayrak & Bilgin 2019 [7]	SLIC	FCM	Histopathological images of kidney renal cell.	KM, DBSCAN	**Pros:** 1) SLIC help to reduce the overall computational time for segmentation. 2) The proposed algorithm gives best result for overlapped datasets.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					3) Enables a data point to be part of more than one cluster. **Cons:** 1) FCM took large computational effort. 2) FCM algorithm is sensitive to outliers (noise). 3) A priori specification of the number of clusters.
Wu et al. 2019 [149]	SLIC	Improved Superpixel based Fast Fuzzy C-Means clustering (ISFFCM)	Colour image	SFFCM	Pros: 1) The proposed algorithm is more robust against noisy and blur image. 2) ISFFCM also took less amount of time for image segmentation. 3) The proposed algorithm is more stable than SFFCM. Cons: 1) A priori specification of the number of clusters. 2) With lower value of β the method gives better result but at the expense of a greater number of iterations.
Mohamed et al. 2019 [104]	SLIC	Statistical Pixel-Level (SPL) method	Retina image	circular Hough transform (CHT) and Fuzzy C-means (FCM)	**Pros:** 1) The SLIC algorithm produced decent outcomes with higher average sensitivity and lower computing cost. 2) In the feature extraction method for the retinal components, the SPL approach is used to retrieve features from every superpixel. **Cons**: 1) One of the major drawbacks is choosing an appropriate number of cluster centre.
Giraud & Berthoumieu 2019 [56]	SLIC	Nearest Neighbour-based Superpixel Clustering (NNSC)	Standard composite texture image	KM	**Pros:** 1) The complexity of extant texture-aware techniques was significantly reduced while segmentation accuracy was maintained.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					2) The proposed method gives efficient performance on both standard colour and texture datasets. **Cons:** 1) Choosing the right cluster number is a difficult task 2) The influence of the patch size on the performance of this method.
Xiang et al. 2019 [152]	Adaptive superpixel generation algorithm with linear feature clustering and edge constraint (ALFCE)	K-Means feature clustering and the Ncuts method	Synthetic Aperture Radar (SAR) image	PILS, SLIC-GGD, and SLIC-MD	**Pros:** 1) The proposed method produces better results and is useful for superpixel-based applications like object segmentation and classification. 2) Because to the Ncuts method and edge information, the image structure can be well retained. 3) This approach is insensitive to the speckle noise that is present in SAR. 4) According to the image content complexity, the proposed approach may adjust the superpixel shape and compactness adaptively. **Cons:** 1) Large data storage requirements and high time complexity. 2) Bias towards partitioning into equal segments
Kumar et al. 2019 [83]	SLIC	Superpixel-based FCM (SPOFCM)	Brain, Mammograms and Breast MR Images	KM, ET, FCM, FCM_S, KFCM	**Pros:** 1) The proposed technique can improve efficiency for suspicious lesion or organ segmentation in computer-assisted clinical applications. 2) For segmenting malignant areas, FCM clustering algorithm is ideal. 3) The proposed algorithm gives best result for overlapped datasets.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					Cons: 1) A priori specification of the number of clusters. 2) The algorithm is sensitive to noise.
Kim et al. 2019 [81]	SLIC	Fast and Robust fuzzy C-means (FRFCM)	Gastric endoscopy image.	FCM	**Pros:** 1) The SLIC superpixel algorithm optimized performance and reduces segmentation computation time. 2) Noise and unconstrained area clustering are suppressed by the FRFCM algorithm. 3) The proposed algorithm suppressed noise and produce better segmentation result. **Cons:** 1) Under the influence of the position coordinate value, the SLIC superpixel is grouped in a small area and divided into a grid of equal size. As a result, there's a good chance that locations other than lesions will be included. 2) The number of clusters has to specified in advance.
Ghaffari et al. 2020 [54]	SLIC	DBSCAN and FRFCM and Fast Weighted CRF (FWCRF) algorithm	Synthetic Aperture Radar (SAR) image	FCM	**Pros:** 1) The proposed method gave better result compared to traditional FCM method. 2) FRFCM also took low computational time. 3) The proposed method needs fewer iterations with more accuracy. **Cons:** 1) 1) When cluster density varies, the DBSCAN algorithm fails. 2) A priori specification of the number of clusters. 3) The proposed method is sensitive to noise.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
Jia et al. 2020 [72]	Watershed transform based on adaptive morphological reconstruction and regional minimum removal (AMR-RMR-WT)	fast and automatic image segmentation using superpixel-based graph clustering (FAS-SGC).	Colour image	HMRF-FCM, FLICM, KWFLICM, Liu's algorithm, FRFCM, DSFCM_N, FNCut, SFFCM, and AFCF.	**Pros:** 1) The proposed method obtains the best segmentation effect from the employment of AMR-RMR-WT. 2) Because to the use of superpixel and graph clustering, it has the simplest computational complexity. 3) For high-resolution image segmentation, the suggested FAS-SGC gives a comprehensive benefit. **Cons:** 1) It's difficult to strike a balance between the amount of precise information and the number of superpixels in superpixel segmentation. 2) The segmentation results obtained by the FAS-SGC are not as good as those obtained by supervised image segmentation techniques.
Ilesanmi et al. 2020 [69]	SLIC	Graph cut method	Breast ultrasounds image	Other state-of-the-art method like Otsu's thresholding method	**Pros:** 1) It is an efficient method for removing Gaussian noise. 2) This method is important in clinical medicine, such as operation navigation and diagnosis using ultrasound. 3) The proposed method gives better segmentation accuracy. **Cons:** 1) The proposed method fail on images with large number of shadows and high speckle noise. 2) The traditional SLIC algorithm has trouble adhering to broad limits.
Siyuan & Xinying 2020 [128]	SLIC	K-Means	Colour image	SLIC and ERS	**Pros:** 1) SLIC-KM produced better results and required less time for segmentation.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					2) The proposed method gives high accuracy and better segmentation result. 3) Measurable and efficient in large datasets. **Cons:** 1) The SLIC algorithm has a regular shape, but more outliers are produced. 2) Requires number of clusters in advance.
Liu et al. 2020 [94]	SLIC	K-Means	Colour image	CMFD	**Pros:** 1) The method generates superpixels that are as compact and neat as the cells, with neighbourhood properties that are simple to convey. 2) K-means cluster give better result. The addition of SLIC in K-mean (the proposed SLIC-KM) took less time for segmentation. 3) The proposed method is more robust than the other algorithms and improve segmentation accuracy. **Cons:** 1) For superpixel segmentation, it is hard to figure out the appropriate number of superpixels. 2) Result varies in the presence of outliers.
Li et al. 2020 [91]	Naive Subspace Clustering (NSC)	Locality-Constrained Subspace Clustering	Colour image	Ncut, Turbopixel, TPS, LRW, SLIC, ASS, FLIC, LSC and BASS.	**Pros:** 1) The proposed method gives best segmentation result. 2) Because to the use of superpixel, it has the simplest computational complexity. 3) To achieve the detailed boundaries, these methods have to increase the number of superpixels and decrease their size. **Cons:** 1) For superpixel segmentation, it is hard to figure out how to balance the amount of detailed information and the number of superpixels.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
					2) Increased superpixel size frequently results in a lot of data redundancy in the sparse area, which makes it unsuitable for practical activities.
Rela et al. 2020 [121]	Multiscale morphological gradient recon-struction op-eration and watershed trans-form (MMGR-WT)	Superpixel based Fast Fuzzy C-Means clustering (SFFCM)	CT abdominal image	CCL, KM, CLAHE-KM, HPF-KM and FCM.	**Pros:** 1) Because a pre-segmentation approach called superpixel image is employed before segmentation, the process is highly quick. 2) The SFFCM outperforms state-of-the-art clustering methods since it gives the best segmentation results and has the shortest runtime. **Cons:** 1) One of the major limitations of this method is that the number of clusters has to specified in advance. 2) To obtain the best segmentation result for an image, the proposed method needs to be executed for several times.
Khosravanian et al. 2021 [77]	Multiscale morphological gradient recon-struction op-eration and watershed trans-form (MMGR-WT)	Enhanced Fuzzy C-Means (En-FCM) and Lattice Boltzmann Method (LBM)	MRI brain tumour image	Other state-of-art method	**Pros:** 1) The suggested approach was resistant to noise, initialising, and non-uniformity in intensity. With an average running time of 3.25 seconds. 2) The proposed method is robust to noise, and initialization. 3) The proposed method could be effective in the segmentation of complex medical images. **Cons:** 1) The proposed method is only suitable for whole tumor segmentation; it cannot segment other sub-regions such as tumor core, edema, and necrosis tissues.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
Chakraborty & Mali 2021 [17]	watershed-based superpixel	SuFMoFPA (Superpixel based Fuzzy Modified Flower Pollination Algorithm)	COVID-19 radiological image	GA, PSO, ACO, Cuckoo search.	**Pros:** 1) The proposed method considerably reduces the overhead of processing a large amount of geographical data, which is advantageous in terms of speedy and accurate diagnosis. 2) The suggested method performs admirably in terms of defining segments from CT scans without relying on expert delineations, which is quite useful for evaluating COVID-19 suspicions. Cons: 1) A priori specification of the number of clusters. 2) The proposed method is sensitive to noise.
Elkhateeb et al. 2021 [45]	SLIC	Superpixel Fuzzy C-Means (SPFCM) and a Modified Chan-Vese active contour model (MCV) SPFCM-MCV	Natural colour image	FCM, SFCM	**Pros:** 1) The SPFCM clustering approach produces coarse sea-land segmentation results, which automatically initialises the CV active contour model instead of manual initialization. 2) It outperformed the previously stated fuzzy ACMs because it integrates textural, spectral, and spatial information, allowing it to handle image inhomogeneity. 3) The process is extremely fast because a pre-segmentation technique called superpixel image is used before segmentation. Cons: 1) One of the method's primary drawbacks is that the number of clusters must be specified in advance. 2) The proposed method cannot classify well the mixed volcanic and non-volcanic regions.

Table 1 (continued)

Author & Year	Superpixel Technique	Clustering Technique	Image	Comparison	Remarks
Elaziz et al. 2021 [1]	Multiscale morphological gradient recon-struction operation and watershed transform (MMGR-WT)	q-Generalized Pareto distribution under linear normalization (q-GPDL) and Hunger Games Search	BSD500 Image dataset	SMA, BMO, ASO, ASOPSO, HGS, FCM, DPC	**Pros:** 1) The proposed method gives best segmentation result with high accuracy. 2) Use of superpixel pre-processing technique reduce the overall computational time. 3) The Hunger games search (HGS) algorithm is produced best result and well preserved the boundary region. Cons: 1) The proposed method is robust to noise, and initialization. 2) The proposed method sometime fails when the size of the dataset is vast.

Table 2 Brief description of the utilized Datasets in literature

Image type	Dataset Description	Reference
Lung nodule image	The data came from two separate databases: Shanxi Provincial People's Hospital, which uses PHILPS 256 CT (Philips iCT) layer speed equipment (240 mA, 120 kV, 1.5 mm slice thickness), and the Lung Image Database Consortium (LIDC) (40,422 mAs, 120,140 kVp, 1 mm to 3 mm slice thickness). The datasets contained 1458 lung CT sequence images from 120 clinical cases, each of which was 512×512 pixels in size.	[10]
Natural image	Here two datasets namely, alphamatting1 and BSDS500 is used. The BSDS500 dataset contains 500 natural images that are explicitly separated into disjoint training, validation, and testing subsets. However, only 50 images in the collection are given ground truth for foreground extraction study. The images from the BSDS500 are nearly 320× 480 pixels in size, whereas the alpha matting images are 600 × 800 pixels in size.	"https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html and www.alphamatting.com"
Colour image	The MSRA10K dataset contains 10,000 images, the majority of which feature a single object with strong contrast between foreground and background objects. The ECSSD dataset contains 1000 images, many of which are structurally complicated and contain objects from a variety of categories. The DUT-OMRON dataset contains 5168 images, the majority of which have complex back-grounds or high contrast in comparison to the subject.	[21, 127]
retinal image	The DiaretDB1 database (Standard Diabetic Retinopathy Database Calibration Level 1, Version 1) is a web-based public database. There are 89 RGB colour fundus images in the database, each having a fixed resolution of 1500 × 1152 pixels and a field of view of 50^0 and Zhang et al. propose the e-ophtha EX database, which is a public database accessible via the Internet. There are 82 retinal images with four resolutions ranging from 1440×960 to 2544 × 1696 pixels and a 45^0 field of view.	[73, 164]
2-D digital images of psoriasis	The 2-D digital images of psoriasis taken by clinical photographers at the RMH over the last three years were used in this investigation. The images were taken with two separate cameras: a Nikon D700 and a Nikon 60 mm f2.8 D90, both under uniform lighting. The acquired photos have resolutions of 1936 1296, 2848 4288, and 2832 4256. In total 676 psoriasis images were collected, representing 44 different patients.	[52]
Colour image	There are 500 images in the BSDS dataset. There are four to nine GT segmentations for each image in BSDS. Different human beings have defined these GT segmentations. The MSRC data set contains 591 natural images divided into 23 object classifications. There is only one pixel-wise labelled GT segmentation for each image in MSRC.	[9]
polarimetric synthetic aperture radar (PolSAR) image	The NYSDOP experimental dataset included a collection of HSR images from the state of New York, including Quick Birds and aerial images with spatial resolutions ranging from 0.6 m to 0.3 m. The ISPRS Potsdam dataset is a 38-dataset open benchmark dataset. Ground truth and ortho-rectified aerial IRRGB images (6000 × 6000 px) with a 5 cm spatial resolution.	[123]

Table 2 (continued)

Image type	Dataset Description	Reference
Brain tumour MRI image	BRATS 2012 dataset contains 80 patient images. Out of the images 25 synthetic images and 20 real images with high grade, and 25 synthetic images and 10 real images with low grade.	[65]
H&E-stained estrogen receptor positive (ER+) breast cancer images	The dataset consists of H&E-stained estrogen receptor positive (ER+) breast cancer images taken at 40x magnification and complemented with domain experts' manually segmented nuclei ground truth images.	[137]
Histopathological images of kidney renal cell.	The data set consisted of high-resolution histopathological images of renal cell carcinoma selected from The Cancer Genome Atlas (TCGA) data portal and publicly available for usage. There are 810 high-resolution 400×400, histopathological images of ten kidney renal cell carcinomas. Images were scanned using 40× magnification.	[70]
Retina image	The database, which contains 166 images, separates them into three categories: normal (92 images), glaucoma (39 images), and suspect of glaucoma (35 images), all of which are accompanied by ground truth images. Manual segmentation was used to annotate the ground truth images in the database, which were annotated by two ophthalmology professionals.	[50]
Standard composite texture image	A dataset of composite texture images (CTI) in the most basic form. It is made up of 10 grayscale images with up to 16 different textures	[118]
Brain, Mammograms and Breast MR Images	The renowned Mammographic Image Analysis Society (MIAS) database contains mammogram images with 1024 × 1024 pixels, from which the actual single-spectrum image data is selected, whereas the 512× 512 pixels comprising breast MRIs were collected from the hospitals, from which the actual multi-spectral image data is selected. In addition, the OASIS database has 512 × 512 pixel-sized brain images are collected.	[131]
Gastric endoscopy image.	There were 667 images in all, 447 normal and 220 aberrant, in the data set. Gastric cancer, stomach ulcers, gastric cancer, and gastric bleeding were among the abnormal images.	[79]
Colour image	All of the test images utilised in the experiment came from the SBU-CM16 dataset, which contains 16 original images and 240 tampered images, each of which has one fabricated portion. Tampered images are made by copying one section of an image and pasting it on another part of the same image, then performing a different assault on the copied region or the entire image.	[160]
CT abdominal image	Liveratlas dataset is used. This approach is tested using 20 CT images from the liveratlas database.	[163]
MRI brain tumour image	The BraTS 2017 dataset was used. BraTS 2017 utilizes multi-institutional pre-operative MRI scans and focuses on the segmentation of intrinsically heterogeneous (in appearance, shape, and histology) brain tumors, namely gliomas.	"https://www.med.upenn.edu/sbia/brats2017.html"
Natural colour image	The natural-colored images from the Landsat-7 ETM+ and Landsat-8 satellites have a medium resolution and a spatial resolution of ≈ 30 m. These images are used to assess the effectiveness of the strategy being given. They came from the United States Geological Survey's Global Visualization Viewer. A total of one hundred big images of various geographical regions were acquired. For the image, they were further cropped with [512×512].	[64]

segments. The objective of superpixel based image clustering is to represent image something more constructive and simpler to examine. So, a detailed survey on various papers is necessary to check the need for a new framework. Literature survey made on various papers which includes the techniques of image segmentation like KM, FCM, GA, PSO etc. and various superpixel generation algorithm like SLIC, MMGR-WT, Ncuts etc.

2.1 Paper sources and keywords

A) **Sources**

The mentioned papers have been collected from the following sources:

(i) Google Scholar—https://scholar.google.com
(ii) IEEE Xplore—https://ieeexplore.ieee.org
(iii) ScienceDirect—https://www.sciencedirect.com
(iv) SpringerLink—https://www.springerlink.com
(v) ACM Digital Library—https://dl.acm.org
(vi) DBLP—https://dblp.uni-trier.de

B) **Keywords**

Each of these above sources is queried with the following combinations of keywords:

KW1: Superpixel image-based segmentation
KW2: Clustering based image segmentation
KW3: Hierarchical and Partitional clustering based image segmentation
KW4: Nature Inspired Optimization Algorithm based image clustering
KW5: Noisy image segmentation using clustering techniques
KW6: Image segmentation using superpixel image-based clustering technique
KW7: Computationally effective and noise robust image segmentation
KW8: Image segmentation using K-Means
KW9: Image segmentation using Fuzzy C-Means
KW10: Image segmentation using Swarm Intelligence algorithms

The graphical analysis has been conducted based on the application of superpixel image for clustering-based image segmentation. The following are the top three factors that were taken into consideration in the graphical analysis: (a) Year wise development of superpixel image for clustering-based image segmentation techniques which has been shown in Fig. 1. The figure represents the year wise development statistics of last five year which clearly shown that the utilization of superpixel image for clustering-based image segmentation is continuously popular. (b) A category wise percentage of various superpixel generating techniques has been presented in Fig. 2. From Fig. 2, it is clearly noticed that one third of applications have been done over the SLIC superpixel generating technique. MMGR-WT is the next most commonly used superpixel generating technique. (c) The percentages of various clustering approaches that have been used are shown in Fig. 3 which shows that FCM is the most used clustering technique, followed by KM, NIOA, and other techniques.

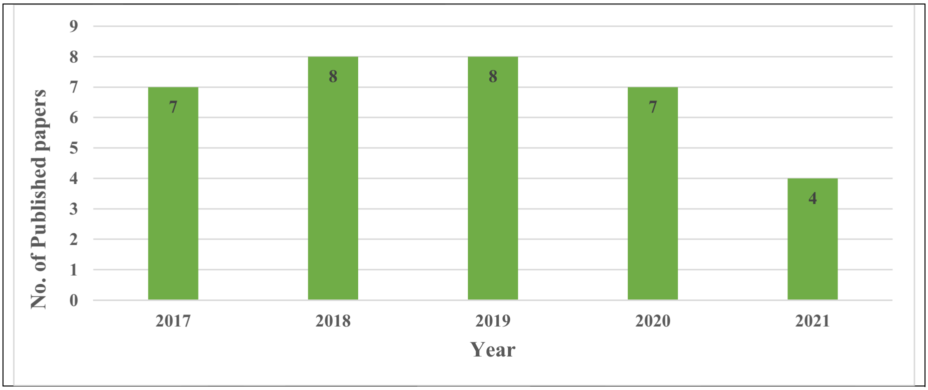

Fig. 1 Year wise development of superpixel image based clustering techniques

3 Discussion on superpixel generating techniques

The objective of superpixel segmentation is to partition pixels in an image into atomic areas with bounds that match the natural object boundaries. In computer vision, superpixel segmentation has sparked a lot of attention because it makes it easy to compute picture attributes and reduces the complexity of future image processing tasks. In recent times, a slew of superpixel segmentation methods have been introduced. Superpixel segmentation techniques are classified into numerous groups based on various categorization criteria. They are described below in detail.

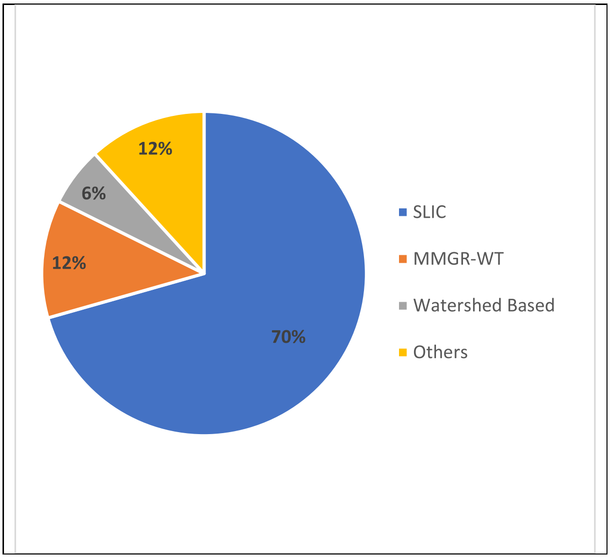

Fig. 2 Category percentage of superpixel techniques

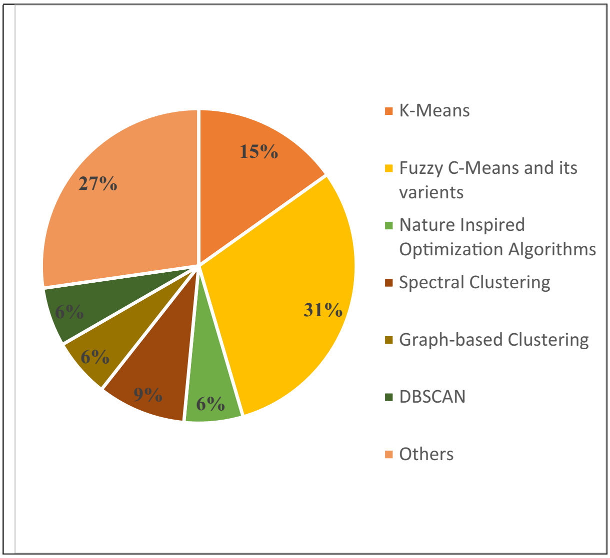

Fig. 3 Category percentage of clustering techniques

3.1 Density-based methods

Density-based algorithms [130] are often classed as over segmentation techniques since they lack control on the amount of superpixels or their compactness. Edge-Augmented Mean Shift (EAMS) [23] and Quick Shift (QS) [139] are two popular density-based methods. In a calculated density image, both execute mode-seeking, every pixel is specified to the method it falls into.

3.2 Watershed-based methods

These methods are based on the watershed algorithm (WT) [98, 130] and typically vary in how the image is pre-processed and how markers are set. The number of superpixels is determined by the number of markers, and some watershed-based superpixel methods provide compressibility control., for example Water Pixel (WP) [95] or Compact Watershed (CW) [108]. Morphological Superpixel Segmentation (MSS) [11] is also a popular density based superpixel algorithm.

3.3 Graph-based methods

Graph-based algorithms [68, 148] consider the image as an undirected graph and divide it into sections based on edge-weights, which are frequently computed as colour differences or similarities. The partitioning techniques differ; for example, Felzenswalb and Huttenlocher (FH) [46], Entropy Rate Superpixels (ERS) [92], and Proposals for Objects from Improved Seeds and Energies (POISE) [67] merge pixels into superpixels from the bottom up, whereas Normalized Cuts (NC) [126] and Constant Intensity Superpixels (CIS) [140] utilise cuts, and Pseudo-Boolean Optimization Superpixels (PB) [162] uses elimination.

3.4 Path-based methods

Path-based methods divide an image into superpixels by connecting seed points to pixel paths that satisfy specific standards. The number of superpixels can be conveniently manipulated, but not their density. These algorithms [43, 130] frequently make use of edge data: Topology Preserving Superpixels (TPS) [48, 133] employs edge detection while Path Finder (PF) [43] uses discrete image gradients.

3.5 Contour evolution-based methods

Contour evolution is one of the popular superpixel generation algorithm [130]. Starting with an initial seed pixel, these techniques portray superpixels as developing outlines. Turbo Pixel (TP) [86] and Eikonal Region Growing Clustering (ERGC) [14] are the example of contour evolution-based method.

3.6 Energy optimization-based methods

These algorithms [130] maximise a formulated energy in a step-by-step manner. As an initial superpixel segmentation step, the image is divided into a regular grid, and based on energy, pixels are interchanged among nearby superpixels. The amount of superpixels can be adjusted, the compactness can be adjusted, and iterations can usually be stopped at any time. Some of the Energy optimization method are Contour Relaxed Superpixels (CRS) [25], Superpixels Extracted via Energy Driven Sampling (SEEDS) [138], Convexity Constrained Superpixels (CCS) [134] and Extended Topology Preserving Segmentation (ETPS) [158].

3.7 Clustering-based methods

These superpixel generation technique [130] are based on clustering algorithms such as k-means, which use colour, spatial, and extra information such as depth and are initialised by seed pixels. The amount of created superpixels and their compactness are intuitively configurable. Although these techniques are iterative, connection must be enforced through post-processing. Some of the clustering-based method is Depth-Adaptive Superpixels (DASP) [146], Vcells (VC) [142] and Simple Linear Iterative Clustering (SLIC) [4, 5]. DASP uses extra depth information. SLIC algorithm generates superpixels by clustering pixels based on their colour similarity and proximity in the image plane. It is one of the most often used algorithms for superpixel generation. SLIC is time efficient. Using a kernel function, Linear Spectral Clustering (LSC) [87] converts image pixels into weighted points in 10-D feature space. The seed pixels are then uniformly sampled for the entire image. The search centres are then used, and the feature vectors are used as the initial weighted means of the relevant clusters. LSC use the spectral clustering technique to arrive at a global optimal solution, which improves boundary adherence even more. Pre-emptive Simple Linear Iterative Clustering (PreSLIC) [114] is also a popular clustering-based superpixel generation algorithm which is proposed by Neubert et al. [109]. To prevent revisiting clusters, Pre-emptive SLIC implements a local terminal criterion for each cluster. As a result, clusters are only updated if there are significant changes in the cluster centre.

4 Clustering techniques based image segmentation

Clustering is a powerful image segmentation technique that has been developed. The taxonomy of the clustering techniques is displayed in Fig. 4. The goal of cluster analysis is to divide an image data set into a number of disjoint groups or clusters with greater intra-cluster similarity but lower inter-cluster similarity. It is obvious that intra-cluster similarity should be enhanced while inter-cluster similarity should be reduced. Based on this concept, objective functions are formulated [30, 36, 39]. The method of minimizing/maximizing one or many objective functions can be used to achieve the better partitioning of a provided data collection. The objective functions are generated by establishing a statistical–mathematical relationship between the independent data items and the proposed set of cluster representatives [30, 36, 39]. The partitions into c classes should preserve the respective characteristics:

1. At least a single vector should be assigned to each cluster. i.e.,

$$c_i \neq \varnothing, \forall i \in \{1, 2, \ldots, c\}$$

2. There should be no data vector in common between two distinct clusters. i.e.,

$$c_i \cap c_j = \varnothing, \forall i \neq j \text{ and } i, j \in \{1, 2, \ldots, c\}$$

3. Each data vector should absolutely be associated with a cluster. i.e.

$$\cup_{i=1}^{c} = D_v$$

Where, D_v is the total number of objects.

The clustering techniques are classified into following categories:

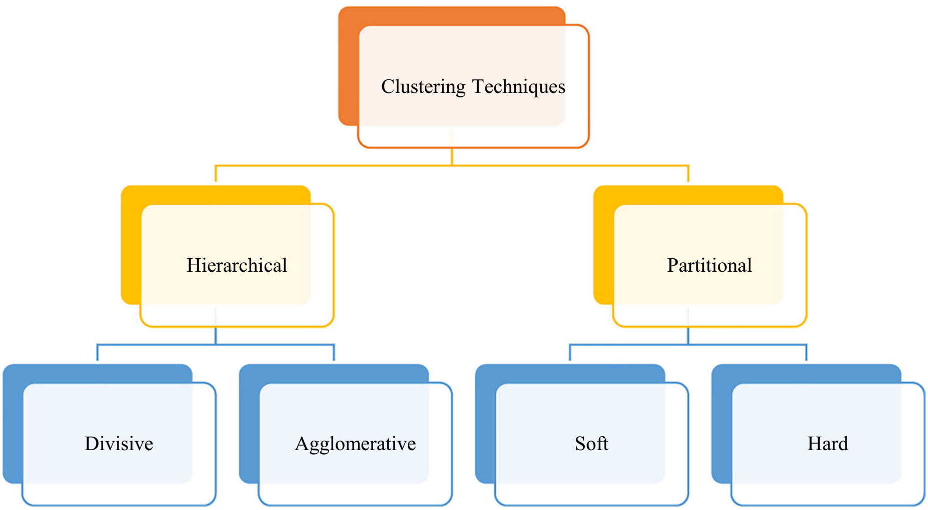

Fig. 4 Clustering-based image segmentation techniques are classified [124]

4.1 Hierarchical clustering

In this clustering method, data is grouped at multiple levels of comparability, which is represented as a dendrogram, a tree-like structure in Fig. 5. In general, there are two techniques to hierarchical clustering: divisive and agglomerative [103, 124]. Hierarchical clustering can be accomplished in two ways. They can be bottom-up or top-down. Large clusters are divided into small clusters, and small clusters of large clusters are combined together. The methods in these two sub-categories are summarised in Table 3. The pros and cons of the hierarchical clustering are as follows:

The Pros are:

- The algorithm does not require the number of clusters (k) to be pre-defined.
- Integrated adaptability with respect to the degree of granularity.
- Creates more comprehensible clusters, which could be beneficial to the discovery.
- Extremely well suited with regard to issues concerning point linkages.
- Allows for the use of any standard units of measurement.
- Beneficial for the presentation of data, as it provides a hierarchical relation between clusters.

The Cons are:

- When used to massive amounts of data, hierarchical clustering is not very effective.
- The algorithm is sensitivity to noise and outliers.
- Once a decision is made in hierarchical clustering, it cannot be reversed.
- When dealing with varying cluster sizes, the algorithm encounters difficulty.
- When the decision to split or merge is made, there is no way to go back and change it.
- The sequence of the data has an impact on the final outcomes with this technique.
- A time complexity of at least $O(n^2 \log n)$ is required, where n is the number of data points.

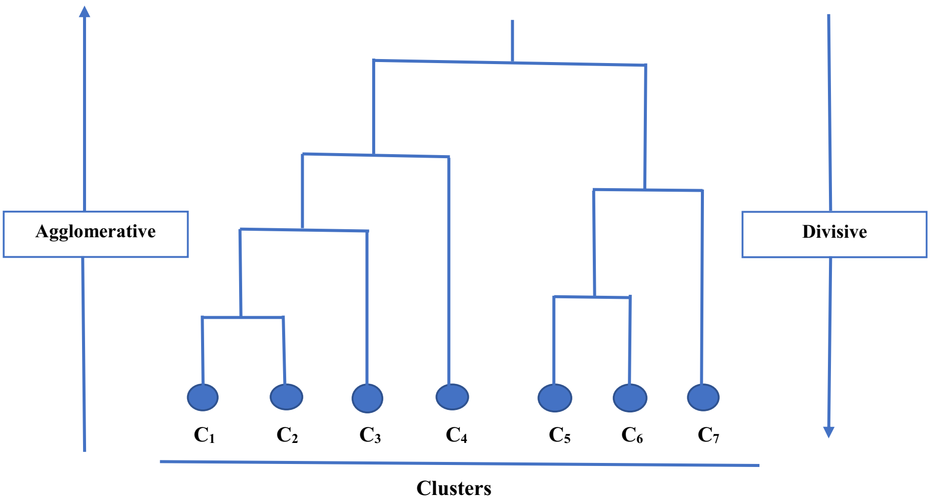

Fig. 5 Categories of hierarchical clustering [103]

Table 3 Major techniques of hierarchical clustering for image segmentation

Category	Techniques	Remarks
Divisive	DIVCLUS-T [18]	It works reasonably better, despite the monothetic constraint, for small number of cluster partitions. At varying levels of similarity, nested grouping is used.
	DITFC [42]	When the training data is sparse, this algorithm outperforms feature selection procedures such as information gain and mutual information in terms of classification accuracy. As a result, this divisive clustering method is a best way to reduce the model complexity of a hierarchical classifier.
	DHCDC [62]	The diameter criteria are used in divisive hierarchical clustering algorithms, which work by iteratively selecting the largest cluster and splitting it into two clusters with the smallest diameters feasible. It was necessary to set the number of clusters.
	CDHC [90]	Using a variable parameter strategy based on spatial cluster characteristics, this technique can extract the internal differentiation regularity of a geospatial objects cluster. This approach avoids the uncertainty that deterministic parameters might cause, as well as the considerable computational cost that typical hierarchical clustering algorithms need.
	SMAA-MDHC [71]	This clustering method, categories alternatives into homogeneous groups with analogous preferences. It gives reasonable and robust solutions.
	VC [16]	The method is based on divisive hierarchical clustering and employs iterative binary splitting of the given image colour space using axis-parallel planes. A few Lloyd–Max iterations after each split can improve the effectiveness of VC at a cost of roughly 6% computing overhead.
	SLINK [60]	This method is good over traditional partitional-based clustering because it does not require the number of clusters as input. However, it does not scale well for huge datasets due to its high time complexity and intrinsic data dependencies.
	CLINK [125]	In this procedure, each object is initially placed in its own cluster, then the clusters are serially combined into larger clusters until all of the data objects are merged into one. Two clusters separated by the shortest distance are joined at each phase.
	UPGMA [61]	The Average linkage or Unweighted Pair Group Algorithm with Arithmetic Mean (UPGMA) is a simple agglomerative hierarchical clustering method. To recreate the structure inherent in a pair wise similarity matrix, its paradigms an entrenched tree. Every iteration, the two clusters that are closest to each other are merged into a higher-level cluster.
	WPGMA [105]	The WPGMA method is identical to the UPGMA scheme, but the distances between newly generated clusters and the rest are weighted according to the quantity of data objects in every cluster.
	UPGMC [13]	Unweighted Pair Group Method Centroid (UPGMC) is also called Centroid linkage method. This method combines the two nearest clusters into a single cluster based on the distance among the centroids of every individual cluster.
	BIRCH [161]	This algorithm is created in order to provide an iterative and interactive categorization tool; however, it might also be used to image compression. It aids in the processing of huge data sets with limited number of resources. Sensitive to noise and outliers.
	CURE [63]	This approach employs a new hierarchical clustering algorithm that sits in the middle of the centroid-based and all-point extremes. It is more resistant to outliers and detects clusters with non-spherical shapes and large size differences. On overlapping clusters, the performance is poor.
	CHAMELEON [75]	This algorithm most notable feature is that it both interconnection and closeness are taken into account in determining which clusters are the most related. For huge datasets, computation is expensive. It is not reliant on a static, user-supplied model and may adjust to the internal properties of the merged clusters automatically.

4.1.1 Divisive clustering

Divisive clustering is a top-down strategy that begins with a singletons cluster or model including all data points and recursively divides it. Initially, all of the data items were assigned to a singletons cluster. This singletons cluster is subdivided into small cluster still a stopping criterion is met or each data item becomes its own cluster. This clustering technique is more complicated than agglomerative clustering because it splits the data till each cluster has only one data item. If every cluster is not divided into distinct data leaves, divisive clustering method will be computationally proficient. This has high computing costs and model selection difficulties, just like agglomerative clustering. Furthermore, because data might be divided into two clusters in the first phase, it is quite sensitive to initialization. Divisive clustering has a high temporal complexity (n^2). Furthermore, divisive clustering is more accurate than top-level partitioning since it considers the global distribution of data while partitioning data. Popular approaches in this area include divisive clustering (DIVCLUS-T) [18], Divisive information theoretic feature clustering (DITFC) [42] and divisive hierarchical clustering with diameter criterion (DHCDC) [62], Cell-dividing hierarchical clustering (CDHC) [90], Stochastic Multi-objective Acceptability Analysis (SMAA) - Multicriteria Divisive Hierarchical Clustering (SMAA-MDHC) [71] and Variance-Cut (VC) [16]. The pros and cons of the divisive clustering are as follows:

The pros are:

- Additionally, it is not necessary to provide a number of clusters in advance while using this approach.
- The divisive algorithm gives more accurate result by taking global distribution of data when making top-level partitioning decisions.
- When making top-level partitioning decisions, divisive clustering considers the global distribution of data.
- Divisive clustering is more efficient if we don't create a complete data hierarchy.

The cons are:

- Rigid, i.e., once a splitting operation has been performed on a cluster, it cannot be undone.
- There is no prior information concerning the minimum required number of clusters.
- Because of the large space and time complexities, the techniques are not suitable for huge datasets.
- The algorithm is Sensitivity to noise and outliers.

4.1.2 Agglomerative clustering

This clustering technique follows bottom-up strategy in which each entity represents its own cluster, which is subsequently combined iteratively until the desired cluster structure is attained. The N-sample algorithm begins with N clusters, each of which contains a single sample. Then, until the number of clusters is decreased to one or the user specifies, two clusters with the greatest similarity will be combined. The parameters used in this approach are minimum, maximum, average, and centre distances. A naive agglomerative clustering has a time complexity of $O(n^3)$, which can be decreased to $O(n^2)$ utilising optimization procedures. Single Linkage (SLINK) [60], Complete Linkage (CLINK) [125], Average Linkage or Unweighted Pair Group Algorithm with Arithmetic Mean (UPGMA) [61], Weighted Pair Group Algorithm with Arithmetic Mean (WPGMA) [105], Unweighted Pair Group Method Centroid (UPGMC) [13], Balanced iterative reducing and clustering using hierarchies (BIRCH) [161], clustering using representatives (CURE) [63], and CHAMELEON [75] are three common agglomerative strategies. The pros and cons of the agglomerative clustering are as follows:

The Pros are:

- There is no need to pre-specify the number of clusters in agglomerative clustering.
- It uses its decisions on the differences that exist between the things that are to be classified together.
- It can generate an object ordering that may be useful for the display.
- The Agglomerative Clustering method will break the data up into smaller clusters, which may discover similarities in data.

The Cons are:

- Only in certain circumstances does the agglomerative approach produce the greatest results.
- The method can't undo previous work, so if items were erroneously sorted, the same outcome should be nearby.
- Varied distance metrics can provide different results when calculating distances between clusters.
- Due to the high time and space complexity, it is not suitable for huge datasets.

Algorithms 1 and 2 show the pseudocode for the divisive and agglomerative clustering techniques, respectively

Algorithm 1 Divisive clustering

1.	**Input:** Initialize the number of clusters to be formed.
2.	Consider all data points as a single cluster.
3.	**Repeat**
4.	Choose the best cluster among all clusters which have the largest inter-cluster distance.
5.	Divide the cluster into two clusters.
6.	Update the divide clusters and Input data set.
7.	**Until** (*Each data is in its own singleton cluster*)
8.	**Output:** Clustered data.

Algorithm 2 Agglomerative clustering

1.	**Input:** Initialize the number of clusters to be formed.
2.	Consider each data points as a single cluster.
3.	**Repeat**
4.	Search closest cluster pair with minimum distance.
5.	Merge the closest cluster pair into single cluster.
6.	Update the merged cluster and Input cluster set.
7.	**Until** (*Only a single cluster remains*).
8.	**Output:** Clustered data.

4.2 Partitional clustering techniques

Due to its computing efficiency, partitional clustering is more common and preferable than hierarchical clustering, particularly for huge datasets. In this clustering approach, the idea of commonality is used as the measuring parameter. In general, partitional clustering divides data into clusters based on an objective function, with data from one cluster being more equivalent to data from other clusters. To accomplish this, the commonality of every data item to each cluster is calculated.

Furthermore, in partitional clustering, the overall concept of the objective function is the minimization of the within-cluster commonality factors, which is commonly calculated utilising Euclidean distance. The objective function represents the quality of each formed cluster and produces the finest presentation from the clusters that have been generated. Furthermore, partitional clustering algorithms ensure that every data element is allotted to a cluster, even if it is located much further from the cluster center. This can lead to cluster shape distortion or erroneous results, especially when there is noise or an outlier.

Image segmentation, robotics, wireless sensor networks, web mining, corporate management, and medical sciences are just a few of the fields where partitional approaches have been used. The data distribution and complexity vary by application domain.

As a result, a single partitional clustering method may not be appropriate for all cases. As a result, the appropriate method is chosen based on the problem and dataset. Hard clustering and soft clustering are the two basic types of partitional image clustering techniques. A pixel becomes a part of a single cluster in hard clustering. As a result, there is a binary membership (i.e., 0 or 1) between clusters and elements. This technique calculates all of the cluster centres and then assigns the elements to the closest cluster. One of the most notable examples of hard clustering is K-means [113]. Soft clustering, on the other side, uses fractional membership, as opposed to hard clustering, which makes it more practical for real-world applications. A pixel can belong to multiple clusters with varying degrees of membership, which are denoted by fractional membership. Fuzzy C-means (FCM) is one of the examples of soft clustering technique that was suggested by Bezdek [12]. The FCM outperforms hard clustering techniques such as K-means in terms of its ability to deal with ambiguity in grey levels.

4.2.1 Classical K-means (KM) Clustering: A pixel based image segmentation strategy

Suppose, we want to segment an image I consisting of N number pixels and L number of gray levels into K clusters. The image I can be regarded as data point set of pixels. Let, $\mathbf{z}_p$ indicates the d components of pixel p. Where d indicates the number of spectral bands presents in the image I. For gray and RGB color image d = 1 and d = 3 respectively.

The K-means algorithm (KM) is a popular clustering technique used for image segmentation in computer vision. KM minimizes the following criteria or objective function [27]:

$$J = \underset{K}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{j=1}^{K} u_{ij} \left\| \mathbf{z}_p^i - \boldsymbol{m}_j \right\|^2 \tag{1}$$

Where, ‖.‖ is an inner product-induced norm in d dimensions which measures the distance among ith pixel $\mathbf{z}_p^i$ and jth cluster center $\boldsymbol{m}_j$. Membership $u_{ij} = 1$ for pixel $\mathbf{z}_p^i$ if it belongs to cluster C_j; otherwise, $u_{ij} = 0$.Now, it is a minimization problem with two steps. At first, we should derogate the objective function J w.r.t. u_{ij} by considering the fixed $\boldsymbol{m}_j$. Then the J is minimized w.r.t. $\boldsymbol{m}_j$ by considering the fixed u_{ij}.

Therefore, the two steps are as follows:

$$\begin{aligned} \frac{\partial J}{\partial u_{ij}} &= \sum_{i=1}^{N} \sum_{j=1}^{K} \left\| \mathbf{z}_p^i - \boldsymbol{m}_j \right\|^2 \\ \Rightarrow u_{ij} &= \begin{cases} 1 \text{if } j = \underset{K}{\operatorname{argmin}} \left\| \mathbf{z}_p^i - \boldsymbol{m}_k \right\|^2 \\ 0 \qquad \text{otherwise} \end{cases} \end{aligned} \tag{2}$$

Therefore, we need to assign the pixels to the closest cluster where the closeness is measured by the span between the concerned pixel and cluster centers. The second step is

$$\begin{aligned} \frac{\partial J}{\partial \boldsymbol{m}_j} &= 2 \sum_{i=1}^{N} u_{ij} \left(\mathbf{z}_p^i - \boldsymbol{m}_j \right) = 0 \\ \Rightarrow \boldsymbol{m}_j &= \frac{\sum_{i=1}^{N} u_{ij} \mathbf{z}_p^i}{\sum_{i=1}^{N} u_{ij}}, \quad 1 \le j \le K \end{aligned} \tag{3}$$

So, recalculation of cluster centers is necessary to divulge the new pixel assignments to the clusters. Relying on the discussion, the algorithm of K-Means clustering is presented as in Algorithm 3.

Algorithm 3 The Classical Pixel based K-Means algorithm for Clustering

1.	Take the number of cluster K and initialize the K cluster centers randomly.
2.	**While** (*termination condition is not satisfied*)
3.	For each pixel, $\boldsymbol{z}_p$ of the image calculates its membership u_{ij} to each center $\boldsymbol{m}_j$.
4.	Recomputed the K cluster centers $\boldsymbol{m}_j$ as per Eq. (3)
5.	**End of While**
6.	**Output:** Segmented image using the final K**cluster centers**.

4.2.2 Classical fuzzy C-means (FCM) clustering: A pixel based image segmentation strategy

Suppose, we want to segment an image I consisting of N number pixels and L number of gray levels into K clusters. The image I can be regarded as data point set of pixels. Let, $\mathbf{z}_p$ indicates the d components of pixel p. Where d indicates the number of spectral bands presents in the image I. For gray and RGB color image d = 1 and d = 3 respectively.

The fuzzy C-means algorithm (FCM) [26, 39, 111] utilizes the principles of fuzzy sets to generate a partition matrix or membership matrix(U) while minimizing the following measure or objective function:

$$J_e = \underset{K}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{j=1}^{K} u_{ij}^{e} \left\| \mathbf{z}_p^i - \boldsymbol{m}_j \right\|^2 \tag{4}$$

Where, ‖.‖ is an inner product-induced norm in d dimensions which measures the distance among ith pixel $\mathbf{z}_p^i$ and jth cluster center $\boldsymbol{m}_j$. Membership or partition matrix $U = [u_{ij}]^{N \times K}$ and $\sum_{j=1}^{K} u_{ij} = 1$. Fuzzy exponent parameter e and $1 \le e \le \infty$. FCM initializes the cluster centers randomly, and then at each iteration, it computes the fuzzy membership of each pixel using the following expression:

$$u_{ij} = \frac{\left(\frac{1}{\left\| \mathbf{z}_p^i - \boldsymbol{m}_j \right\|^2} \right)^{\frac{1}{e-1}}}{\sum_{k=1}^{K} \left(\frac{1}{\left\| \mathbf{z}_p^i - \boldsymbol{m}_k \right\|^2} \right)^{\frac{1}{e-1}}}, \text{ for } 1 \le j \le K; 1 \le i \le N \tag{5}$$

The cluster centers are calculated by using the expression given below:

$$\boldsymbol{m}_j = \frac{\sum_{i=1}^{N} u_{ij} \mathbf{z}_p^i}{\sum_{i=1}^{N} u_{ij}}, \quad 1 \le j \le K \tag{6}$$

Depending on the discussion, the algorithm of FCM clustering is presented as Algorithm 4.

Algorithm 4 The Classical Pixel based Fuzzy C-Means Algorithm for Clustering

1.	Take the number of clusters K and fuzzification parameter e. Initialize randomly the membership partition matrix U^0.
2.	**While** (termination *condition is not satisfied*)
3.	Compute the K cluster centers $\boldsymbol{m}_j$ as per Eq. (6).
4.	For each pixel, $\boldsymbol{z}_p$ of the image calculates its membership u_{ij} to each center $\boldsymbol{m}_j$ using Eq. (5).
5.	**End of While**
6.	**Output:** Segmented image using the final K**cluster centers** and **Membership matrix** U.

4.2.3 Three global challenges of KM and FCM

Although KM and FCM are common clustering techniques, they have three significant shortcomings, which are as follows:

1. **Higher Computational Time:** In the clustering procedure, the distance among all N pixels of the image and the K cluster centres is calculated repeatedly. As a result, as the image size and number of clusters grow larger, a large amount of computational effort is required. Generally, the time complexity of the KM [27, 113] and FCM [39, 85] is O(N × K × d × t). Where, N, d, and Kdenotes the number of pixels, clusters, and dimension correspondingly and generally, $d, K \ll N$. As a result, image size is a major consideration. Finally, t denotes the number of iterations required to finish the clustering process.
2. **Local optima trapping:** Because of the random centre initialization, KM and FCM are avaricious in nature and commonly focuses to local optima, resulting sin vacuous clusters. Because it is a local optimizer, its efficiency is heavily influenced by the original cluster center selection. Various initializations might result in dissimilar clusters. As a result, KM's and FCM's convergence into global optima is a major problem. The numbers of ways of N pixels are sundered into K non-empty clusters are represented by Stirling numbers of the second type:

$$S(N,K) = \frac{1}{K!}\sum_{i=0}^{K}(-1)^{K-i}\binom{K}{i}i^N \tag{7}$$

It can be easily noticed that the number of ways of partition can be approximated by $\frac{K^N}{K!}$ which is colossal number. As a result, the entire enumeration of every potential clustering to identify the global optima of Eq. (1) is clearly computationally prohibitively expensive, unless for very smaller image. In addition to that, it is proved that this non-convex minimization problem is NP-hard even for $d = 2$ or $K = 2$.

FCM is greedy by nature, and because to the random centre initialization, it commonly accumulates to local optima and might even yield empty clusters [26]. Because it is a local optimizer, its efficiency is heavily influenced by the initial cluster center choosing. Various initializations might result in dissimilar clusters. As a result, in FCM, convergence into global optima is a severe issue. It is easy to demonstrate like in K-means that the full enumeration of every potential clustering to discover the global optima of Eq. (4) is unquestionably computationally too expensive, and this non-convex minimization problem is NP-hard.

3. **Sensitive to Noise:** The distributed features of the pixels have a major impact on the convergence rate of KM and FCM. If the image's histogram is identical, it's challenging to discover ideal cluster centres in a short amount of time [27, 39, 85]. However, A histogram with multiple noticeable peaks is simple to cluster. Furthermore, KM and FCM produce poor results for noisy images and take a long time.

4.3 Problem solving strategies

Researchers analyse the three major problems with KM and FCM and report some solutions in the literature. The following section discusses the reported solution strategies for the aforementioned problems.

4.3.1 Image histogram based clustering: A time reduced approach

Both KM and FCM are associated with a good deal of time complexity and this is the main reason for the degradation of its performance with the very large dataset. It is previously mentioned that the time complexity of KM and FCM is O(N × c × d × t), where, N, d, and Kdenotes the number of pixels, clusters, and dimension correspondingly, and generally, d, K $\ll N$. As a result, the size of the image is an enormous matter. The number of iterations required to finish the entire grouping process is denoted by t. To avoid the time complexity problem, segmentation was performed on a grey level histogram rather than image pixels in this paper. Because the grey levels are frequently much less than the number of pixels in the image, the computation time is short. As a result, the histogram-based KM and FCM are presented as follows:

(a) **Histogram based K-Means (HBKM) Algorithm: A Time Reduced Hard Clustering Strategy**

To overcome the significant time complexity problem, this Histogram based K-Means (HBKM) approach clusters on grey level histograms rather than pixels in the image. As a result, the computing time is short because the number of grey levels in an image is typically much fewer than the number of pixels [27, 40]. As a consequence, the objective function may be written as follows:

$$J = \underset{K}{\operatorname{argmin}} \sum_{i=1}^{L} \sum_{j=1}^{K} \gamma_i u_{ij} \left\| g_i - \boldsymbol{m}_j \right\|^2 \tag{8}$$

Where, L indicates the number of grey levels of the image. As an example, there are 256 different grey levels in an 8-bit image. ‖.‖ is an inner product-induced norm in d dimensions which compute the distance between gray level g_i and cluster center $\boldsymbol{m}_j$ and γ_i is the total number of pixels with g_i gray level and hence, $\sum_{i=1}^{L} \gamma_i = N$ and $1 \leq i \leq L$. Membership $u_{ij} = 1$ for pixel $\mathbf{z}_p^i$ if it belongs to cluster C_j; otherwise, $u_{ij} = 0$. Mathematically, in the same way the memberships of the gray levels are calculated as follows:

$$u_{ij} = \left\{ 1 \quad \text{if } j = \underset{k}{\operatorname{argmin}} \left\| g_i - \boldsymbol{m}_k \right\|^2 \text{ 0otherwise} \right. \tag{9}$$

Therefore, we have to disperse the grey levels to the adjoining cluster where the closeness is measured by the distance between the concerned grey levels and cluster centers. These cluster centers are computed by the following expressions:

$$\begin{aligned} \frac{\partial J}{\partial \boldsymbol{m}_j} &= 2 \sum_{i=1}^{L} \gamma_i u_{ij} \left(g_i - \boldsymbol{m}_j \right) = 0 \\ \Rightarrow \boldsymbol{m}_j &= \frac{\sum_{i=1}^{L} \gamma_i u_{ij} g_i}{\sum_{i=1}^{L} u_{ij}} \end{aligned} \tag{10}$$

So, revaluations of cluster centers are obligatory to reveal the new gray level assignments to the clusters. Based on the above discussion, the algorithm of histogram-based K-Means (HBKM) clustering is presented as in Algorithm 5.

Algorithm 5 The Histogram based K-Means algorithm

1.	Take the number of cluster K and initialize the K cluster centers randomly.
2.	**While** (*termination condition does not satisfied*)
3.	For each gray level, g_i of the image histogram calculates its membership u_{ij} to each center $\boldsymbol{m}_j$.
4.	Recomputed the K cluster centers $\boldsymbol{m}_j$ as per Eq. (10).
5.	**End of While**
6.	**Output:** Segmented image using the final K **cluster centers**.

(b) **Histogram based Fuzzy C-Means (HBFCM) Algorithm: A Time Reduced Soft Clustering Strategy**

To overcome the huge time complexity issue, this Histogram based Fuzzy C-Means (HBFCM) [39, 40, 85] method clusters grey level histograms rather than pixels in the image. As a result, because grey levels are typically significantly less than the number of pixels in an image, the computing time is low. Hence, the objective function can be described as

$$J_e = \underset{K}{\operatorname{argmin}} \sum_{i=1}^{L} \sum_{j=1}^{K} \gamma_i u_{ij}^e \left\| g_i - \boldsymbol{m}_j \right\|^2 \tag{11}$$

Where, L denotes the number of gray levels of the image. As an example, there are 256 different grey levels in an 8-bit image. ‖.‖ is an inner product-induced norm in d dimensions which compute the distance between gray level g_i and cluster center $\boldsymbol{m}_j$ and γ_i is the total number of pixels with g_i gray level and hence, $\sum_{i=1}^{L} \gamma_i = N$ and $1 \le i \le L$. Fuzzy exponent e and $1 \le e \le \infty$. The members. Membership or partition matrix $U = [u_{ij}]^{L \times K}$ and $\sum_{j=1}^{K} u_{ij} = 1$. The following is how the membership and centres are calculated:

$$\boldsymbol{m}_j = \frac{\sum_{i=1}^{L} \gamma_i u_{ij}^e g_i}{\sum_{i=1}^{L} \gamma_i u_{ij}^e}, 1 \le j \le K \tag{12}$$

$$u_{ij} = \frac{\left(\frac{1}{\left\| g_i - \boldsymbol{m}_j \right\|^2} \right)^{\frac{1}{e-1}}}{\sum_{k=1}^{K} \left(\frac{1}{\left\| g_i - \boldsymbol{m}_k \right\|^2} \right)^{\frac{1}{e-1}}}, \text{for } 1 \le j \le K, 1 \le i \le L \tag{13}$$

Because of histogram-based clustering, a membership partition matrix $\mathrm{U} = [\mathrm{u}_{\mathrm{ij}}]^{\mathrm{L} \times \mathrm{K}}$ is obtained. But, u_{ij} is a fuzzy membership of gray value i with respect to cluster j, a new membership partition matrix $\mathrm{U}' = \left[\mathrm{u}'_{\mathrm{ij}} \right]^{\mathrm{N} \times \mathrm{K}}$ which corresponds to the original full image I(x, y), is obtained by:

$$u'_{ij} = u_{ij}, \text{if } I(x, y) = g_i \tag{14}$$

where, $I(x, y)$ indicates intensity value of original image I at location (x, y).

As a result, all the pixels with intensity value g_i correlated with membership value u'_{ij}. Based on the analysis, the algorithm for histogram based fuzzy C-Means (HBFCM) clustering is described as Algorithm 6.

Algorithm 6 The Histogram based Fuzzy C-Means algorithm

1.	Take the number of clusters K and fuzzification parameter e. Initialize randomly the membership partition matrix U^0.
2.	**While** (termination *condition is not satisfied*)
3.	Compute the K cluster centers $\boldsymbol{m}_j$ as per Eq. (12).
4.	For each gray level, g_i of the image calculates its membership u_{ij} to each center $\boldsymbol{m}_j$ using Eq. (13).
5.	**End of While**
6.	Derive **modified membership partition matrix** corresponding to the full image as per Eq. (14).
7.	**Output:** Segmented image using final K**cluster centers** and **modified Membership matrix**.

In the case of HBKM and HBFCM, some pros and cons which are described below.

1. **Time Complexity:** The key benefit is that reduce the time complexity. The time complexity of HBKM and HBFCM is $O(L \times K \times \mathrm{d} \times t)$, and $L \ll N$ in an image. Where L is determined by the number of bits assigned to each pixel. For an 8-bit image, the value of L is always 256. As a result, the clustering method is independent of image size, resulting in a significant reduction in time complexity when using this histogram-based image clustering method. On the other hand, HBFCM and HBKM have two major drawbacks, one is sensitive to noise and the other is local optima trapping.
2. **Local Optima Trapping:** Because of the random center initialization, HBKM and HBFCM are greedy in nature and converge to local optima frequently. The initial cluster center selection has a significant impact on the efficiency of the HBKM and HBFCM. Different clusters may result from different initializations. As a result, convergence into global optima is a severe issue in both HBKM and HBFCM. In HBKM, the number of ways of L grey levels are partitioned into K non-empty clusters which is represented by Stirling numbers of the second form:

$$S(L,K) = \frac{1}{K!}\sum_{i=0}^{K}(-1)^{K-i}\binom{K}{i}i^L \tag{15}$$

It can be easily seen that the number of ways of partition can be approximated by $\frac{K^L}{K!}$ which is also a big number although $L \ll N$.As a result, finding the global optima of Eq. (8) using the whole inventory of every conceivable clustering is computationally expensive. As a result, this non-convex minimization issue qualifies as NP-hard.

It is true for HBFCM that although $L \ll N$, however, the entire enumeration of all potential clustering to obtain the global optima of Eq. (11) is unquestionably computationally costly. As a result, this non-convex minimization issue qualifies as NP-hard.

3. **Sensitive to Noise:** It is previously stated that A histogram with multiple noticeable peaks is straightforward to cluster. However, noise obliterates the histogram's peaks and alters the features of the pixel's dispersal throughout the image. As a result, clustering based only on histograms produces poor results and takes a long time.

4. **Problem with Color image:** Extending the histogram-based clustering technique to segment color images is difficult due to the complexity of determining the color image's histogram [112]. Another reason is that the number of different colors is large and hence, it often goes near to the number of pixels present in a color image. Superpixel can be utilized to deliberate this problem.

4.3.2 Noise robust K-means and fuzzy C-means approaches

The summaries of strategies that are utilized to make KM and FCM noise-robust are as follows: (i) incorporation of spatial information, or adaptive spatial information, or weighted spatial information into KM and FCM; (ii) filtering of noisy images before the commencement of actual clustering process. Some notable filtering techniques are Mean filter, median filter, non-local mean filter, morphological reconstruction, bilateral filter; (iii) Filtering of membership [39, 85] or incorporation of spatial information into membership function of FCM [93].

For example, Ahmed et al. [6] proposed the FCM method considering spatial constraints (FCM_S) based on local spatial information. In FCM_S, the cost function of the original FCM has been modified by considering the inhomogeneity intensity and the labelling of a pixel influenced based on the labels in its nearest immediate neighbourhood. The main issue of FCM_S was its large computational time due to the computation of local information median filter. However, both the variant unable to deliver satisfactory outcomes over different noise-corrupted images. Szilagyi et al. [35] developed an Enhanced FCM (EnFCM). EnFCM is based on the linearly weighted sum image, which is estimated from the input image and the average gray level of the local neighbourhood of each pixel. Here, the clustering is performed using the gray level histogram. As a result, a reduced computational time is observed. However, the segmentation accuracy of EnFCM is only comparable to FCM_S. The segmentation accuracy of EnFCM depends on the parameter α (or λ), the size of the chosen window and the filtering method used. Krinidis and Chatzis [82] proposed a parameter-free FCM variant called fuzzy local information c-means clustering algorithm (FLICM), which incorporated a state-of-art fuzzy factor into the cost function to deliberate the parameter α (or λ) of EnFCM. The fuzzy factor enhanced the ability of noise reduction and sharpness preservation. The main demerit of FLICM was the utilization of fixed spatial distance, which degraded the robustness. Gong et al. [58] incorporated a local variable coefficient instead of static to develop a superior variant of FLICM called Reformulated FLICM (RFLICM). Later, the same author developed another variant of FLICM (KWFLICM) [59] by incorporating a trade-off mechanism of weighted fuzzy factor and a kernel metric to increase the performance regarding noise reduction and outliers. But KWFLICM was a parameter-free variant but had a higher computational time compared to FLICM.

The approaches mentioned above suffer from high computational costs due to the repetitive computation and incorporation of local spatial information into objective function. In order to reduce the cost of computation without discarding local spatial information, proposed by Chen and Zhang [19] two variants of FCM_S known as; FCM_S1 and FCM_S2 depending on the use of mean and median filters respectively over the image before the starting of iteration stage. Therefore, time was reduced because of the pre-computation of local spatial information of the image. As FCM_S1 utilized a mean filter, it was robust to Gaussian noise. On the other hand, FCM_S2 robust to salt & pepper noise due to the utilization of the median filter. A fast and robust FCM (FRFCM) in [85] proposed by Lei et al., where a morphological reconstruction-based (MR) approach was applied to reduce the error due to noise. Niharika et al. [110] utilized median filter before applying K-means based clustering in Synthetic Aperture Radar (SAR) image segmentation field. Due to the application of median filter, K-means utilized not only the gray level information, but spatial information also. Finally, morphological closing reconstruction was incorporated to provide accurate segmentation. The experimental results proved that the proposed segmentation technique associate with less error percentage in a noisy environment. In addition to that, some improved or adaptive K-means variants had been developed. For example, Yao et al. [157] proposed an improved K-means algorithm by combining the traditional K-means, Otsu technique, and morphological reconstruction for the accurate segmentation of fish images. At first, the number of clusters was determined by the number of prominent gray histogram peaks. Then cluster centers computed by traditional K-means were filtered by comparing the mean with the threshold computed by Otsu. Finally, morphological opening and closing operations had been employed to find the contour of the fish body.

Filtering of membership also makes the FCM noise robust. For instance, median filtering has been applied to the membership matrix to decrease pixel misclassification due to noise. The membership filtering can be done on each iteration, but this will significantly increase the processing time, making the method more complex. As a result, membership filtering is performed only once over the final membership matrix generated, resulting in a reduction in computing effort. In reality, the fuzzy C-means use local spatial information in the same way as membership filtering does to improve segmentation accuracy. Membership filtering [26, 111] can be used to take the place of incorporating local spatial information.

4.3.3 Superpixel image based segmentation: A noise robust and time reduced approach

Although many updated algorithms solve the issue by including local spatial information in the cost function, this promotes higher computational complexity. The above said FCM variants are challenging to apply for color images. Fortunately, superpixel [92] can handle the problem. Superpixel is a pre-processing image task which over-segments an image into several smaller sections. In an image, a superpixel region is typically characterised as homogenous and cognitively uniform sections [143]. Due to two benefits, Superpixel can improve image segmentation effectiveness and efficiency. On the one hand, superpixel can do image pre-segmentation based on the images' local spatial information. Commonly, neighbouring windows used by FCM S, FLICM, FGFCM, KWFLICM, NWFCM, NDFCM, and FRFCM provide poorer local spatial information than the pre-segmentation obtained by superpixel. Superpixel, on the other hand, can reduce the number of different pixels in an image by replacing all pixels in a region with the superpixel region's mean value [20, 80]. Some basics superpixel generators can be found in [130]. Lei et al. [84] developed a superpixel-based fast FCM clustering technique (SFFCM) for color image segmentation that was substantially faster and more robust than existing clustering techniques. To create a superpixel image with correct contour, a multi-scale morphological gradient reconstruction (MMGR) procedure was initially performed. In contrast to traditional adjacent windows of fixed shape and size, the superpixel image delivers more adaptive and irregular local neighbours that help in color image segmentation. Second, the original color image is effectively condensed based on the generated superpixel image, and its histogram is easily generated by counting the number of pixels in each superpixel region. Ultimately, the superpixel image was subjected to FCM using the histogram parameter to achieve the final segmentation result. The experimental results over the noisy synthetic image and general color images demonstrated that the SFFCM was superior to state-of-the-art clustering algorithms. Wu et al. [149] presented an improved SFFCM approach (ISFFCM), which substitutes fuzzy simple linear iterative clustering for the MMGR in SFFCM (Fuzzy SLIC). For the majority of types of noise, such as Gaussian, multiplicative and salt and pepper, Fuzzy SLIC outperforms MMGR in terms of performance and robustness. Anter and Hassenian [8] employed FCM over adaptive watershed generated superpixel images. The findings reveal that the proposed FCM variant takes less time to compute and performs better on non-uniform CT images by considering less sensitivity to noise. Kumar et al. [83] have suggested a super-pixel-based FCM (SPOFCM) strategy that incorporates the consequences of spatially neighbouring and equivalent superpixels and yielded excellent results.

Another usefulness of superpixel is the reduction of time complexity of FCM when segmenting color as well as gray images. Histogram based clustering is tough to apply for color images. The number of regions in the super-pixel image is significantly less than the original color image's pixel count. Therefore, the computational time can be reduced to some extent by using superpixel images especially for color images.

(a) **Clustering based Superpixel image Segmentation**

Clustering based on superpixels for color image segmentation [84], the objective function is taken as:

$$J_{SC} = \sum_{l=1}^{ns}\sum_{k=1}^{K} S_l u_{kl}^{e}\left\|\left(\frac{1}{S_l}\sum_{p\in R_l}\boldsymbol{z}_p\right)-\boldsymbol{m}_k\right\|^2 \tag{16}$$

Where, l is color level and $1 \leq l \leq ns$, the number of regions in the superpixel image is given by ns. S_l is the number of pixels in the lth region R_l, and z_p is the color pixel within the lth region of the superpixel acquired by any superpixel generating method.

For hard clustering like K-Means, the membership U and centers have been computed as follows:

$$\boldsymbol{m}_k = \frac{\sum_{l=1}^{ns} u_{kl}^{e}\sum_{p\in R_l}\boldsymbol{z}_p}{\sum_{l=1}^{ns} S_l u_{kl}^{e}} \tag{17}$$

$$u_{kl} = \begin{cases} 1 & \text{if } k = \underset{K}{\operatorname{argmin}}\left\|\left(\frac{1}{S_l}\sum_{p\in R_l} z_p\right)-\boldsymbol{m}_k\right\|^2 \quad 0 \text{otherwise}\end{cases} \tag{18}$$

For soft clustering like FCM, the membership U and centers have been computed as follows:

$$u_{kl} = \frac{\left\|\left(\frac{1}{S_l}\sum_{p\in R_l} z_p\right)-\boldsymbol{m}_k\right\|^{-2/(e-1)}}{\sum_{j=1}^{K}\left\|\left(\frac{1}{S_l}\sum_{p\in R_l} z_p\right)-\boldsymbol{m}_j\right\|^{-2/(e-1)}} \tag{19}$$

The K cluster center $\boldsymbol{m}_k$ has been computed by the Eq. (17). Therefore, the algorithms for superpixel based KM, FCM, and NIOA are represented as Algorithm 7, 8, and 9 respectively.

Algorithm 7 The Superpixel based K-Means algorithm for Clustering

1.	Compute ns superpixel region by using any superpixel generating technique.
1.	Take the number of cluster K and initialize the K cluster centers randomly.
2.	**While** (*termination condition is not satisfied*)
3.	For each superpixel, calculates its membership u_{ij} to each center $\boldsymbol{m}_j$ as per Eq. (18)
4.	Recomputed the K cluster centers $\boldsymbol{m}_j$ as per Eq. (17)
5.	**End of While**
6.	**Output:** Segmented image using the final K**cluster centers**.

Algorithm 8 The Superpixel based Fuzzy C-Means Algorithm for Clustering

1.	Compute ns superpixel region by using any superpixel generating technique.
2.	Take the number of clusters K and fuzzification parameter e. Initialize randomly the membership partition matrix U^0.
3.	**While** (stopping condition) does not meet
4.	Compute the K cluster centers $\boldsymbol{m}_j$as per Eq. (17).
5.	For each superpixel, calculates its membership u_{ij} to each center $\boldsymbol{m}_j$using Eq. (19).
5.	**End of While**
6.	**Output:** Segmented image using the final K**cluster centers** and **Membership matrix** U.

Algorithm 9 General strategy of Superpixel based Clustering using NIOA

1.	Compute ns superpixel region by using any superpixel generating technique.
2.	Take the objective functions as prescribed in Eq. (16).
3.	Initialize each NIOA solution with K cluster centres chosen at random.
4.	Evaluate each solution's fitness by allocating every superpixel to a cluster/clusters based on the distance rule of the relevant algorithm.
5.	**While** (termination *condition is not satisfied*)
6.	Using NIOA's operators, update the solution.
7.	For every solution of NIOA
8.	For every pixel of the image
9.	Evaluate the distance between every superpixel and the centre of every cluster.
10.	According to the distance rule of the relevant algorithm, allocate the superpixel to the cluster/clusters.
11.	Again, evaluate the fitness of the solutions.
12.	Choose the finest global solution.
13.	**End of While**

4.3.4 Nature-Inspired Optimization Algorithms (NIOA) based Clustering: An efficient way to tackle local optima trapping

It is previously noticed that although we are able to time complexity but both classical and histogram-based KM and FCM are regarded as NP-hard and frequently stuck into local optima. The main contribution to solve this local optimum trapping problem is the utilization of Nature-Inspired Optimization Algorithms (NIOA) which are optimization methods used to find the optimal solution for complex problems where mathematical approaches are ineffective [32, 37, 38, 41].

By simulating the behaviour of natural and biological systems, nature-inspired optimization algorithms have been developed. They are simple and effective techniques for dealing with very non-linear and multi-modal real-world issues. According to the No Free Lunch (NFL) theory, just because one algorithm is good at one type of problem does not mean it will be good at all types of problems [147]. As a result, a slew of NIOAs have sprouted up in several optimization fields. Some well-known NIOA are Genetic Algorithm (GA) [57], Differential Evolution (DE) [116], Ant colony optimization (ACO) [96], Particle swarm algorithm (PSO) [44], Artificial bee colony (ABC) [74], Firefly algorithm (FA) [153], Cuckoo Search [156], Bat Algorithm [154], Flower Pollination Algorithm [155] etc. In [our five survey studies [6, 40, 58, 82, 93], we present an overview of NIOA and its characteristics. Image clustering is considered an optimization issue by NIOA, and it is solved repeatedly by minimising or exploiting one or more objective functions. The general procedure of NIOA is represented as Algorithm 10.

Algorithm 10 General procedure of NIOA

1.	**Population Initialization:** For an optimization problem, create random solutions and then fix them if any of the constraints are violated;
2.	Assess all initialized individuals;
3.	**While** (*terminate condition*) does not meet
4.	Regenerate individuals in order to create a new population.
5.	Assess the fitness of every solution.
6.	Choose solutions with higher fitness values.
7.	Update the archiving solutions.
8.	**End of while**
9.	**Output:** Relatively good solution(s).

Algorithm 11 General approach of Pixel based Clustering using NIOA

Algorithm 11. General approach of Pixel based Clustering using NIOA	
1.	Take the objective function.
2.	Initialize every solution to contain randomly selected K cluster centers.
3.	Calculate each solution's fitness by allocating each pixel to a cluster/clusters based on the distance rule of the concern algorithm.
4.	**While** (*termination condition does not satisfied*)
5.	Using NIOA's operators, update the solution.
6.	For every solution of NIOA
7.	For every pixel of the image
8.	Computes the distance between each pixel and the center of each cluster.
9	Allocate pixels to the cluster/clusters based on the distance rule of the concerned algorithm
10.	Again, compute the fitness of the solutions.
11.	Choose the optimum global solution.
12.	**End**

Algorithm 12 Procedure of the histogram based Hard Clustering using NIOA

1.	Take the objective function as per Eq. (8).
2.	Initialize every solution of NIOA to contain randomly selected K cluster centers.
3.	**While** (*termination condition does not satisfied*)
4.	For every solution of NIOA
5.	For every gray level of the image
6.	Computes distance between each gray level and the center of each cluster.
7.	Allocate the grey levels to the clusters based on their distance.
8.	Computes the fitness of every solution
9.	Identify the optimum global solution or the optimal K cluster centers.
10.	Using NIOA's operators, update the solution.
11.	**end while**
12.	**Output:** Segmented image using final K **cluster centers**.

Algorithm 13 Procedure of the histogram based Fuzzy Clustering using NIOA

1.	Consider the objective function as per Eq. (11).
2.	Initialize every solution of NIOA to contain randomly selected K cluster centers and also initialize the Membership partition matrices.
3.	**While** (*termination condition does not satisfied*)
4.	For every solution of NIOA
5.	For every gray level of the image
6.	Compute membership of the gray level to the clusters.
7.	Compute the fitness of every solution
8.	Identify the optimum global solution or optimal K cluster centers and membership partition matrix.
9.	Using NIOA's operators, update the solution.
10.	**end while**
11.	Find corresponding modified membership partition matrix as per Eq. (14).
12.	**Output:** Segmented image using final K**cluster centers** and **modified Membership matrix.**

The NIOA stopping, or terminating condition/criteria, is a parameter that specifies when an algorithm should be stopped [33, 93, 120]. For various NIOAs, determining the stopping condition is critical. A number of iterations (NIs), also known as generation, and a number of function evaluations (FEs) are two of the most prevalent types of terminating criteria. According to current research, **FEs** are preferred over **NIs** by today's researchers. The number of iterations is always included when a constructed terminating condition is applied. Other terminating criteria include, exceeded threshold value, optimal solution reached, and the objective function is equal to zero, etc.

In literature some NIOA based crisp and fuzzy clustering have been developed which are mentioned as follows. A modified cuckoo search (CS) [34] based crisp clustering model had been developed which gave superior outcomes compared to traditional CS, PSO, Bat algorithm (BA), Firefly algorithm (FA), and other existing modified CS based clustering models. Traditional CS [31] also showed its efficient performance in the breast histology image clustering domain by outperforming classical K-means. A modified Flower Pollination Algorithm (FPA) [35] based crisp clustering model was also proposed in the pathology image segmentation domain. The suggested modified FPA outperformed various well-known NIOAs such as BA, FA, PSO, and others, according to experimental results. Stochastic Fractal Search (SFS) based crisp clustering technique had been utilized for the accurate segmentation of white blood cells (WBC) from the blood pathology images of leukaemia patients [36]. Numerical results showed that the SFS gave nonpareil outcomes to other tested NIOA and some state-of-the-art image clustering approaches. Dash et al. [29] instigated seeker optimization (SO), artificial bee colony (ABC), ant colony optimization (ACO), and particle swarm optimization (PSO) based on crisp and fuzzy clustering techniques for the optimal lesion segmentation and established satisfactory outcomes. In [76, 78], researchers also announced the NIOA with K-means to implement proper clustering-based image segmentation practices.

NIOA are also employed in fuzzy clustering domain for image segmentation. For example, Tongbram et al. [136] developed whale optimizer based fuzzy clustering model which had the better efficiency over conventional FCM clustering for MRI image segmentation. Vishnoi et al. [141] developed a nuclei segmentation model for breast histology by employing roulette wheel selection whale optimization (RSWOA) based fuzzy clustering. The proposed RSWOA outperformed differential evolution (DE), grey wolf optimizer (GWO), bat algorithm (BA), and grasshopper optimizer (GO) in this fuzzy image clustering domain. Narmatha et al. [107]

developed a brain-storm optimization algorithm based FCM for the precise tumor region segmentation from MRI images. The proposed technique gave competitive results compare to PSO, glow swarm optimization (GSO), and whale swarm optimization (WSO) based clustering models. Tiwari and Jain [135] proposed an exponential grasshopper optimization algorithm-based fuzzy clustering model for histopathological image segmentation. The simulation results demonstrated the efficiency of the proposed one over other tested classical clustering techniques such as K-means and fuzzy c-means. Fred et al. [47] proposed a crow search algorithm (CSA) based FCM for the accurate segmentation of abdomen CT images. The proposed clustering model provided better segmented outcomes compared to Artificial Bee Colony (ABC), Firefly, Cuckoo, Cuckoo Search (CS), and Simulated Annealing (SA) based FCM models. A comparative study among NIOA based KM and NIOA based FCM had been done for skin lesion segmentation by Dash et al. [57]. Experimental results showed that Seeker optimization (SO) algorithm with FCM gave superior results to SO with KM to segment the lesion optimally and SO also provided competitive results compare to ACO, ABC, and PSO. For noisy image segmentation, Rapaka et al. [119] developed a morphological reconstruction fuzzy c-means clustering (MRFCM) based on an improved differential search algorithm for iris image segmentation where morphological reconstruction incorporates the power of noise immunity. The proposed technique outperformed improved particle swarm optimization based morphological reconstruct fuzzy c-means (IPSO-MRFCM), PSO-FCM in terms segmentation accuracy. Depending on the cooperation principle, Abdellahoum et al. [2] developed a Cooperative System using Fuzzy C-Means (CSFCM) methodology by using Biogeography Based Optimization (BBO), Genetic Algorithm (GA), and Firefly Algorithm (FA). Experimental results showed that the CSFCM provided good segmentation result by outperforming other tested algorithms such as PSO and ABC.

There are other ways where NIOA and KM or FCM can be hybridized to develop efficient clustering strategies. The effectiveness and superiority of one NIOA over another is problem dependent, according to the NFL theorem. However, it is also true that the algorithm design perspective has a significant impact on the effectiveness of any algorithm, and NIOA are no exception. As a result, it is clear that some NIOA are flawed in terms of basic abilities such as individual mixing and diversity, a best balance between exploration and exploitation search abilities, and so on. The trade-off between exploration/global search and exploitation/local search affects every NIOA technique. Randomization in the NIOA essentially aids them in performing a global search. As a result, because KM or FCM are very efficient local optimizers and greedy by nature, they can be included into NIOA as a local search component during clustering [40, 113]. As a result, a well-balanced exploration and exploitation is provided by randomization-based global search and traditional clustering algorithm-based local search for the NIOA.

As an instance, Hrosik et al. [66] created an enhanced image clustering strategy based on the Firefly algorithm, where the k-means clustering algorithm improves the Firefly algorithm's results. Experiments indicated that the suggested strategy outperformed traditional KM and NIOA-based clustering algorithms.

Again, the combination of NIOA and KM/FCM can be performed in other way. The global optimal solution discovered by NIOA can be used to start the KM/ FCM algorithm. This concept can help to solve the problem of local trapping caused by random centre initialization. As an instance Li et al. [88] proposed a PSO-based K-Means algorithm for image segmentation, which used the global optimal solution to initialize the K-Means algorithm. Experimental results shows that the approach overcomes the issue of easy falling into local optimum and produced excellent outcomes.

Incorporating the output solutions of the K-means algorithm as input to NIOA is another technique to improve the performance of the algorithm. For example, Nanda et al. [106] improved the efficiency of Galactic Swarm Optimization (GSO) by using the K-means algorithm's resultant solutions as input of GSO. The K-Means method is run for a set number of iterations in this hybrid approach, and the outcome is used as the GSO's population's starting solution. All the above discussed techniques are pixel-based clustering. Some histogram-based clustering techniques are developed in [15, 27, 39, 85, 120, 132] and they gave satisfactory results within less time.

5 Experimental results

The experimental study has been carried out over 100 Rosette plant images and 100 Oral histopathology images using MatlabR2018b and Windows-10 OS, ×64-based PC, Intel core i5 CPU with 8 GB RAM. The following two dataset is used in this study.

1) The Rosette plant images are collected from Computer Vision Problems in Plant Phenotyping (CVPPP) benchmark datasets [99] and the web-link is: https://download.fz-juelich.de/ibg-2/Plant_Phenotyping_Datasets.zip. A1, A2 and A3 datasets are include in benchmark dataset. A1 contains RGB images of wild-type Arabidopsis plants. A2 contains RGB images of four distinct Arabidopsis mutants with varying leaf forms and sizes. A3 dataset consists of tobacco plant images. The genotype, background appearance, and composition of these datasets vary due to the different experimental setups used. The images in each dataset have various dimensions 500 × 530 pixels in A1, 530 × 565 in A2 and 2448 × 2048 pixels in A3.
2) The Oral histopathology images are collected from [117] and the weblink is: https://data.mendeley.com/datasets/ftmp4cvtmb/1. It is the most widely used dataset for oral histopathology images. The dataset contains total 1224 images. The images are split into two groups, each with a different resolution. The first collection includes 89 histological images of normal oral epithelium and 439 images of Oral Squamous Cell Carcinoma (OSCC) at a magnification of 100x. The second collection includes 201 images of normal oral cavity epithelium and 495 histopathological images of OSCC at 400x magnification. The images were taken with a Leica ICC50 HD microscope from H&E-stained tissue slides from 230 patients. The slides were collected, prepared, and catalogued by medical experts.

In the field of agriculture plant growth is the major component that is why plant image analysis play an important role. It allows for the frequent and precise recording of morphological plant features. The growth of the plant analysed by the deeply rely on the leaves and their segmented image. The Rosette plant images are collected from [99], which contain the original images as well as the corresponding ground truth images.

Oral cancer is now a days a common cancer in the world. As per Oral clinicians, it is established that the Oral submucous fibrosis (OSF) initially originates and propagates in the epithelial layer. So, more accurate segmentation of this layer is extremely for clinician to make a diagnostic decision. That is why Oral histopathology plays a very important role to diagnosing the oral cancer. The Oral histopathology images collected from [117]. It consists of total 528 images; out of which of 89 are histopathological images with the normal epithelium of the oral cavity and 439 images are in Oral Squamous Cell Carcinoma (OSCC) category in 100x magnification.

For pre-processing task, the Simple Linear Iterative Clustering (SLIC) is employed to generate superpixels. The four most often used clustering algorithms, namely K-Means (KM), Fuzzy C-Means (FCM), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) has been used for leaf segmentation of Rosette plant images and epithelium layer of Oral histopathology images. A comparative study is done among the above clustering techniques and their performance both with and without superpixel pre-processing. The following are the parameters for the corresponding clustering techniques:

K is the desired number of roughly equal-sized superpixels, takes as input for SLIC algorithm. The approximate size of each super-pixel in an image of N pixels is N/K pixels. Every grid interval would have a superpixel centre for nearly equal-sized superpixels $S = \sqrt{N/K}$. Number of superpixel used to segment the input image (K) = 2000 is set, which is optimally set from the experience. The user determines the number of cluster prototypes, which is set at 3 for all clustering techniques. The KM algorithm is stopped, if the change in centroid values is smaller than η . For FCM, the fuzzification parameter is set to 2, and the procedure is stopped if the largest difference between two successive partition matrices U is lesser than the minimal error threshold η. Mathematically, if $[\mathrm{Max}\{U^t - U^{t+1}\}] < \eta$ *then stop*, where minimal error threshold $\eta = 10^{-5}$.The probabilities of crossover and mutation, the population size, and the number of generations are all factors that are included in Genetic Algorithm. For PSO, the acceleration factors c_1 and c_2 control the impact of the best local and global solutions on the existing solution. In the experiment both c_1 and c_2 are set to 2. The experiment was conducted with a population size (n) = 50. The number of function evaluations $NFE = 500 \times d$ is taken into account for each execution of the tested objective function, as the optimization process's stop condition, where d is the number of clusters. In an optimization problem formulation, this refers to the d-dimensional search space.

5.1 Performance evaluation parameters

To ensure a method's validity, it must be evaluated in terms of its performance. The performance of the utilized clustering techniques has been evaluated by calculating four ground truth-based performance evaluation parameters which are summarized in Table 4. Here, TP - true positive, FP - false positive, TN - true negative, FN - false negative.

In digital imaging processing, the image performance evaluation parameters play a crucial role. Therefore, it's vital to look at the accuracy, precision and other parameters of the clusters created by the methodologies used. It is also important to examine whether the concerned clustering techniques give the higher similarities between the data objects of same cluster and give lower similarities between the data object which are not in the same cluster. Quality evaluation parameters are basically two types, one is Ground Truth (GT) based quality parameters and another one is Referenced or Original image-based quality parameters.

1) **Ground Truth (GT) based quality parameters:** Ground truth-based image segmentation quality parameters namely Segmentation Accuracy (SA) [55], Precision Index (PI) [55], Specitivity Index (SI) [55], Recall Index (RI) [55], Dice Index (DI) [55], Jaccard

Table 4 Performance parameters considered for evaluation of the clustering methods

Sl.	Parameters	Formulation	Remarks
Ground Truth based quality parameters			
1.	Segmentation Accuracy (SA)	$SA = \frac{(TP+TN)}{}(FN + FP + TP + TN)$	The accuracy is one of the most popular metrics for evaluating classification models. We calculate the accuracy to know how good our model predicts. Accuracy comes out to 0.91, or 91% that means the model makes 91 correct predictions out of 100 total examples. Higher value indicates the better results.
2.	Precision Index (PI)	PI=TP/(TP+FP)	Positive predictive value is another term for precision. The percent of pairings appropriately placed in the same cluster is used to calculate precision. Higher the value, then better the outcome.
3.	Specitivity Index (SI)	SI=TN/(TN+FP)	Specitivity is a valuable metric for determining the genuine negative rate because it represents the proportion of negatives that are correctly classified as such. The higher the Specitivity rating, the better the performance.
4.	Recall Index (RI)	RI=TP/(TP+FN)	The recall is the percentage of successfully identified pairs. It's also known as the Sensitivity Index. The higher the recall value, the better the performance.
5.	Dice Index (DI) (F-score, F-measure or Dice)	$DI = \frac{2\times TP}{(2\times TP+FP+FN)}$	It combines information retrieval's precision and recall ideas. It's the arithmetic average of precision and recall. The DI values are in the range [0, 1], and the higher the value, the better the clustering quality.
6.	Jaccard Index (JI)	JI=DI/(2−DI)	The Jaccard similarity index determines how similar two sets are. It's calculated by dividing the size of the intersection of two sets by the size of their union. The greater the value, the more similar the two objects are.
7.	Matthews Correlation Coefficient (MCC)	$MCC = \frac{(TP\times TN-FP\times FN)}{\sqrt{((TP+FP)}}\times(TP + FN)\times(TN + FP)\times(TN + FN))$	(MCC) is a more reliable statistical rate that yields a high score only if the prediction performed well in all of the TP, TN, FP, and FN categories, and proportionally to the number of positive and negative items in the dataset. The higher the value, the better the outcome.
8	Comparison Score (CS)	$CS = \sum_{k=1}^{c} \frac{A_k \cap C_k}{A_k \cup C_k}$	CS stands for the degree of equality between pixel sets and the Ground Truth. A higher CS number denotes a better outcome.
9.	Boundary Displacement Error (BDE)	$BDE = \begin{cases} \frac{u-v}{L-1}, 0 < (u-v) \\ 0, (u-v) \end{cases} < 0$	Calculates the boundary pixel displacement error between two segmented images.
10.	Probability Rand Index (PRI)	$PRI = \frac{a+b}{a+b+c+d} = \frac{a+b}{L}$	Determines whether the segmented image and its ground truth are labelling consistent.
11.	Variation of Information (VoI)	$VoI = H(S_1) + H(S_2) - 2I(S_1, S_2)$	In terms of distance, determines the randomness in one segmentation from a given segmentation.
12.	Global Consistency	$GCE = \frac{1}{n}\{\sum_i E(S_1 , S_2 , p_i), \sum_i E(S_2 , S_1 , p_i)\}$	This metric compares the refinement of one segmentation to the other.

Table 4 (continued)

Sl.	Parameters	Formulation	Remarks
	Error (GCE)		
Referenced image-based quality parameters			
13.	Feature Similarity Index (FSIM)	$FSIM = \sum_{x\in\Omega} \frac{S_L(x).PC_m(x)}{\sum_{x\in\Omega}} PC_m(x)$	Defines the quality score for a local structure, which represents its importance. The higher the value, the better the outcome. .
14.	Root Mean Squared Error (RMSE)	$RMSE = \sqrt{MSE\left(\widehat{\theta}\right)} = \sqrt{E\left\{\left(\widehat{\theta}-\theta\right)\right.}$ $\left.^2\right\}$	Calculates the difference between a model's or an estimator's predicted value and the actual value. Better outcomes are indicated by a low RMSE value.
15.	Peak Signal to Noise Ratio (PSNR)	$PSNR = 10log_{10}\left(2^b-1\right) \frac{2}{\sqrt{MSE}}$	Represents the proportion of a signal's maximum achievable power to the power of corrupting noise. A high PSNR number denotes a better outcome.
16.	Structural Similarity Index (SSIM)	$SSIM = \left(2\times\overline{X}\times\overline{Y}+c_1\right) \frac{\times(2\times\sigma_{XY}+c_2)}{(\sigma_X{}^2+\sigma_Y{}^2+c_2)} \times\left(\overline{X}^2+\overline{Y}^2+c_1\right)$	Determines whether a segmented image and an uncompressed or distortion-free image are similar. A higher SSIM score denotes a better outcome.
17.	Normalized Cross-Correlation (NCC)	$NCC = \frac{1}{n}\sum_{x,y}\frac{1}{\sigma_X}\sigma_Y\left(X(x,y)-\overline{X}\right) \left(Y(x,y)-\overline{Y}\right)$	Images are first adjusted because of lighting and exposure circumstances before being used for template matching. The higher the NCC value, the better the outcome.
18.	Average Difference (AD)	$AD = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\{X(x,y)-Y(x,y)\}$	The average difference between the pixel values is calculated. A lower AD value denotes a better outcome.
19.	Maximum Difference (MD)	$MD=\max\lvert X(x,y)-Y(x,y)\rvert$	The difference between the original image and the segmented image is used to calculate the maximum error signal. A lower MD value denotes a better outcome.
20.	Normalized Absolute Error (NAE)	$NAE = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}\lvert X(x,y)-Y(x,y)\rvert}{\sum_{x=1}^{M}\sum_{y=1}^{N}\lvert X(x,y)\rvert}$	Calculates the absolute difference between the original and segmented pictures, normalised. A low NAE value denotes a better outcome.

Index (JI) [55], Matthews Correlation Coefficient (MCC) [55], Comparison Score (CS) [101], Boundary Displacement Error (BDE) [101], Probability Rand Index (PRI) [101], Variation of Information (VoI) [101], and Global Consistency Error (GCE) [101] are the techniques for represent the quality of the segmented image. For labelling information of the pixel, these parameters are use.

2) **Referenced or Original image-based quality parameters:** Referenced or Original image-based quality parameters namely Feature Similarity Index (FSIM) [28, 101], Root Mean Squared Error (RMSE) [101], Peak Signal to Noise Ratio (PSNR) [28, 101], Structural Similarity Index (SSIM) [101], Normalized Cross-Correlation (NCC) [101], Average Difference (AD), Maximum Difference (MD) [101], Normalized Absolute Error (NAE) [101]. SSIM and FSIM are two of these measures that consider perceived image quality and quantitatively analyse the segmentation results against the consequence of human observers. Instead of using pixel labelling information, these parameters employ pixel information.

5.2 Results and discussion over rosette plant images

KM, FCM, GA and PSO, the four well known clustering algorithm have been utilized to segment the leaves of the rosette plant images. For superpixel creation, SLIC method is used. Firstly, the images are segmented using four simple clustering technique and that has been compared with the superpixel based image clustering technique. The performance between simple clustering and clustering with superpixel pre-processing is discuss in this section. The above clustering method also compared with SFFCM algorithm. Fig. 6 represents the original color rosette plant image and their segmented leaf part by the four utilized algorithms with and without superpixel pre-processing. Figure 7 demonstrates the ground truth images of the leaf segmentation provided by the experts and the binary segmented leaf part provided by the employed clustering algorithms. The visual analysis of the both Figs. 6 and 7 clearly show that the SFFCM provides the best leaf-based segmentation results. Not only visual analysis, the segmentation efficacy of the clustering algorithms has been analysed by computing four well-known segmentation quality parameters namely Accuracy, MCC, Dice and Jaccard. The average values of the segmentation quality parameters over 100 images are given in Table 5. The best numerical values of the Table 5 are given in bold. Most of the values of the quality parameters clearly reveal that SFFCM provides superior outcomes over other clustering algorithms. The graphical representation of the average quality parameters (recorded in Table 5) is also showed in Fig. 8. The average execution times of the four clustering algorithms over 100 images are also presented in Table 5.

It is clearly noticed that use of superpixel as a pre-processing task decrease overall computational time. As an example, for plant images the computational time of PSO algorithm is 14.30 sec but use of superpixel decrease the PSO computational which is 13.73 sec.

5.3 Result and discussion over Oral histopathology images

The four well known clustering algorithm, namely KM, FCM, GA and PSO have been utilized to segment the epithelium layer of Oral histopathology images. For superpixel creation, SLIC method is used. Firstly, the images are segmented using four simple clustering technique and that has been compared with the superpixel based image clustering technique. The performance between simple clustering and clustering with superpixel pre-processing is discuss in this section. The above clustering method also compared with SFFCM algorithm. Figure 9 represents the original color Oral histopathology images and their segmented epithelium layer part by the four utilized algorithms with and without superpixel pre-processing. Figure 10 demonstrates the ground truth images of the epithelium layer segmentation provided by the experts and the binary segmented epithelium layer part provided by the employed clustering algorithms. The visual analysis of the both Figs. 9 and 10 clearly show that the SFFCM provides the best epithelium layer segmentation results. Not only visual analysis, the segmentation efficacy of the clustering algorithms has been analysed by computing four well-known segmentation quality parameters namely Accuracy, MCC, Dice and Jaccard. The average values of the segmentation quality parameters over 100 images are given in Table 6. The best numerical values of the Table 6 are given in bold. Most of the values of the quality parameters clearly reveal that SFFCM provides superior outcomes over other clustering algorithms. The graphical representation of the average quality parameters (recorded in Table 6) is also showed in Fig. 11. The average execution times of the four clustering algorithms over 100 images are also presented in Table 6.

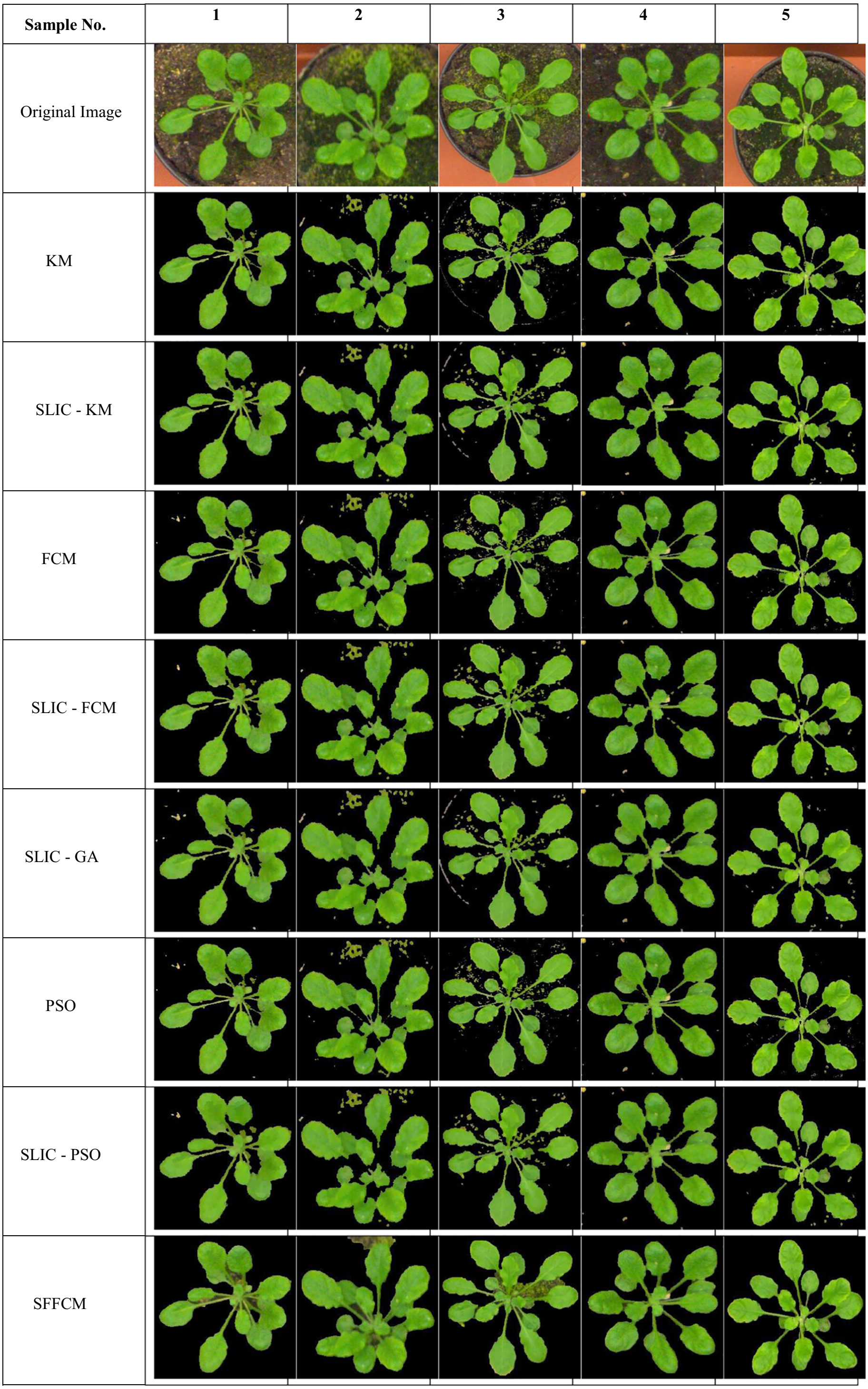

Fig. 6 Segmentation Results of Clustering techniques over five Rosette plant sample images

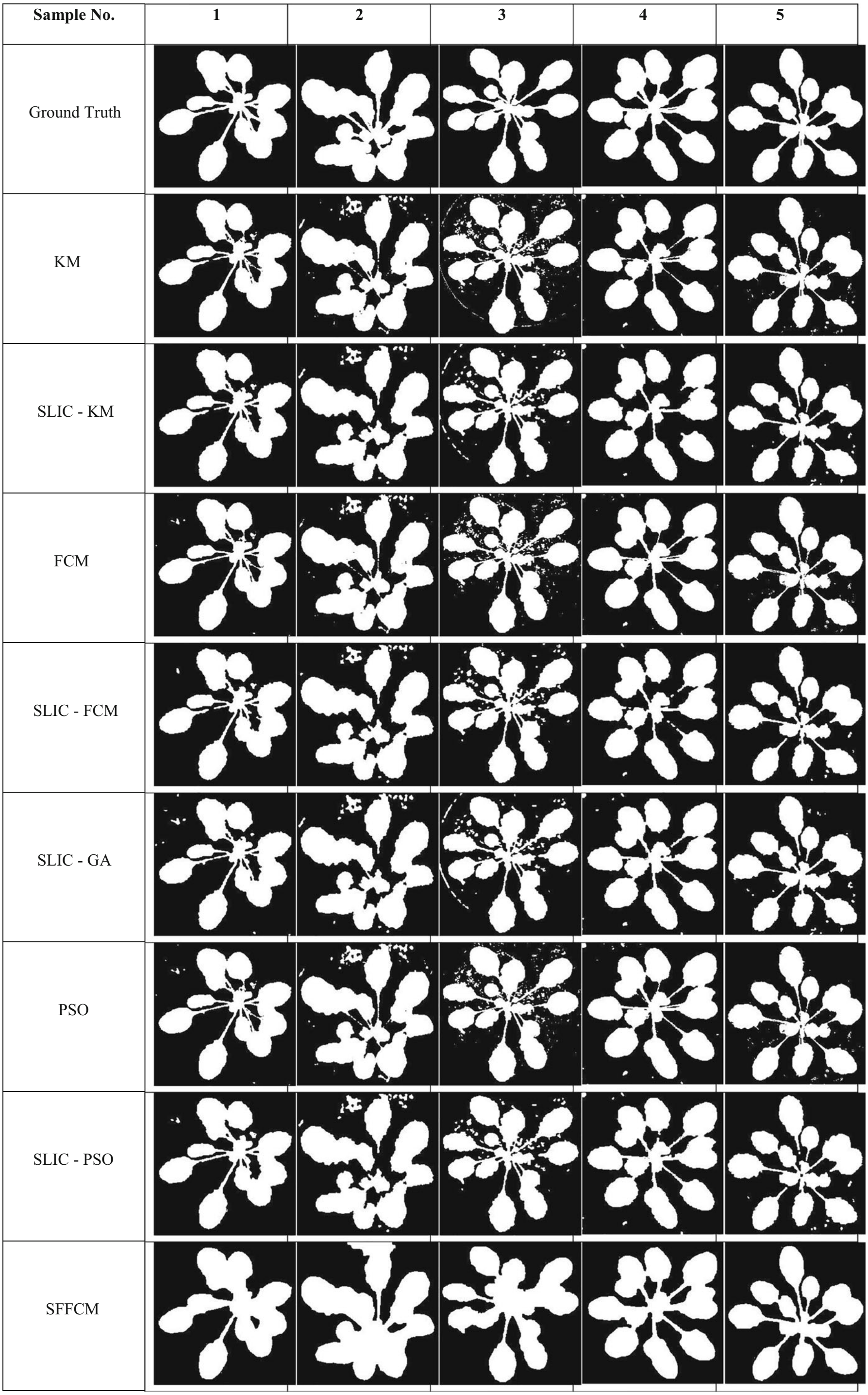

Fig. 7 Comparison among ground truth and binary segmentation results of clustering techniques over five Rosette plant sample images

Table 5 Average Numerical values of segmentation quality parameters over 100 Rosette plant sample images

METHOD	ACCURACY	MCC	DICE	JACCARD	TIME
KM	0.9611	0.9147	0.9427	0.8923	1.30 Sec
SLIC-KM	0.9599	0.9119	0.9407	0.8886	**1.15 Sec**
FCM	0.9659	0.9251	0.9504	0.9060	1.93 Sec
SLIC-FCM	0.9642	0.9213	0.9477	0.9011	1.22 Sec
SLIC-GA	0.9621	0.9164	0.9443	0.8950	49.16 Sec
PSO	0.9661	0.9253	0.9507	0.9064	14.30 Sec
SLIC-PSO	0.9659	0.9247	0.9503	0.9058	13.73 Sec
SFFCM	**0.9664**	**0.9273**	**0.9524**	**0.9096**	1.63 Sec

Best results obtained are given in bold

For Oral histopathology images the execution time of PSO and SLIC-PSO is 14.75 sec and 14.44 sec respectively. It is clearly noticed that use of SLIC pre-processing technique reduce the overall computation time. As the number of superpixel used to segment the input image (K) value depends on user the time complexity for superpixel generation may vary.

6 Conclusion and future directions

Image segmentation is always a demanding task but producing segmented image with an ideal time is very challenging. So, minimizing pixel quantity can decrease the computation time. Another significant advantage of superpixel based image segmentation is the noise immunity capability. In this situation, superpixels are become increasingly popular in many computers vision application. Therefore, this study provides an in-depth review on the utilization of the superpixel images for accurate image segmentation while employed with clustering techniques. The literature survey of the past five years has been presented in Table 1. Then the brief discussion on the recent superpixel generation techniques has also been presented in the paper. However, it is found that selecting the right superpixel algorithm and its parameters for

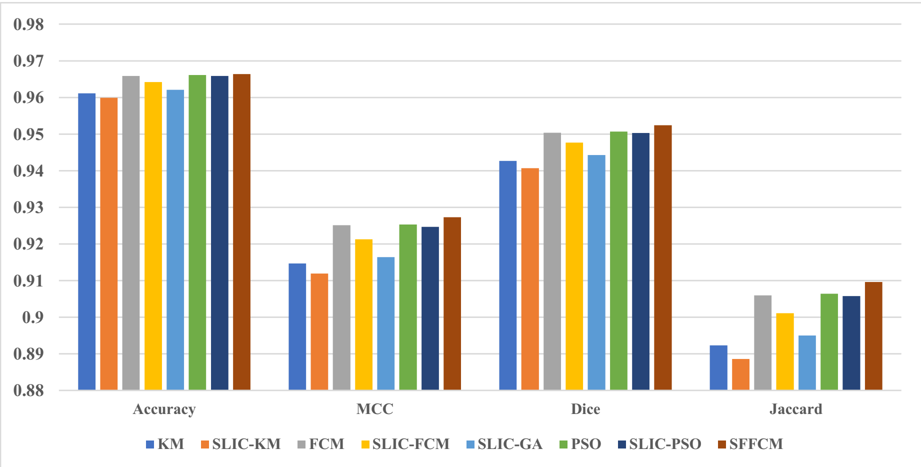

Fig. 8 Graphical analysis of average quality parameters for clustering techniques over 100 Rosette plant sample images

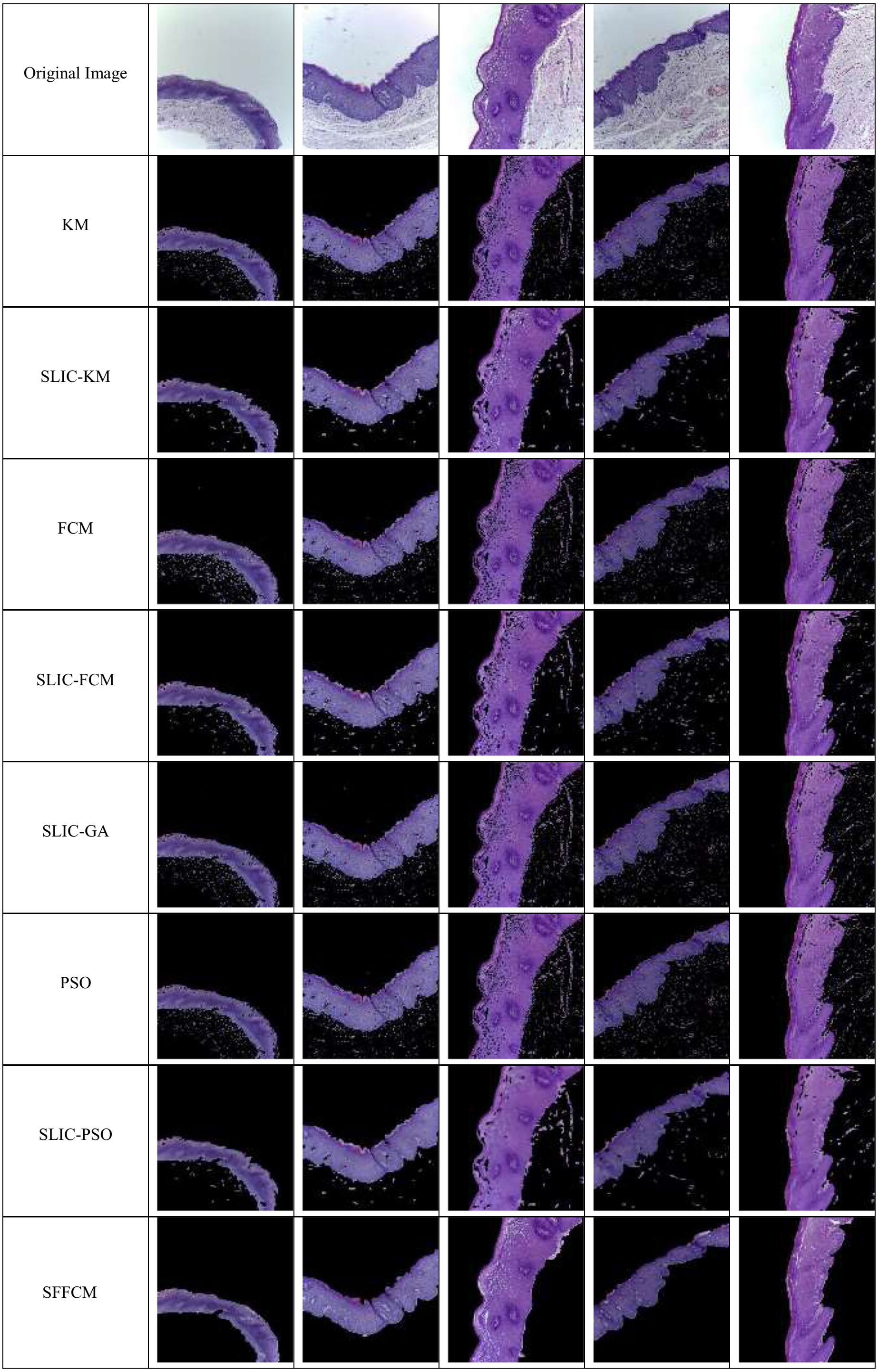

Fig. 9 Segmentation Results of Clustering techniques over five Oral histopathology sample images

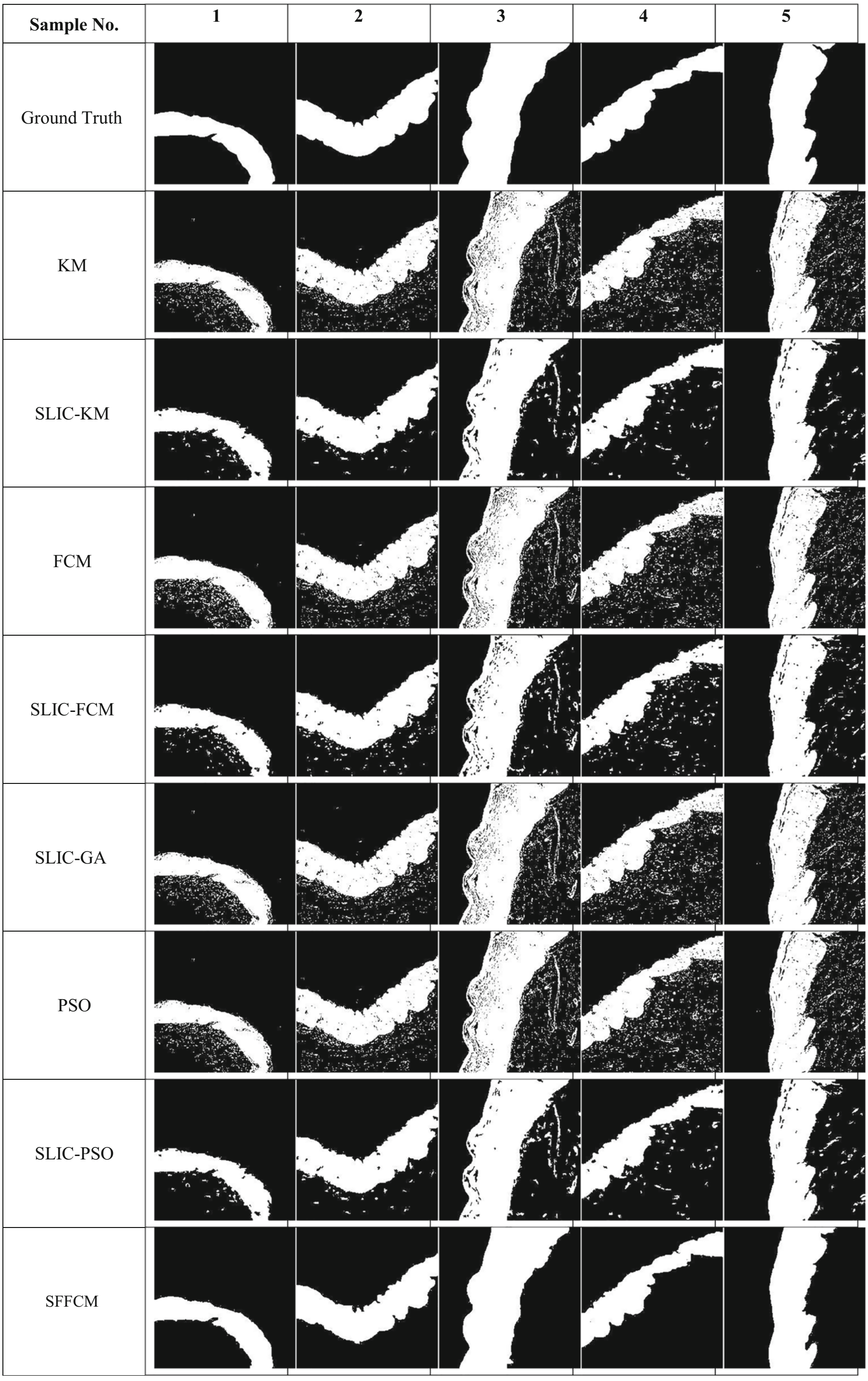

Fig. 10 Comparison among ground truth and binary segmentation results of clustering techniques over five Oral histopathology sample images

Table 6 Average Numerical values of segmentation quality parameters over 100 Oral histopathology sample images

Method	Accuracy	MCC	Dice	Jaccard	Time
KM	0.9470	0.8602	0.8961	0.8148	1.68 Sec
SLIC-KM	0.9672	0.9107	0.9326	0.8764	**1.53 Sec**
FCM	0.9461	0.8585	0.8950	0.8130	2.24 Sec
SLIC-FCM	0.9599	0.8927	0.9201	0.8543	2.14 Sec
SLIC-GA	0.9465	0.8604	0.8963	0.8151	48.58 Sec
PSO	0.9463	0.8591	0.8954	0.8137	14.75 Sec
SLIC-PSO	0.9682	0.9139	0.9359	0.8812	14.44 Sec
SFFCM	**0.9868**	**0.9639**	**0.9730**	**0.9476**	1.68 Sec

Best results obtained are given in bold

the particular application are crucial. But, out of many superpixel algorithms, SLIC is the mostly used superpixel generation algorithm in the published research works. Clustering is a simple but effective image segmentation procedure. Hence, this study concentrates on the measuring their efficacy while employed over superpixel images. A depth presentation and discussion on the well-known clustering techniques and their pros-cons have been performed here. The discussion demonstrates that the ideal dataset for hierarchical clustering is arbitrary shape and attribute of arbitrary type. Hierarchical clustering algorithms create a hierarchy of data pieces, they are suitable for both convex and arbitrary data. Partitional clustering technique is mostly used. Because the image is separated on the basis of different features, the image segmentation approach can be employed according to the application or usage. According to some pre-set objective functions, partitional clustering algorithms produce disjoint clusters. Because of their excellent computing efficiency and low time complexity, partitional clustering algorithms are recommended. Partitional clustering methods are chosen over other clustering approaches for large datasets. Despite the fact that partitional clustering is computationally efficient, the number of clusters must be defined advance. Furthermore, partitional clustering algorithms are sensitive to outliers and can trap local optima in some

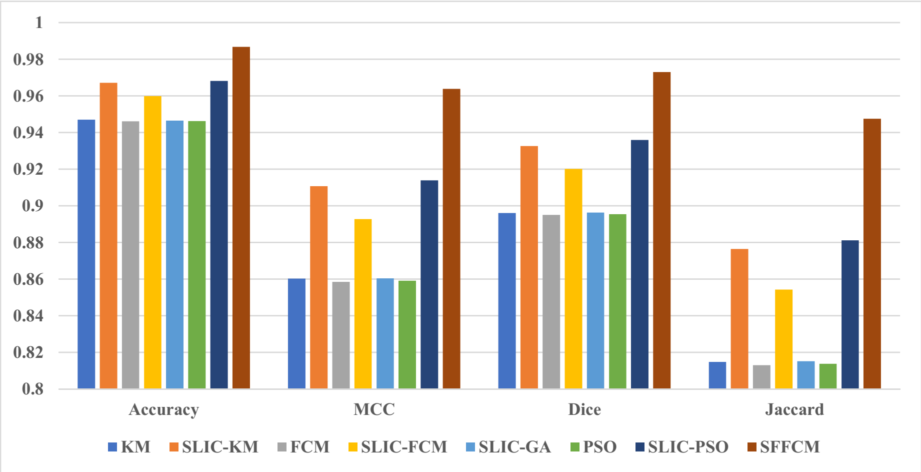

Fig. 11 Graphical analysis of average quality parameters for clustering techniques over 100 Oral histopathology sample images

cases. However, choosing the right clustering algorithm basically depends on certain parameters such as type of data, scalability, sensitivity towards noise and number of clusters.

At last, this study performs a comparative study among the four widely used clustering techniques namely K-Means (KM), Fuzzy C-Means (FCM), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used for segmenting leaves of Rosette plant images and Epithelial layer of Oral histological images. For superpixel generation, one of the most prominent methods, Simple Linear Iterative Clustering (SLIC), is used. These techniques are also compared to SFFCM algorithm which used MMGR-WT for producing superpixel image. In terms of visual and numerical analysis of the used segmentation quality parameters, experimental results show that SFFCM gives the best results for both Rosette plant images and Oral histopathology images. For Rosette plant images, segmentation accuracy of the SFFCM is 96.64%. Whereas, KM, SLIC-KM, FCM, SLIC-FCM, SLIC-GA, PSO, SLIC-PSO associate with 96.11%, 95.99%, 96.59%, 96.42%, 96.21%, 96.61%, and 96.59% segmentation accuracy respectively. For Oral images, segmentation accuracy of the SFFCM is 98.68%. Whereas, KM, SLIC-KM, FCM, SLIC-FCM, SLIC-GA, PSO, SLIC-PSO associate with 94.70%, 96.72%, 94.61%, 95.99%, 94.65%, 94.63% and 96.82% segmentation accuracy respectively. Based on the mentioned findings, we infer that superpixel image-based clustering algorithms perform better in terms of segmentation accuracy and other quality parameters than typical clustering-based algorithms. Superpixel techniques add a compact restriction to the objectness function, resulting more compact, coherent, and regular superpixels. The trade-off between speed and accuracy in superpixel image-based segmentation is worthwhile to examine. The time it takes for certain algorithms to run is mostly determined by the number of iterations they go through during optimization.

It is our assumption that this study will be valuable to researchers working on superpixel segmentation, clustering with superpixel images and related topics and also their application. Several future directions can be found depending on this analytical review paper and are listed as follows.

The main future work which can be done based on only superpixel generation techniques is the utilization of proper superpixel generation technique for different kinds of images which is fully automatic i.e., there is no need of parameter tuning including the selection of number of superpixels. In addition to the above future work, incorporation of Deep learning in superpixel based image segmentation can be a bright future direction.

For clustering techniques like KM and FCM, the four major future directions are: (i) Selection of proper cluster number in prior to clustering automatically. (ii) Enhancement of their clustering efficacy for the noisy images especially without knowing the noise-type. (iii) Development of proper centres initialization techniques so that they do not converge prematurely. On the other hand, the local trapping problem of KM or FCM can be overcome by some future strategies so that they can able to find the actual or nearly global optima. (iv) The computational time of the KM and FCM for image segmentation significantly depends on the image size i.e., number of pixels. Therefore, finding image size independent fast, accurate, and noise-robust clustering techniques will be an emerging future direction.

Acknowledgements This work has been partially supported with the grant received in research project under RUSA 2.0 component 8, Govt. of India, New Delhi.

Data availability My manuscript has no associated data.

Declarations

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest. The authors declare that they have no conflict of interest.

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