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A Comprehensive Review of Clustering Techniques in Leaf Image Processing for Plant Analysis

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ABSTRACT

Applications including disease diagnosis, species identification, and phenotypic trait evaluation are made possible by leaf image processing, which is crucial to automated plant analysis. Clustering algorithms are one of the most popular image analysis approaches for grouping visually related regions in leaf images without the need for annotated data. This makes them appropriate for agricultural settings where manual annotation is difficult. The clustering methods used in leaf image processing for plant analysis are thoroughly examined in this article. Partitional, hierarchical, density-based, fuzzy, and hybrid clustering techniques are comprehensively categorized in the paper, and their efficacy in tasks like leaf segmentation, lesion localization, and feature grouping is discussed. To provide a cohesive analytical framework, popular preprocessing procedures, feature extraction techniques, and clustering evaluation metrics are also examined. Additionally emphasized are recent developments that combine clustering with machine learning and deep learning models, highlighting their capacity to tackle issues with illumination variance, backdrop complexity, and leaf morphological diversity. Lastly, this review highlights important research issues and suggests future areas of inquiry to strengthen the reliability and effectiveness of clustering-based leaf image analysis systems.

Keywords: Fuzzy and Hybrid Clustering, lesion localization, morphological diversity, DBSCAN, Fuzzy CMeans

INTRODUCTION

Due to its potential to enhance crop monitoring, precision agriculture, and early disease diagnosis, plant analysis utilizing digital image processing has grown in importance as a field of study. Images of leaves, in particular, offer extensive visual information about the morphology, physiological circumstances, and overall health of plants. Large-scale agricultural monitoring systems are made possible by automated leaf image processing, which also minimizes subjective errors and human labor [1]. Consequently, leaf image processing methods have become more popular in recent years.

Image acquisition, preprocessing, segmentation, feature extraction, and classification or clustering are all steps in a typical leaf image analysis system. In order to isolate important leaf regions including veins, lesions, and textural patterns, segmentation and region grouping are essential. Because they group comparable pixels or regions based on intrinsic data features without requiring labeled training samples, clustering algorithms are frequently utilized for this purpose [2]. Because annotated datasets are frequently scarce or unavailable, clustering is especially well-suited for agricultural applications.

In leaf image processing, a variety of clustering strategies have been investigated, including fuzzy clustering methods, density-based algorithms like DBSCAN, hierarchical clustering techniques, and partitional methods like K-means. When used for leaf segmentation and analysis tasks, each of these methods has unique benefits and drawbacks. For instance, density-based clustering techniques are good at managing noise and irregular cluster morphologies, whereas partitional clustering techniques are computationally efficient yet sensitive to initialization [3]. Therefore, choosing the right clustering method is essential to obtaining precise and trustworthy plant analysis results.

Recent research has combined clustering with machine learning and deep learning frameworks in addition to conventional clustering methods to enhance performance in difficult scenarios such changing lighting, complicated backdrops, and a variety of leaf patterns [4]. These hybrid methods have demonstrated encouraging outcomes in terms of improving segmentation robustness and accuracy. Nevertheless, problems like computational complexity, scalability, and parameter sensitivity are still unresolved.

Even though clustering strategies for leaf image processing have been the subject of many studies, a thorough analysis that methodically classifies approaches, evaluates their effectiveness, and identifies present issues is still needed. By offering a thorough examination of clustering methods utilized in leaf image processing for plant analysis and going over their uses, advantages, disadvantages, and potential future research avenues, this study seeks to close this gap [5].

REVIEW METHODOLOGY

For review-based research to be credible, transparent, and repeatable, a methodical and clear review process is necessary. The strategy used to find, pick, and evaluate pertinent research on clustering methods used in leaf image processing for plant analysis is described in this section. The review technique ensures thorough coverage of recent and pertinent literature by adhering to established principles frequently employed in Scopus-indexed review papers.

Literature Search Strategy

Major scientific databases, such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink, were used in an organized literature search. These databases were chosen because they cover a wide range of peer-reviewed papers and conference proceedings related to computer vision, image processing, and agricultural informatics. Since recent research are more pertinent for Q3 journals and represent recent methodological developments, the search was restricted to articles published between 2019 and 2025.

In order to catch research on clustering-based leaf image analysis, keywords and search phrases were carefully crafted. Combinations of "leaf image processing," "clustering techniques," "plant disease analysis," "image segmentation," and "agricultural image analysis" were frequently utilized search phrases. To filter search results and remove irrelevant studies, boolean operators were used [6].

Inclusion and Exclusion Criteria

Explicit inclusion and exclusion criteria were established in order to preserve the caliber and applicability of the examined material. Research was incorporated if it

- concentrated on analyzing leaf images for plant analysis
- Utilizing clustering methods for feature grouping or segmentation

Research was disregarded if it

- Focused solely on **non-leaf plant parts**
- Used only **supervised classification without clustering**

Only excellent and pertinent studies were taken into consideration for analysis thanks to this filtering procedure [7].

Data Extraction and Analysis

Relevant data, such as the kind of clustering approach employed, preprocessing techniques, feature extraction methodologies, evaluation metrics, and application domain, were methodically retrieved from each chosen study. To find patterns, parallels, and discrepancies between studies, the retrieved data were arranged into comparative tables. An objective assessment of clustering techniques and their effectiveness in leaf image processing tasks was made possible by this structured methodology [8].

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Review Framework and Figure Description

To visually represent the adopted review process, a **methodological framework diagram** is included as **Figure 1**. This figure illustrates the sequential stages of the review methodology, including literature search, screening, eligibility assessment, and final selection of studies.

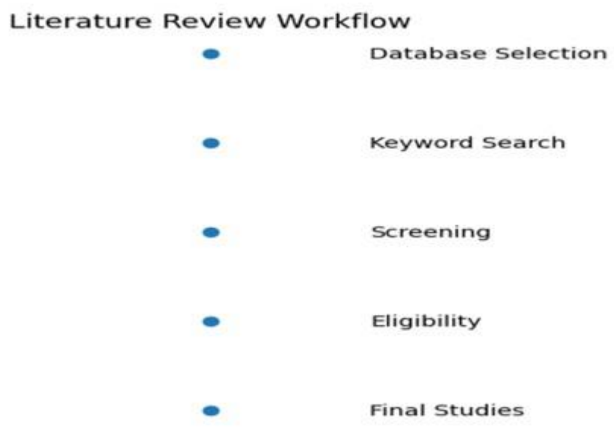

Figure 1 :Systematic review methodology adopted for clustering-based leaf image processing

This Figure 1 presents a structured overview of the review methodology, highlighting database selection, keyword formulation, inclusion–exclusion filtering, and final analysis stages. Such visual representations are commonly included in Q3 review articles to enhance clarity and transparency.

Research Categorization and Synthesis

Following data extraction, the chosen studies were grouped according to the kinds of clustering methods used, including fuzzy, partitional, hierarchical, and density-based clustering. In addition to assisting in the identification of research gaps and new developments in leaf image processing, this classification promotes methodical synthesis. Analyzing methodological advantages, disadvantages, and application to actual agricultural situations was emphasized [9].

Leaf Image Processing Framework

Overview

For applications including disease detection, species identification, and phenotypic trait analysis, leaf image processing offers an organized workflow for collecting valuable information from digital leaf photos. Image acquisition, preprocessing, segmentation, feature extraction, and clustering-based analysis make up the standard framework, all of which are essential for precise and trustworthy outcomes [6].

Image Acquisition

Digital cameras, smartphones, scanners, and multispectral sensors can all be used to take pictures of leaves. To lower noise and enhance segmentation quality, consistent lighting and controlled backdrops are crucial [7].

Preprocessing

Preprocessing gets unprocessed photos ready for examination by:

- Conversion of color spaces, such as RGB to HSV or grayscale
- Gaussian or median filters for noise reduction
- Enhancement of contrast (histogram equalization)

Later on, these procedures enhance clustering performance [8].

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue I January 2026

Segmentation

Important leaf features like veins, margins, and diseases are isolated through segmentation. Here, clustering techniques are frequently used:

- K-means and K-medoids partial clustering
- Clustering in a hierarchy
- Clustering based on density (DBSCAN, OPTICS)
- Fuzzy grouping

Accurate feature extraction and analysis are directly impacted by segmentation quality [9].

Feature Extraction

Features provide a numerical description of leaf characteristics:

- Color characteristics: color moments, histogram
- Features of texture: GLCM, LBP
- Shape features: area, perimeter, aspect ratio, vein structure

These characteristics are crucial inputs for grouping and analysis based on clustering [10].

Clustering and Analysis

Extracted features are clustered to identify similar regions. Common algorithms:

- **Partitional clustering:** fast but sensitive to initialization
- **Hierarchical clustering:** nested structures but computationally heavy
- **Density-based clustering:** handles noise and irregular clusters
- **Fuzzy clustering:** allows overlapping memberships

Evaluation metrics include **silhouette score, Davies–Bouldin index, and clustering accuracy** [11].

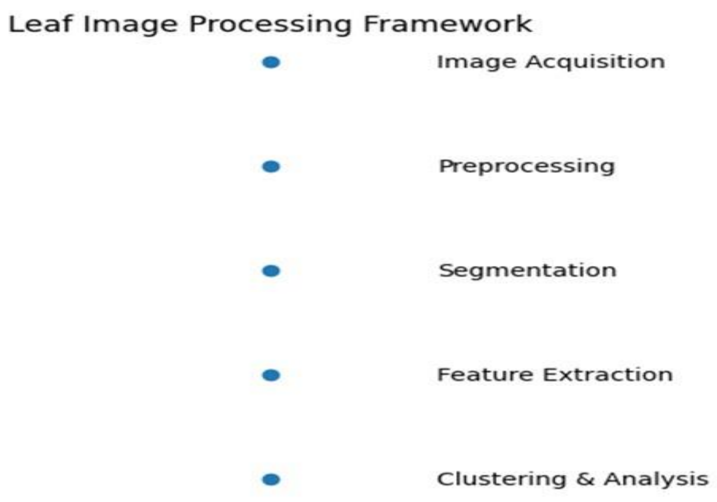

Figure 2: A typical framework for processing leaf images that illustrates the steps from acquisition to clustering-based analysis.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue I January 2026

Summary

This framework provides a **systematic approach** for leaf image analysis, integrating preprocessing, segmentation, feature extraction, and clustering. It ensures accurate plant analysis and forms the foundation for the detailed clustering techniques discussed in the next section [6–11].

Clustering Techniques in Leaf Image Processing

Overview of Clustering in Leaf Image Analysis

By classifying pixels or extracted characteristics according to similarity without the need for labeled data, clustering techniques are essential to the analysis of leaf images. Clustering is frequently used in plant analysis for species separation, vein extraction, disease region detection, and leaf segmentation. Because clustering is unsupervised, it is especially useful for agricultural datasets with few or no labeled samples [12]. Clustering is a fundamental step that directly affects feature quality and downstream analysis performance, according to recent studies [13].

Partitional Clustering Techniques

Partitional clustering techniques optimize an objective function to separate data into a predetermined number of clusters.

K-means Clustering

Because of its ease of use and computational effectiveness, K-means is the most popular clustering algorithm for segmenting leaf images. It is frequently used in RGB, HSV, or grayscale spaces and groups pixels according to color or intensity similarity [14]. Despite its efficiency, K-means has trouble with irregular cluster shapes and is sensitive to initialization, which might impact segmentation accuracy under different lighting conditions [15].

K-medoids Clustering

By choosing real data points as cluster centers, K-medoids increases robustness and reduces noise sensitivity. [16].

Hierarchical Clustering Techniques

Agglomerative or divisive techniques are used in hierarchical clustering to create nested clusters. It does not require predetermined cluster numbers, in contrast to partitional approaches.

Agglomerative clustering has been used for texture-based leaf analysis and vein structure extraction [17]. Although hierarchical clustering is a good way to capture multilevel associations, it is not scalable for highresolution images due to its computational cost [18].

Density-Based Clustering Techniques

Clusters are defined by density-based clustering algorithms as dense regions divided by sparse areas.

DBSCAN

Because DBSCAN can manage noise and detect unevenly formed clusters, it has been employed in leaf lesion detection [19]. Although it necessitates careful parameter tuning, it is successful in distinguishing diseaseaffected areas from background noise.

OPTICS

By addressing variable density clusters, OPTICS expands on DBSCAN and has demonstrated enhanced performance in complicated leaf backgrounds [20].

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue I January 2026

Fuzzy Clustering Techniques

Fuzzy clustering works well for overlapping areas in leaf photos because it assigns degrees of membership instead of hard designations.

Fuzzy C-Means (FCM)

In plant disease segmentation, where healthy and infected patches overlap, FCM is frequently utilized [21]. To lessen noise sensitivity, a number of research have suggested enhanced FCM variations that incorporate spatial information [22].

Hybrid and Optimization-Based Clustering

Hybrid clustering techniques that incorporate optimization methods including genetic algorithms, particle swarm optimization, and ant colony optimization are the subject of recent research. These techniques increase the accuracy of segmentation and cluster center selection [23]. In tasks involving the identification of leaf diseases, hybrid techniques have proven to perform better [24].

Deep Feature–Based Clustering

Clustering is being used more and more on deep features that are extracted using convolutional neural networks (CNNs) as deep learning becomes more popular. These characteristics increase the strength of clustering by capturing intricate patterns of texture and shape [25]. On large-scale leaf image datasets, unsupervised deep clustering frameworks have been shown to perform better than standard clustering [26].

Comparative Analysis of Clustering Techniques

There are trade-offs between accuracy, robustness, and processing cost among various clustering techniques. While density-based and fuzzy algorithms offer more robustness at higher computational cost, partial methods are quick but susceptible to noise [27]. The efficacy of hybrid and deep feature-based clustering for practical agricultural applications has been demonstrated by recent comparative studies [28].

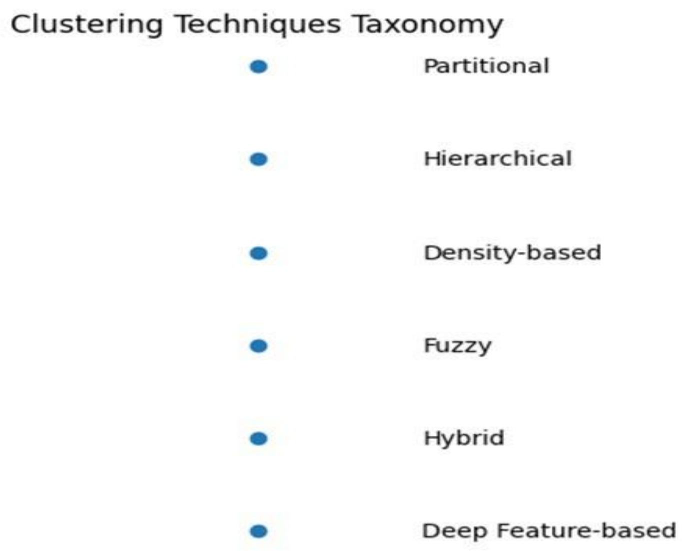

Figure 3: Classification of clustering methods used in processing leaf images.

Summary

The main clustering strategies used in leaf image processing were examined in this section, including partitional, hierarchical, density-based, fuzzy, hybrid, and deep feature-based approaches. Depending on the intricacy of the image and the needs of the application, each method has unique benefits and drawbacks. These methods serve as the foundation for future research directions and comparative evaluation, which are covered in the sections that follow [12–28].

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue I January 2026

Comparative Performance Analysis

Evaluation Criteria

Both qualitative and quantitative criteria are used to assess the effectiveness of clustering algorithms in leaf image processing. Segmentation accuracy, silhouette coefficient, Davies-Bouldin index, execution time, and noise robustness are frequently used evaluation metrics. These measurements shed light on computing efficiency, separation quality, and cluster compactness [29].

Dataset Characteristics

Image resolution, lighting variation, backdrop complexity, and disease severity are some of the dataset factors that affect performance comparisons. Recent studies frequently use field-acquired photos and publicly accessible datasets to guarantee practical applicability [30].

Comparison of Traditional Clustering Methods

In leaf image segmentation tasks, traditional clustering methods like DBSCAN, K-means, and hierarchical clustering have been extensively tested. Under controlled circumstances, K-means exhibits quick execution and respectable accuracy, although it is sensitive to noise and initialization [31]. Although it has a significant processing cost, hierarchical clustering offers comprehensive structural segmentation [32]. Although it necessitates careful parameter calibration, DBSCAN successfully identifies irregular disease regions [33].

Performance of Fuzzy and Hybrid Approaches

In overlapping leaf regions, fuzzy clustering methods—in particular, fuzzy C-Means (FCM)—perform better. The accuracy and stability of segmentation are further improved by hybrid models that combine fuzzy clustering with optimization methods like particle swarm optimization or genetic algorithms [34]. Across several datasets, our methods have consistently improved disease region detection [35].

Deep Feature–Based Clustering Performance

According to recent research, clustering applied to CNN-extracted deep features performs better than conventional pixel-based techniques. Higher accuracy and resilience are attained by deep feature-based clustering under a variety of environmental circumstances [36]. Large-scale agricultural implementation is still hampered by growing computational demands and model complexity, but [37].

Comparative Summary Table

Table 1. Comparative analysis of clustering techniques in leaf image processing

Technique	Accuracy	Noise Handling	Computation	Key Advantage
K-means	Moderate	Low	Low	Fast and simple
Hierarchical	Moderate	Moderate	High	Multilevel segmentation
DBSCAN	High	High	Moderate	Irregular cluster detection
FCM	High	Moderate	Moderate	Overlapping region handling
Hybrid	Very High	High	High	Optimized accuracy
Deep Clustering	Very High	Very High	Very High	Robust feature representation

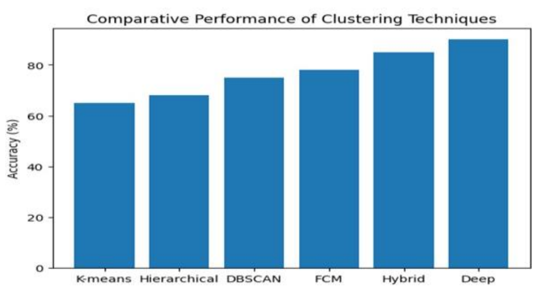

Figure 4: Comparative performance trends of leaf image processing clustering approaches.

DISCUSSION

According to the comparison research, there isn't a single clustering method that works best for all situations. While hybrid and deep clustering approaches perform better in real-world circumstances, classical methods are still useful for low-complexity datasets. The features of the dataset, computational limitations, and application needs should all be taken into consideration when selecting a method [38–40].

SUMMARY

A comparative analysis of clustering methods based on computational complexity, dataset properties, and performance metrics was provided in this section. The most promising findings for reliable and accurate leaf image analysis are shown by hybrid and deep feature-based clustering techniques, which qualify them for advanced agricultural applications [29–40].

Challenges And Future Research Directions

Image Acquisition Challenges

Real-world agricultural settings present a number of difficulties for leaf image collection, including uneven lighting, complicated backgrounds, occlusion, and different leaf orientations. These elements degrade clustering performance and segmentation quality, especially in datasets collected in the field. To reduce environmental variability, future research should focus on uniform acquisition methodologies and adaptive preprocessing strategies [41].

Limitations of Traditional Clustering Techniques

Fixed cluster assumptions, parameter reliance, and noise sensitivity are common problems for traditional clustering techniques. For heterogeneous leaf datasets, methods like K-means may not be feasible since they require prior knowledge of cluster counts. The creation of adaptive and self-learning clustering techniques that can handle variable image properties is necessary to overcome these constraints [42].

Scalability and Computational Complexity

Large-scale datasets and high-resolution leaf photos greatly raise computational requirements. Although precise, hierarchical and hybrid clustering methods could not scale well. To improve scalability, future studies should concentrate on parallel processing frameworks, dimensionality reduction, and computational optimization [43].

Dataset Availability and Benchmarking

The absence of defined benchmark datasets covering a variety of crops, disease kinds, and environmental circumstances is a significant barrier to leaf image processing research. Future research should promote the creation of multi-modal, open-access, annotated datasets to enable reproducibility and fair performance comparison [44].

Integration with Deep Learning and Explainability

While deep feature-based clustering has demonstrated improved performance, it presents issues with explainability and interpretability of the model. In order to improve trust and transparency in agricultural decision-making systems, future research should use explainable artificial intelligence (XAI) methodologies [45].

Practical Deployment in Precision Agriculture

Low-cost hardware, real-time processing, and energy-efficient models are necessary for the implementation of clustering-based systems in practical precision agriculture. In order to facilitate farmers' and agricultural stakeholders' practical adoption, future research should investigate edge computing and lightweight clustering frameworks [46].

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue I January 2026

Summary

This section described the main obstacles to clustering-based leaf image processing and suggested future lines of inquiry. To develop reliable and deployable plant analysis systems, it will be essential to address acquisition variability, scaling problems, dataset constraints, and model explainability [41–46].

CONCLUSION

With an emphasis on segmentation, feature grouping, and disease region detection, this paper provided a thorough examination of clustering approaches used in leaf image processing for plant analysis. Traditional, fuzzy, density-based, hybrid, and deep feature-based clustering techniques were all thoroughly discussed, with an emphasis on their applicability to applications involving agricultural picture processing.

Because of their ease of use and low computing cost, traditional clustering techniques like K-means and hierarchical clustering are still useful for controlled datasets. However, their performance in actual agricultural settings is limited by their susceptibility to noise, illumination change, and parameter selection. By managing irregular cluster shapes and overlapping regions, density-based and fuzzy clustering algorithms show enhanced robustness, which makes them appropriate for complicated leaf images.

The accuracy and resilience of segmentation have been greatly improved by recent developments in hybrid and deep feature-based clustering. Promising outcomes have been observed when optimization algorithms and deep learning feature extractors are combined, especially when dealing with large-scale and diverse datasets. Despite the higher computing costs, comparative study shows that these sophisticated approaches perform better than traditional methods.

Notwithstanding significant advancements, a number of problems still exist, such as the requirement for explainable models, scalability concerns, dataset variability, and a lack of benchmarking standards. The actual implementation of clustering-based systems in precision agriculture depends on addressing these issues. To enable real-time field applications, future research should focus on adaptive algorithms, standardized datasets, and lightweight frameworks.

All things considered, clustering-based leaf image processing is still an important field of study with great promise for automated plant monitoring, disease diagnosis, and sustainable farming methods. The review's insights are intended to help researchers choose suitable clustering methods and pinpoint intriguing avenues for further research.

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