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A Hybrid Framework for Plant Leaf Region Segmentation: Comparative Analysis of Swarm Intelligence with Convolutional Neural Networks

Check for updates

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Abstract: Agriculture is important for the survival of humanity since about 70% of the world's population is engaged in agricultural pursuits to varying degrees. The previous and present methodology lacks ways to identify diseases in different crops within an agricultural environment. The crops most impacted by these illnesses are tomatoes, leading to a significant increase in the price of tomatoes. Controlling tomato illnesses is crucial for optimal development and production, making early diagnosis and disease detection vital. Early disease diagnosis and treatment in tomato plants can lead to improved yields. Tomato plants are susceptible to illnesses, which can significantly affect the quality, quantity, and productivity of the crop if not properly treated. Despite many unsuccessful efforts to utilize machine learning methods for detecting and classifying illnesses in tomato plants. This study introduces a comparative framework for segmenting tomato leaf regions using both conventional and swarm intelligence methodologies to determine the more effective approach. This framework enables the development of a tomato plant diagnosis system capable of analyzing various sorts of images, including both standard and custom image datasets. The obtained evaluation parameters of the proposed model in terms of average precision, recall, f-measure, error, and accuracy are 0.914, 0.915, 0.915, 1.55% and 98.45%, respectively. We performed a comparative examination of six scenarios: T-model, K-model, TPSO-model, KPSO-model, TGO-model, and KGO-model. The combination of K-means with the GO algorithm proved to be a powerful hybrid technique, with an accuracy of 96.45%. Comparatively, the T-model, K-model, TPSO-model, KPSO-model, and TGO-model attained accuracies of 85.73%, 86.61%, 87.54%, 88.64%, and 92.21% correspondingly.

Introduction

Agricultural productivity is a crucial factor in any nation's economy and it is directly proportional to farming. Agricultural influences not only the economy it also affects various aspects such as food security, employment and balancing of trade growth (Noonari et al., 2015). Food insecurity is a prominent cause of plant diseases and a significant global challenge for humanity in contemporary times (Chowdhury et al., 2021). The design of modern Artificial Intelligence (AI) based agriculture prioritizes increasing crop yield and improving its quality. The prevalence of crops has increased throughout the years, and the nature of diseases has gotten increasingly intricate. The ability to accurately observe crop diseases relies on expertise for plants like tomatoes. Tomato plants are prone to a multitude of illnesses, and their inherent features render them especially susceptible, particularly during the initial phases of development. Tomatoes possess tender tissues and a significant amount of water, rendering them appealing to infections. The fruit's succulent nature creates an ideal setting for the proliferation and dissemination of illnesses (Thangaraj et al., 2022). The importance of disease detection in tomato plants in the field of agriculture lies in the frequent occurrence of diseases. Inadequate oversight can lead to significant effects, manifesting as detrimental symptoms in plants that can adversely affect both the amount and quality of

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the crop (Sahoo et al., 2011). The automated approach of tomato Plant Disease Detection (PDD) utilizing AI-enabled image processing in the field of computer vision offers the advantage of reducing manual labor by eliminating the need for prolonged monitoring. In the field of AI, the concept of Artificial Neural Network (ANN) is a foundational method employed in numerous disease detection from plants, while an improved ANN for image data that is known as Convolutional Neural Network (CNN) has gained more attention in terms of maximum detection accuracy as deep learning and helps to minimize manual effort (Tian et al., 2019). However, the detection accuracy of any model is directly dependent upon the input data with their quality. Where, segmentation of leaf region from the capture images of tomatoes plays a significant role. If the input of CNN is very precise according to the disease or affected area, then CNN will perform better feature engineering that would be beneficial for model. The process of diagnosing plant diseases is crucial due to the presence of several localized spots on plant leaves, stems, and other elements (Singh et al., 2012). Leaf region or region of leaf (ROL) segmentation enables the discernment and scrutiny of the well-being of individual leaves. Alterations in the colour, shape, or texture of leaves can serve as indicators of illnesses, pests, or nutritional inadequacies, allowing for timely action to uphold the well-being of plants.

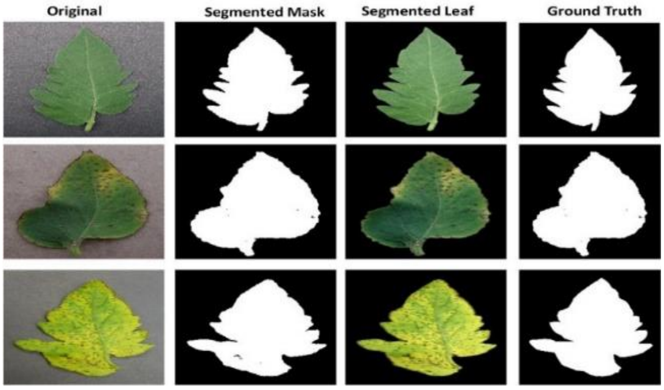

Figure 1. ROL Segmentation from Images.

ROL segmentation facilitates the isolation and analysis of particular sections of leaves that diseases may afflict. The utilization of automated detection methods aids in the prompt identification of areas affected by diseases, facilitating early diagnosis and precise treatment, hence impeding the dissemination of diseases inside the plant. Tomato ROL segmentation is a demanding effort for both professionals and researchers in order to achieve optimal performance (Dutta et al., 2021). Nevertheless, numerous researchers have already tried to develop a proficient method for the segmentation of ROL from the images in order to facilitate the identification of diverse types of tomato disorders. A sample of ROL segmentation is shown in Figure 1. Leaf segmentation plays a crucial role in accurately mapping the spatial distribution of plant health data in precision agriculture (Kumar and Aggarwal, 2023). This data facilitates the accurate allocation of resources, such as water, fertilizers, and pesticides, to maximize resource efficiency and reduce environmental harm. Thus, in this research, we propose a comparative paradigm for tomato leaf segmentation from images that combine Swarm Intelligence (SI) with CNN as deep learning. SI techniques provide a robust and flexible process for segmenting leaf regions from tomato plant images. SI can optimize parameters, manage complexity, adjust to changing conditions, and interface with other technologies, rendering it highly beneficial in increasing precision agriculture and AI-based plant health monitoring. There is the total of two distinct ROL segmentation methods are used in this comparative framework:

1. Traditional Segmentation (Thresholding and K-means),
2. SI-based [Particle Swarm Optimization (PSO) and Grasshopper Optimization (GO)]

Thresholding-based ROL segmentation is a method of image segmentation that distinguishes the foreground (ROL) from the background (Extra Area) of an image, as revealed in Figure 2. This is a straightforward technique used for segmenting a tomato image in the field of image processing. Whereas, K-means clustering is a widely used unsupervised machine learning approach that can be applied to segment tomato ROL by dividing images into distinct zones of interest that are known as clusters. It facilitates the clustering of pixels with similar colour or intensity, which is very gainful for detecting healthy and unhealthy regions on tomato leaves or plants. SI-based segmentation is important for accurately dividing leaf regions in the field of ROL segmentation for precision agriculture (Kennedy and Eberhart, 1990). The intricate arrangement and intricacy of plant images, encompassing differences in illumination, backdrop, and leaf structure, present obstacles for conventional segmentation techniques. SI algorithms are well-suited for dealing with the various and nuanced characteristics seen in plant photos due to their versatility and capacity to explore difficult solution spaces.

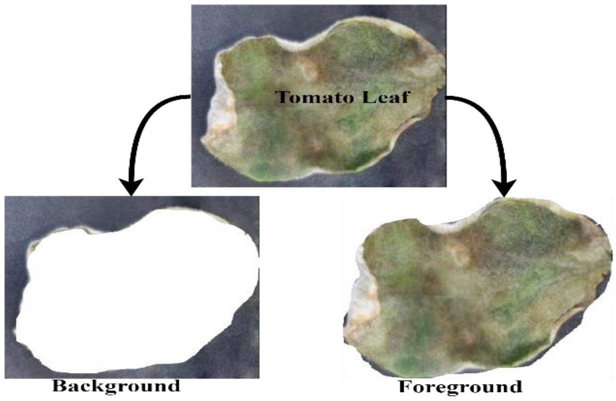

Figure 2. Tomato ROL Segmentation.

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Motivation: Agriculture is the primary source of income in India for many people and plant diseases have a significant impact on farmers as they occur naturally and can have serious consequences on plants, affecting their quality, productivity, and quantity if not properly managed (Karaboğa, 2005). The primary objective is to propose a method for identifying plant diseases and enhancing productivity levels but mostly classification process is dependent on the ROL segmentation. Thresholding, as well as clustering-based plant leaf image segmentation, is a default method that aims to collect a set of objects or pixels into subsets or collections by the background and front of the image, as shown in Figure 2. The goal is to create clusters or parts that fit inside but are very different from each other. In simple terms, pixels in the same category should be as similar as possible, and objects in the same category should be very different from those in another cluster. Some challenging factors are given that gave us the motivation:

- ♦ The huge number of research articles are available on this topic, but lack of appropriate comparisons of Traditional and SI-based segmentation to find out better and robust approach.
- ♦ Plant leaf segmentation is a challenging task and still, lots of improvements are needed to develop a better agriculture diagnosis system, especially in case of multiple diseases in a single leaf.
- ♦ Most of the models are suffering from over-fitting problems and need to tackle such kind of difficulty to detect the diseases in the early stage for better productivity. The issue of overfitting in deep learning typically arises when there is an improper region of the leaf is passed to the CNN model (Upadhyay et al., 2024).

Contributions: Currently, the utilization of SI for ROL segmentation from plant leaf images is an essential necessity for several purposes. Thus, in this study, we have introduced a comparative framework for plant leaf segmentation using both traditional as well as SI-based methods. The primary contributions of this research are as follows:

- ☞ To study the existing tomato plant leaf region segmentation algorithms to find out better ones.
- ☞ Develop an innovative pre-processing technique for plant leaf images, such as enhancing quality and contrast.
- ☞ To segment ROL from plant leaf images, thresholding and K-means are used as a traditional approach.
- ☞ In the next scenario, ROL segmentation is performed with hybridization of SI techniques such as PSO and GO.
- ☞ To validate the proposed hybrid framework, performance evaluation parameters like Precision, Recall, F-measure and Accuracy with Matthews's correlation coefficient (MCC), Dice coefficient (DC), and Jaccard coefficient (JC) are calculated.

This comparative research article focuses on a ROL segmentation from plant leaf images that would be beneficial for multi-class disease classification. The other sections of the article are organized as follows: Section 2 presents an overview of relevant related work, while Section 3 outlines the approach of the suggested hybrid ROL segmentation mechanism. Section 4 presents simulation results with appropriate discussion focusing on the performance evaluation parameters and Section 5 concludes the study and provides future directions.

Literature Survey

In this section of the research article, we present a survey about existing models related to tomato leaf disease segmentation as well as their cataloging. Tomato leaf characteristics, such as colour, shape, texture, and other attributes, had to be manually extracted in the study in order to segment and classify the diseases that affect tomato leaves. Concepcion et al. (2020) have developed a model based on the swarm-based Artificial Bee Colony (ABC) algorithm to analyse the necrotic and chlorotic zones of tomato plants affected by the Septoria leaf spot. The authors suggested the use of computer vision (CV) techniques and computational intelligence to evaluate tomato diseases. The dataset utilized consists of tomato leaves that are both healthy and diseased. To eliminate non-vegetation pixels from the images, the authors employed the CIE-Lab colour space at the starting stage then a segmentation approach based on thresholds was employed, followed by the extraction of texture information from the segmented portion of the leaf. In order to enhance the quality of pixels affected by Septoria leaf spots while minimizing their negative effects on unaffected green pixels, ABC was employed to standardize the visible red reflectance and establish red-green and red-blue reflectance ratios. The model that was created attained an accuracy of 97.46%, surpassing the performance of previous works (Concepcion et al., 2020). A model using the concept of PSO with CNN was developed by Darwish et al. (2020) in the same year to diagnose plant leaf diseases at an early stage which helps to improve productivity. In this study, the researchers employed a novel technique called orthogonal learning PSO (OLPSO) to optimize the hyperparameters of CNN. Unlike conventional methods like manual hit and trial or trial and error, OLPSO aims to identify optimal values for hyperparameters that affect the output of model. The present study employs an architecture known as Exponentially Decaying Learning Rate (EDLR) to train CNN with high efficiency and to circumvent the issue of becoming stuck in local minimums. This study uses random minority oversampling and random majority under-sampling techniques to address the issue of the imbalanced dataset and to overcome limitations in sample number and diversity. The authors accomplished a significant milestone in disease categorization, with an accuracy of 98.2% with the assistance of OLPSO (Darwish et al., 2020). Anam & Fitriah (2021) developed a model with the help of K-means along with the Swarm Intelligence-based algorithm to segment and classify the Early Blight disease for tomato leaves. Tomato plants worldwide are commonly afflicted by a devastating fungal disease that significantly reduces their yield. In this study, the experts employed the K-means method as a clustering technique (unsupervised) to partition the damaged region from the leaves picture for the purpose of disease identification in its first phase. Additionally, they present the notion of the PSO, as it is regarded as a prominent method among swarm intelligence-based algorithms because of its ability to effectively balance exploration and exploitation. The input for the HSV colour system is the Hue. Based on the experimental results, it can be deduced that the segmentation technique for early blight disease, which utilizes the K-means algorithm with a swarm intelligence-based algorithm, exhibits superior performance. The tomato leaf disease segmentation strategy utilizing the K-means algorithm had an average computation time that was 7.184 seconds greater compared to the suggested method. The proposed method had an average computation time of 142.062 seconds and achieved a 41.8% F-measure. When using the K-means algorithm with PSO, the F-measure reaches a value close to 90%, which is significantly higher than the F-measure achieved without PSO (Anam and Fitriah, 2021). The concept of a novel Chaotic Salp Swarm (CSS) swarm-based optimization for feature selection to detect the disease from the Apple and Tomato Plant Leaf was proposed by Venkata Subramanian in 2021. In this context, the author employs the Bi-directional Long Short-Term Memory (Bi-LSTM) technique to classify diseases in apples and tomatoes. They employed the Bi-LSTM architecture to detect diseases using the PlantVillage dataset. The model that was built attained a testing phase accuracy of 96%, surpassing the performance of other existing works (Venkatasubramanian, 2021). David et al. (2023) utilized a combination of multilevel thresholding and K-means clustering together with an optimization technique. The authors employ an Adaptive Extreme Learning Technique (AELT) to classify the condition in their research. Prior to the classification phase, the segmentation and feature extraction processes are conducted in order to enhance the precision of disease detection. The paper presents a technique for segmenting leaf regions using a K-means clustering method with multilevel thresholding. The clustering process is enhanced by incorporating a butterfly optimization process guided by probability. Plant images are utilized to extract attributes based on entropy (David et al., 2023). Jamjoom et al. (2023) devised an approach that utilizes unsupervised K-means clustering and Support Vector Machine (SVM) to separate the afflicted area of plant leaves for disease categorization. In this study, the author aims to enhance the performance of the K-means algorithm by including SVM for the segmentation-based classification of Phytophthora infestans, *Fusarium graminearum*, *Puccinia graminis* and tomato yellow leaf curl. The SVM idea is employed as a classifier to categories diseases by utilizing several image processing phases, including image capture, pre-processing, segmentation of affected regions, precise feature extraction, and subsequent classification. The identification of the damaged area of the plant leaf and the classification of the disease were achieved by utilizing the Grey Level Co-Occurrence Matrix (GLCM) idea in conjunction with Local Binary Pattern (LBP) features. The proposed model and algorithm surpassed the current state-of-the-art work and obtained an accuracy of 97.2% (Jamjoom et al., 2023). Umamageswari et al. (2023) introduced a similar idea using the Chameleon Swarm-based Fuzzy C-means (FCM) method to identify and segment the afflicted area. They subsequently employed the Progressive Neural Architecture (PNA) Search for classification purposes. The authors have created a proposed model that comprises four distinct steps: pre-processing, affected region segmentation, feature extraction, and disease categorization. During the pre-processing stage, they employ noise reduction techniques and address overfitting issues. They then proceed to segment the afflicted area using the Chameleon swarm-based FCM approach. Upon determining the precise area of the leaf that was impacted, they proceeded to conduct feature extraction utilizing the GLCM method. Finally, the PNA search method was employed to categories diseases found in different plants, including apples, cherries, corn, grapes, peppers, potatoes and tomatoes. The author justified the job efficiency based on several metrics, including precision, recall, sensitivity, specificity, and accuracy.

The respective values for these parameters are 0.9612, 0.9721, 0.9700, and 0.9743. These values are greater than those achieved by previous state-of-the-art studies (Umamageswari et al., 2023). Ulutaş and Aslantaş (2023) employed the PSO to enhance the hyperparameter optimization of CNN models. They introduced four distinct CNN: MobileNetV3Small, EfficientNetV2L, InceptionV3, and MobileNetV2. In addition, they employed the grid search mechanism to optimize the weights of these structures. The experimental findings demonstrate that the proposed ensemble models exhibit rapid training and testing capabilities, achieving a classification accuracy of 99.60%. This discovery will facilitate prompt diagnosis of plant issues by professionals and aid in the prevention of future diseases (Ulutaş and Aslantaş, 2023). After analysing existing research-related work in the field of tomato leaf segmentation for their classification, certain limitations have been identified and will now be explained:

- The main drawback of the present clustering-based segmentation approach is the presence of overlapping between the foreground and background parts of the tomato leaf during the segmentation.
- To solve such a problem, the utilization of swarm-based methodologies would be beneficial.
- Optimization-based approaches often utilize bio-inspired algorithms, which might result in lengthier execution times for the segmentation process of the leaf region.
- This is mostly due to the presence of an unknown and potentially large number of clusters.
- The literature review emphasizes the difficulties encountered in the process of segmenting images of tomato plant leaves. These obstacles originate from issues related to image quality and the imperative to enhance the quality of these images.
- Researchers frequently encounter the issue of pixel mixing due to rapid fluctuations in the values of neighboring pixels.

From the studies described earlier, it can be deduced that the segmentation of tomato plant leaves is an intricate process that includes multiple important steps, each designed to suit the individual attributes of the data involved. Leaves, which consist of various arrangements of pixels, can undergo a procedure known as segmentation to provide more accurate analysis. Essentially, this technique seeks to partition the image into two distinct pieces by identifying the clusters of pixels within the image referred to as background and foreground. Insufficient foreground quality can lead to misclassification in the classification process, which can be addressed by employing swarm algorithms. Several swarm-based optimization algorithms, including as PSO, GO, ABC, etc. can be employed to improve the accuracy of segmentation. In addition, researchers have devised more innovative methods to further improve the process of segmenting images of tomato plant leaves. Nevertheless, the current traditional approaches suffer from reduced efficacy as a result of their practical incompatibility with diverse medical imaging modalities. It is essential to determine the best combination that can effectively solve the problem of clustering-based segmentation methodology, thereby enhancing the effectiveness of the agriculture diagnostic system.

Proposed Model

Here, we outline the sequence of steps involved in the suggested comparative hybrid framework for plant leaf region segmentation. In this model, we used two different approaches for segmentation, the first is traditional segmentation (Thresholding and K-means) and second is SI-based segmentation where PSO and Grasshopper Optimization (GO) are used. This section of the article provides an elaborate description of each proposed hybrid model, which is a novel model developed for identifying diseases in tomato leaves. There is total six models to segment the ROL from tomato leaf images name as T-model (Thresholding-based model), K-model (K-means-based model), TPSO-model (Thresholding with PSO-based model), KPSO-model (K-means with PSO-based model), TGO (Thresholding with GO-based model) model and KGO model (K-means with GO-based model). Each model is described one by one in the below section with algorithms.

T-model: In this model, the concept of fundamental tomato leaf image segmentation is used to segment the ROL from the used dataset. In the field of image segmentation, the concept of thresholding is a basic method used in numerous fields, such as medical imaging, automatic vehicle driving, military, agriculture etc. Thresholding is a straightforward and computationally efficient method used in tomato leaf segmentation to distinguish the leaf area (ROL) from the background (irrelevant part). Although not the most sophisticated technique, it offers a valuable foundation and can be efficient in some situations. Here, firstly, we apply image pre-processing to improve the image quality and then we move towards the tomato leaf segmentation using the T-model and Thresholding-based segmentation algorithm as:

Algorithm 1: Thresholding-based Segmentation

```
Input: PLI → Pre-processed Leaf Image
Output: BI and FI (ROL) → Background and Foreground Image
Start
Define Threshold Value, T_V = Pixel value (PLI)
Calculate the size of PLI, [R, C, P] = Size (PLI)
While Pixel (PLI) = True
    For I_1 in range of R
        For I_2 in range of C
            If PLI (I_1, I_2) < T_V
                BI (I_1, I_2) = PLI (I_1, I_2)
            Else
                FI (I_1, I_2) = PLI (I_1, I_2)
            End – If
        End – For
    End – For
End – While
Return: BI and FI as a ROL
End – Algorithm
```

Thresholding-based tomato leaf segmentation in T-model offers a basic yet valuable approach for specific applications. Its simplicity and efficiency make it a good starting point, but more advanced techniques like clustering-based might be necessary for complex scenarios. Some benefits of used Thresholding-based segmentation are listed as:

- ✓ Straightforward and computationally efficient, making it ideal for real-time applications or devices with limited resources.
- ✓ Involves minimum coding and comprehension of intricate algorithms.
- ✓ Performs effectively with photographs taken in uniform lighting and backdrop settings.

There are some limitations of thresholding-based segmentation that are listed as:

- ✓ Performance may diminish when lighting changes or while dealing with cluttered backgrounds.
- ✓ Difficulty with intricate leaf arrangements or leaves that overlap.
- ✓ Selecting the appropriate threshold can be difficult and may necessitate manual adjustment.

To solve such problem and improve the quality of the T-model, the concept of K-means is adopted in this research.

K-model: In this model, the concept of K-means algorithm is used instead of Thresholding-based segmentation. It is a clustering approach that is a commonly used method for segmenting images, often applied to tasks such as segmenting tomato leaves. Although not flawless, it provides a more comprehensive method than basic thresholding, particularly when addressing color and illumination fluctuations. Similar to thresholding, pre-processing steps are often applied to enhance tomato image quality for better segmentation. It involves some steps to perform clustering-based segmentation:

1. Pixels are represented using features like their intensities in different RGB color channels.
2. A number of clusters (K) identification is a crucial parameter that decides how many distinct color groups (clusters) the algorithm identifies in the image. Choosing the right K value significantly impacts segmentation accuracy (Bulawit et al., 2024).
3. The initialization of K as an initial cluster center (centroids) is randomly chosen within the feature space.
4. After that, each pixel is assigned to the nearest cluster based on its feature distance (Euclidean Distances) to the centroids.
5. Centroids are recalculated based on the average features of all pixels assigned to their respective clusters that is known as the updating of centroid value.
6. Steps 4 to 5 are repeated until best convergence, where centroids no longer change significantly, indicating stable clusters.
7. One or more clusters typically represent the leaf region based on their color characteristics. Prior knowledge or manual selection might be needed to identify the correct cluster(s).
8. Pixels belonging to the leaf cluster(s) are labeled as foreground, while others are considered background.

Algorithm 2: K-means based Segmentation

Input: PLI → Pre-processed Leaf Image
Output: BI and FI (ROL) → Background and Foreground Image
Start
Set cluster number (K = 2)
Calculate the size of PLI, [R, C, P] = Size (PLI)
While Pixel (PLI) = True
  For I1 in range of R
    For I2 in range of C
      If PLI (I1, I2) < TV
        BI (I1, I2) = PLI (I1, I2)
      Else
        FI (I1, I2) = PLI (I1, I2)
      End – If
    End – For
  End – For
Segregate G = G1 & G2 // Where G1 for BI and G2 for ROL
While Pixel (PLI) = True
  For I_1 in range of R
    For I_2 in range of C
      If PLI (I_1, I_2) == G1
        BI (I_1, I_2) = PLI (I_1, I_2)
      Else if PLI (I_1, I_2) == G2
        FI (I_1, I_2) = PLI (I_1, I_2)
      End – If
    Adjust Centroid C using their mean
    G = Average (BI, FI) using equation 1

$$G_{mn} = \sum_{m=1}^{Row} \sum_{n=1}^{Col} \frac{G1_{mn} + G2mn}{2} \qquad (1)$$

  End – For
End – For
End – While
Return: BI and FI as a ROL
End – Algorithm

The K-means algorithm in the K-model provided improved segmentation compared to the previous Thresholding-based algorithm. The achieved improvement is shown in the Figure 3.

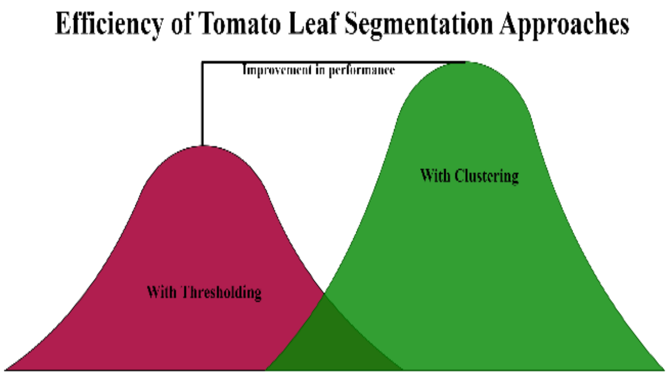

Figure 3. Comparison of Performance for With and Without Clustering.

Both thresholding and clustering-based approaches are utilized for tomato leaf segmentation, each with its strengths and weaknesses. Here's a comparative analysis to help you choose the most suitable method:

Accuracy

Thresholding:

- Generally, less accurate, especially in complex scenarios with varying lighting and backgrounds.
- Sensitive to accurate threshold selection, which can be challenging.

Clustering:

- More robust to color variations and moderate lighting changes.
- Can adapt to diverse scenarios by adjusting parameters like the number of clusters and color features.
- However, still struggles with intricate leaf shapes, overlapping leaves, and complex textures.

Computational Efficiency

Thresholding:

- Highly efficient and fast, making it suitable for real-time applications or resource-constrained devices.
- Simple to implement with minimal coding requirements.

Clustering:

- Less efficient than thresholding due to iterative calculations.
- Requires more complex implementation and parameter tuning.

Ease of Use

Thresholding:

- Simplest approach, easily understandable and implementable.
- Requires minimal prior knowledge or expertise.

Clustering:

- Requires understanding of clustering algorithms and parameter selection strategies.
- Might involve manual intervention to identify the correct leaf cluster.

Basically, clustering-based segmentation is more versatile, handling moderate variations in lighting and background. Due to this reason, it is suitable for real-world image processing applications with some complexities. The findings are displayed together with the original tomato images in Figure 4.

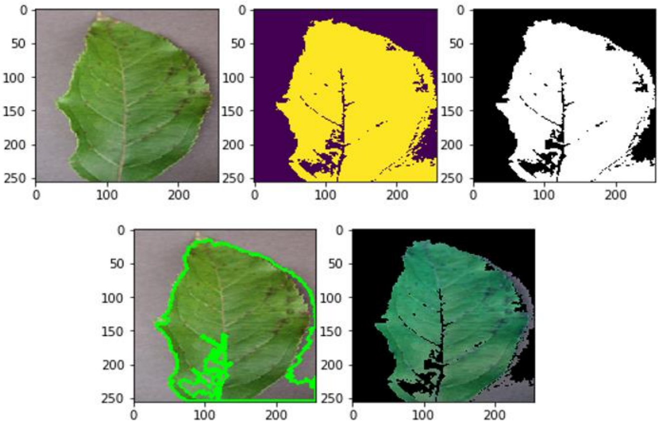

Figure 4(a). Original (b) Clustered (c) Mask (d) Region Localization and (e) ROL.

TPSO-model: In this model, the concept of PSO algorithm is used with traditional Thresholding-based segmentation. Although typical thresholding is simple for segmenting tomato leaves, it may face difficulties with issues such as inconsistent lighting and intricate backdrops. Implementing PSO in the process enhances its dynamism and adaptability, potentially overcoming the constraints of fixed threshold selection. PSO imitates the group hunting actions of a swarm of particles. Each particle in this context symbolizes a possible threshold value. They navigate the "fitness landscape," where their "fitness" score indicates the quality of the segmentation accomplished with their respective threshold. Particles interact and adapt by modifying their positions to investigate favorable areas and come together towards the most effective threshold for achieving optimal segmentation and Thresholding with PSO-based segmentation algorithm written as:

Algorithm 3: TPSO Segmentation

Input: ROL → Region of Leaf as a Foreground Image
Output: IROL → Improved Region of Leaf as a Foreground Image
Start
We optimized the ROL by utilizing the PSO algorithm and initializing it with the following parameters:
– Iterations (T)
– Population-size (S)
– Lower-Limit (LB)
– Upper-Limit (UB)
– Fitness function
– Number of selection (N)
Calculate the size of ROL, [R, C, P] = Size (ROL)
Calculate size in terms of T = R × C.
Define Fitness function using equation 2

$$fit\ (fun) = \begin{cases} \mathbf{1} & \boldsymbol{if\ pixel\ is\ less} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \qquad \textbf{(2)}$$

For l in T

$fs = \mathrm{ROL}(l)$

$ft = \frac{\sum_{i=1}^{Pixels} ROL(l)}{Length\ of\ ROL\ Pixels}$

$fit(fun)$ = using equation 2

$T_v = PSO\big(P, T, LB, UB, N, fit(fun)\big)$

End – For
Define optimization iterations, O-Rep = N
While Pixel(T) = True
$\boldsymbol{Thr} = T_v$
Mask = Binary (ROL, Thr)
ROL Boundaries = Boundary (Mask)
For k = 1→ D
IROL = ROL × ROL Boundaries
End – For
End – While
Return: IROL Improved Region of Leaf as a Foreground Image
End – Algorithm

KPSO-model: Similar to the previous model, in this model, just the concept of K-means is used along with the PSO for K-means outputs. So, the algorithm of this model is similar to the prevision one. While both K-means clustering and PSO have individually shown their strengths in tomato leaf segmentation, combining them can create a powerful and adaptable approach. This symbiosis leverages the benefits of each method, potentially overcoming their individual limitations. K-means excels at identifying distinct color clusters within an image. However, choosing the optimal number of

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clusters (K) and ensuring they accurately represent the leaf can be challenging. PSO comes to the rescue by optimizing the K-means process. Particles in the swarm represent different combinations of K and initial cluster positions. They are evaluated based on how well the resulting segmentation aligns with predefined criteria, leading PSO to guide K-means toward the most effective configuration.

TGO-model: This model incorporates the GO algorithm with classic Thresholding-based segmentation to segment the exact region of leaf (ROL). While standard thresholding is effective for separating tomato leaves, it may struggle with challenges like varying lighting conditions and complex backgrounds. The GO algorithm, a nature-inspired metaheuristic algorithm, can enhance the thresholding process to address these limitations and perhaps improve the segmentation's robustness and adaptability. Algorithm for utilizing a GO-based segmentation method for thresholding is written as:

Algorithm 4: TGO Segmentation

Input: ROL → Region of Leaf as a Foreground Image
Output: IROL → Improved Region of Leaf as a Foreground Image
Start
We optimized the ROL by utilizing the GO algorithm and initializing it with the following parameters:
– Define the number of grasshoppers (swarm size)
– Set the maximum number of iterations (Max_iter)
– Define the search space for the threshold (e.g., minimum and maximum intensity values)
– Initialize a swarm of swarm_size grasshoppers.
For each grasshopper:

$$fs = \mathrm{ROL}(l)$$

$$ft = \frac{\sum_{i=1}^{Pixels} ROL(l)}{Length\ of\ ROL\ Pixels}$$

$$T_v = GO\big(P, T, LB, UB, N, fit(fun)\big) \quad //$$

Evaluate the fitness of the grasshopper using a chosen metric (e.g., Jaccard similarity index, F1 score) based on the segmentation achieved with its corresponding threshold.
End – For
Define optimization iterations, O-Rep = N
While Pixel(T) = True
$\boldsymbol{Thr} = T_v$
Mask = Binary (ROL, Thr)
ROL Boundaries = Boundary (Mask)
Identify the grasshopper with the highest fitness score (best_grasshopper)
For k = 1→ D
IROL = ROL × ROL Boundaries
End – For
End – While
Return: IROL Improved Region of Leaf as a Foreground Image
End – Algorithm

KPSO-model: Similar to the previous model, in this model, just the concept of K-means is used along with the PSO for K-means outputs. So, the algorithm of this model is similar to the prevision one. While both K-means clustering and PSO have individually shown their strengths in tomato leaf segmentation, combining them can create a powerful and adaptable approach. This symbiosis leverages the benefits of each method, potentially overcoming their individual limitations. K-means excels at identifying distinct color clusters within an image. However, choosing the optimal number of clusters (K) and ensuring they accurately represent the leaf can be challenging. PSO comes to the rescue by optimizing the K-means process. Particles in the swarm represent different combinations of K and initial cluster positions. They are evaluated based on how well the resulting segmentation aligns with predefined criteria, leading PSO to guide K-means toward the most effective configuration.

TGO-model: This model incorporates the GO algorithm with classic Thresholding-based segmentation to segment the exact region of leaf (ROL). While standard thresholding is effective for separating tomato leaves, it may struggle with challenges like varying lighting conditions and complex backgrounds. The GO algorithm, a nature-inspired metaheuristic algorithm, can enhance the thresholding process to address these limitations and perhaps improve the segmentation's robustness and adaptability. Algorithm for utilizing a GO-based segmentation method for thresholding is written as:

Algorithm 4: TGO Segmentation

Input: ROL → Region of Leaf as a Foreground Image
Output: IROL → Improved Region of Leaf as a Foreground Image
Start
We optimized the ROL by utilizing the GO algorithm and initializing it with the following parameters:
– Define the number of grasshoppers (swarm size)
– Set the maximum number of iterations (Max_iter)
– Define the search space for the threshold (e.g., minimum and maximum intensity values)
– Initialize a swarm of swarm_size grasshoppers.
For each grasshopper:

$$fs = \mathrm{ROL}(l)$$

$$ft = \frac{\sum_{i=1}^{Pixels} ROL(l)}{Length\ of\ ROL\ Pixels}$$

$$T_v = GO\big(P, T, LB, UB, N, fit(fun)\big) \quad //$$

Evaluate the fitness of the grasshopper using a chosen metric (e.g., Jaccard similarity index, F1 score) based on the segmentation achieved with its corresponding threshold.
End – For
Define optimization iterations, O-Rep = N
While Pixel(T) = True

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$\boldsymbol{Thr} = T_v$
Mask = Binary (ROL, Thr)
ROL Boundaries = Boundary (Mask)
Identify the grasshopper with the highest fitness score (best_grasshopper)
For k = 1→ D
IROL = ROL × ROL Boundaries
End – For
End – While
Return: IROL Improved Region of Leaf as a Foreground Image
End – Algorithm

Thresholding based on the GO algorithm shows potential for improving tomato leaf segmentation, especially in situations with different lighting conditions and backdrops. It utilizes GOA's optimization skills to address the drawbacks of static thresholding while being relatively simple in comparison to deep learning techniques (Mishra et al., 2024). The benefits of TGO-based segmentation are listed as:

1 GOA can autonomously determine the best threshold for various lighting and background situations, surpassing fixed thresholds.

2 Various fitness functions can be utilized to meet specific segmentation objectives, such as maximizing leaf coverage or minimizing noise.

3 GO can reach the optimal threshold quicker than an exhaustive search, particularly in search areas.

Based on TGO Segmentation, we achieved an excellent result in the segmentation improvisation that is shown in the Figure 5.

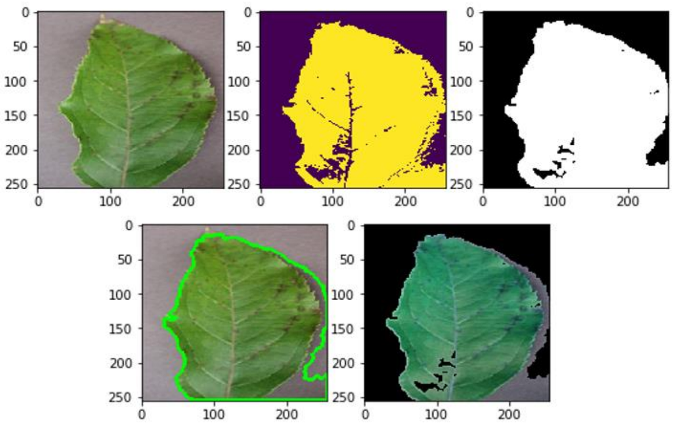


Figure 5(a). Original (b) Clustered (c) Mask (d) Region Localization and (e) ROL using TGO.

KGO-model: Integrating K-means clustering with the GO algorithm offers a potentially robust method for segmenting tomato leaves. This method combines the characteristics of both techniques to overcome their respective limits and create strong and adaptive segmentation, particularly in varied lighting and background situations. The algorithm and working process of KGO model is similar to TGO model and based on KGO Segmentation, but in terms of segmentation slightly improvement is noticed and we achieved an excellent result in the segmentation improvisation that is shown in the Figure 6.

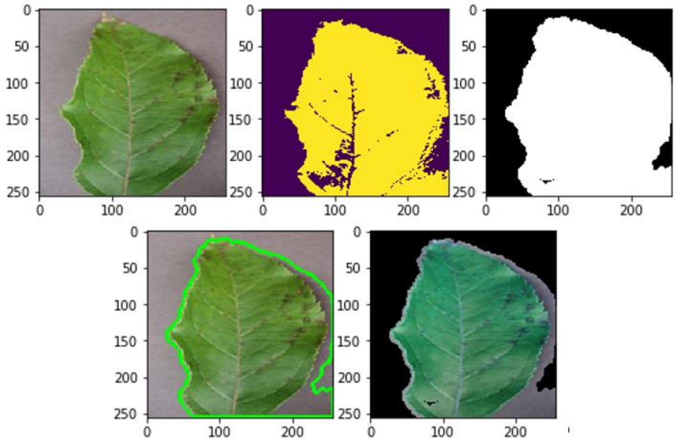


Figure 6(a). Original (b) Clustered (c) Mask (d) Region Localization and (e) ROL using KGO.

K-means combined with GO algorithm presents a viable method for segmenting tomato leaves, especially in situations with varied illumination and backdrops. It utilizes K-means clustering capabilities in conjunction with GO algorithm to optimize its configuration, perhaps attaining better performance than utilizing each method separately. For benefit, further investigation will be beneficial

1 Explore several fitness functions tailored for K-means algorithm in conjunction with GO algorithm for the purpose of segmenting tomato leaves.

2 Compare this strategy with other optimization approaches or deep learning algorithms for leaf segmentation.

3 Examine precise methods for adjusting parameters in both K-means and GO algorithm to achieve the best performance.

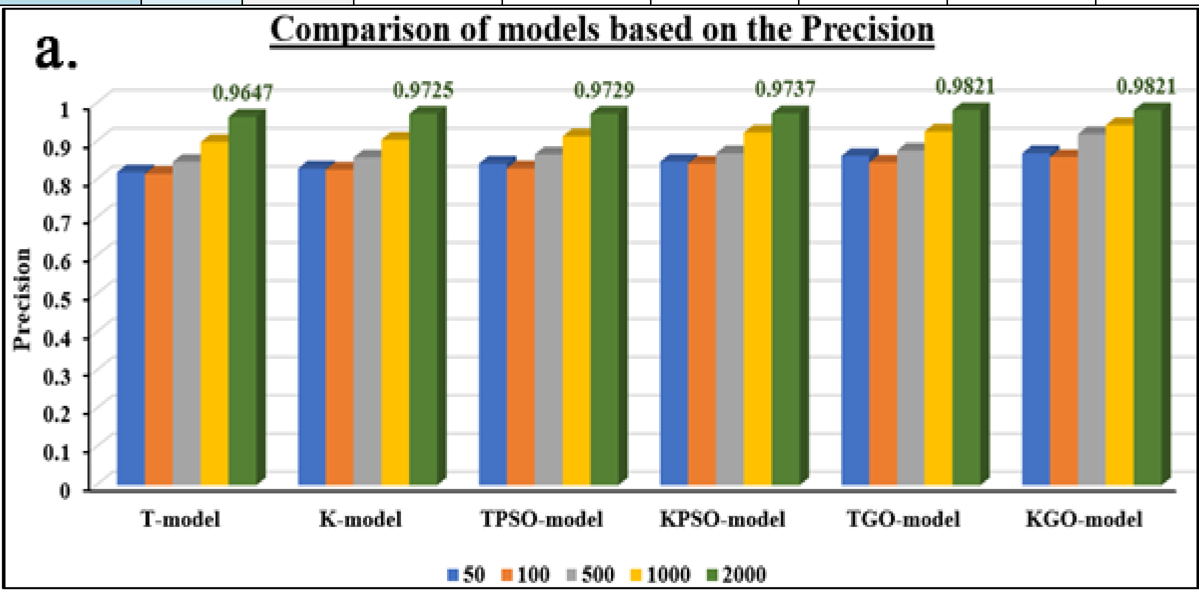
After adhering to the specified methodology, performance was evaluated based on various metrics outlined in the results and discussion section.

Results and Discussion

This section details the findings and analysis derived from evaluating the planned work. The evaluation considers QoS factors like Precision, Recall, F-measure, Error, and Accuracy. Comparative analysis is conducted to verify the credibility of the presented work. This research introduces a comparative framework for tomato leaf region segmentation using six scenarios: T-model, K-model, TPSO-model, KPSO-model, TGO-model and KGO-model. Simulation results of the provided scenario are displayed in Table 1, based on the quantitative parameters.

Table 1. Comparing simulation outcomes using quantitative parameters.

PARAMETERS			T-model	K-model	TPSO-model	KPSO-model	TGO-model	KGO-model
Precision	**No. of Images**	50	0.8198	0.8291	0.8422	0.8474	0.8627	0.8699
		100	0.8154	0.8261	0.8295	0.8422	0.8448	0.8591
		500	0.8469	0.8583	0.8667	0.8694	0.8765	0.9197
		1000	0.8988	0.9052	0.9138	0.9237	0.9265	0.9431
		2000	0.9647	0.9725	0.9729	0.9737	0.9821	0.9821
Recall	**No. of Images**	50	0.8097	0.8307	0.8441	0.8575	0.8599	0.8611
		100	0.8268	0.8282	0.8392	0.8430	0.8651	0.8701
		500	0.8608	0.8642	0.8792	0.8895	0.8999	0.9190
		1000	0.8864	0.8892	0.8924	0.9037	0.9232	0.9421
		2000	0.9617	0.9661	0.9673	0.9803	0.9831	0.9851
F-measure	**No. of Images**	50	0.8147	0.8298	0.8364	0.8524	0.8612	0.8654
		100	0.8211	0.8271	0.8325	0.8426	0.8548	0.8645
		500	0.8537	0.8612	0.8686	0.8793	0.8880	0.9193
		1000	0.8925	0.8971	0.8987	0.9135	0.9248	0.9426
		2000	0.9631	0.9692	0.9698	0.9769	0.9825	0.9835
Accuracy	**No. of Images**	50	78.8307	79.5256	80.3841	81.5816	87.8346	96.8732
		100	80.3989	81.4237	82.5393	84.3495	89.8007	97.913
		500	85.0235	86.7798	89.0326	90.0117	90.1153	98.799
		1000	88.3359	89.2489	89.6378	89.6862	94.7604	98.9569
		2000	96.0569	96.0690	96.1101	97.6035	98.5501	99.6902
Error	**No. of Images**	50	21.1693	20.4744	13.4393	19.616	12.1654	7.1568
		100	19.6011	18.5763	10.3607	17.4607	10.1993	4.8970
		500	14.9765	13.2202	6.2858	10.9674	9.8847	3.6301
		1000	11.6641	10.7511	4.9269	10.3622	5.2396	1.7431
		2000	3.9431	3.931	2.4456	3.8899	1.4499	0.3098



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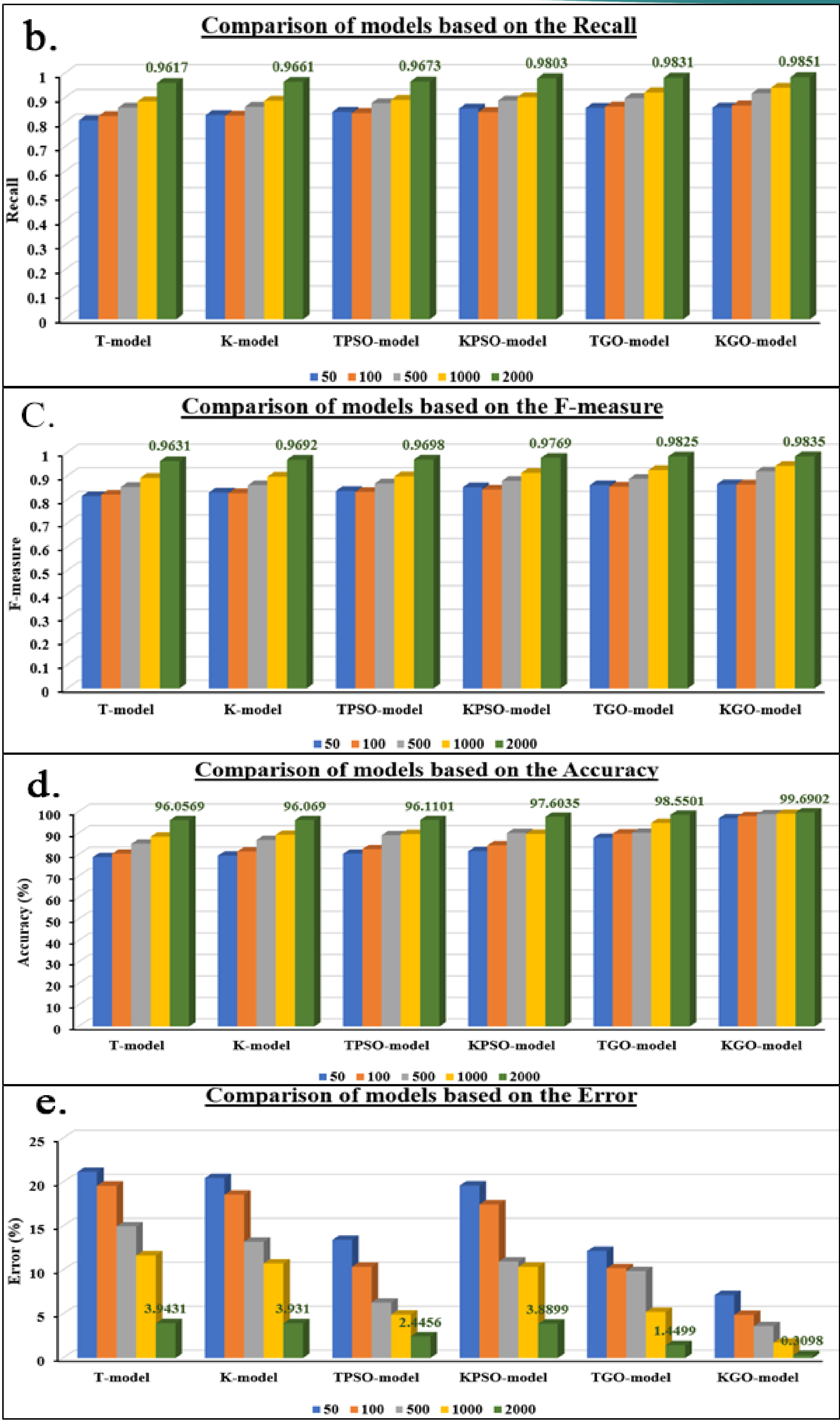

Figure 7(a,b,c,d,e). Comparing simulation outcomes using quantitative parameters.

Table 2. Comparing simulation outcomes using similar parameters.

PARAMETERS			T-model	K-model	TPSO-model	KPSO-model	TGO-model	KGO-model
MCC	No. of Images	50	0.7749	0.7917	0.8014	0.8447	0.8893	0.9706
		100	0.7792	0.7999	0.8108	0.8651	0.9157	0.9713
		500	0.8008	0.8216	0.8125	0.8858	0.9394	0.984
		1000	0.8022	0.8305	0.8587	0.8882	0.945	0.9857
		2000	0.8151	0.8656	0.8734	0.9023	0.9485	0.9979
JC	No. of Images	50	0.7626	0.8085	0.8047	0.8418	0.8982	0.9668
		100	0.7853	0.8135	0.8092	0.8602	0.8993	0.9717
		500	0.7804	0.8324	0.8416	0.8834	0.9165	0.9793
		1000	0.8184	0.8406	0.8562	0.8912	0.9363	0.9867
		2000	0.8225	0.8562	0.8758	0.8957	0.9489	0.9871
DC	No. of Images	50	0.7806	0.8349	0.8433	0.8897	0.8941	0.9608
		100	0.8240	0.8407	0.8528	0.8975	0.8986	0.9610
		500	0.8245	0.8431	0.8638	0.9158	0.9076	0.9695
		1000	0.8546	0.8462	0.8777	0.9221	0.9215	0.9865
		2000	0.8692	0.8879	0.8781	0.9473	0.9272	0.9888
Time	No. of Images	50	7.8986	8.17185	8.21999	8.25839	8.45225	8.5419
		100	8.1251	8.12981	8.13375	8.37362	8.50933	8.53367
		500	8.41027	8.47856	8.66652	8.79246	8.83669	9.18777
		1000	8.82637	8.90073	8.92192	9.01242	9.28575	9.4042
		2000	9.60145	9.63701	9.69636	9.74011	9.76711	9.79502

Table 3. Evaluation of Prior Research for Efficiency Comparison.

Works	Accuracy (%)
Ensemble classifier (M Jamjoom et al., 2023)	89.00
FCM with Chameleon Swarm (A Umamageswari et al., 2023)	97.43
Ensemble CNN Model (H Ulutaş & V Aslantaş, 2023)	95.45
T-model	85.73
K-model	86.61
TPSO-model	87.54
KPSO-model	88.64
TGO-model	92.21
KGO-model	98.45

From Table 1 and Figure 7, we observed that the simulation results of proposed frameworks, hybridization of the K-means with GO algorithm is superior to other modules in terms of the quantities parameters, but we need to validate the model based on similarities parameters such as MCC, DC, JC and computational time. Therefore, the simulation results in comparative analysis based on the similarities value given in Table 2.

K-means with GO algorithm outperforms other modules in terms of similarity parameters. The suggested framework aims to achieve maximum accuracy by providing fast response to segmentation with pre-processing. The proposed system provides a highly adaptable and independent mechanism with numerous deep-learning interfaces. To validate the system's efficiency, we must compare it with state-of-the-art work based on their correctness in Table 3.

K-means with GO algorithm achieved an accuracy of 96.45% and Figure 8 displays a graphical comparison of frameworks including T-model, K-model, TPSO-model, KPSO-model, TGO-model and KGO-model. So, in the future model of tomato plant disease detection and classification, we will utilize the concept of the proposed KGO-model for segmentation and then we will pass this segmented data to CNN for further model training for classification tasks.

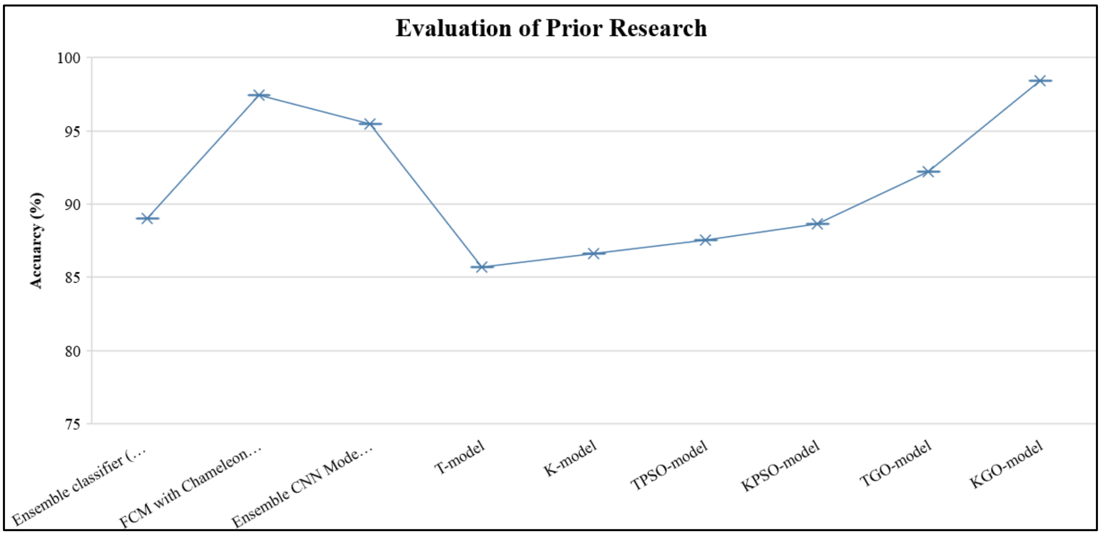

Figure 8. Evaluation of Prior Research for Efficiency Comparison.

Conclusion and Future Work

This research presents a comparative paradigm for tomato leaf region segmentation using traditional as well as swarm intelligence-based methods to find out a better approach. This framework facilitates the creation of a tomato plant diagnosis system that can analyse many types of images, including standard as well as own images. We conducted a comparison analysis involving six scenarios: T-model, K-model, TPSO-model, KPSO-model, TGO-model and KGO-model. The effectiveness of combining K-means with GO algorithm was demonstrated to be a potent hybrid approach, achieving an accuracy of 96.45%. In comparison, other methods achieved accuracies of 85.73%, 86.61%, 87.54%, 88.64%, and 92.21% using T-model, K-model, TPSO-model, KPSO-model, and TGO-model respectively. We aim for the migration of plant image segmentation from research labs to practical or real-time applications in the future with their various aspect, like fruits, stems, leaves, etc., in a single application.

References

Anam, S., & Fitriah, Z. (2021). Early Blight Disease Segmentation on Tomato Plant Using K-means Algorithm with Swarm Intelligence-based Algorithm. *International Journal of Mathematics and Computer Science*, *16*(4), http://ijmcs.future-in-tech.net

Bulawit, G., Palaoag, T., & Bulawit Jr, B. (2024). African Swine Fever Disease Risk Assessment Using Multi-Criteria Decision Analysis: An Input for GIS-Based Risk Mapping. *International Journal of Experimental Research and Review*, *40*(Spl Volume), 1-10. https://doi.org/10.52756/ijerr.2024.v40spl.001

Chowdhury, M. E., Rahman, T., Khandakar, A., Ayari, M. A., Khan, A. U., Khan, M. S., ... & Ali, S. H. M. (2021). Automatic and reliable leaf disease detection using deep learning techniques. *AgriEngineering*, *3*(2), 294-312.

Concepcion, R., Lauguico, S., Dadios, E., Bandala, A., Sybingco, E., & Alejandrino, J. (2020). Tomato septoria leaf spot necrotic and chlorotic regions computational assessment using artificial bee colony-optimized leaf disease index. IEEE Region 10 Annual International Conference, *Proceedings/TENCON*, 2020-November, pp. 1243–1248. https://doi.org/10.1109/TENCON50793.2020.9293743

Darwish, A., Ezzat, D., & Hassanien, A. E. (2020). An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseases diagnosis. *Swarm and Evolutionary Computation*, *52*. https://doi.org/10.1016/j.swevo.2019.100616

David, B., David, D. B., & Gomathi, R. (2023). Improved Segmentation with Optimization Based Multilevel Thresholding and K-Means Clustering for plant disease identification improved segmentation with optimization based multilevel thresholding and k-means clustering for plant disease identification. https://doi.org/10.21203/rs.3.rs-2373358/v1

Dutta, A., Pal, A., Bhadra, M., Khan, M. A., & Chakraborty, R. (2021). An Improved K-Means Algorithm for Effective Medical Image Segmentation. *In Proceedings of International Conference on Innovations in Software Architecture and Computational Systems*: ISACS 2021, Springer Singapore, pp. 169-182. https://doi.org/10.1007/978-981-16-4301-9_13

Jamjoom, M., Elhadad, A., Abulkasim, H., & Abbas, S. (2023). Plant Leaf Diseases Classification Using Improved K-Means Clustering and SVM Algorithm for Segmentation. *Computers, Materials & Continua*, *76*(1), 367–382. https://doi.org/10.32604/cmc.2023.037310.

Karaboğa, D. (2005). An Idea Based on Honey Bee Swarm for Numerical Optimization. *Journal of Advanced Computer Science and Applications, 13*(1).

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95-International Conference on Neural Networks, 4*, 1942-1948. https://doi.org/10.1109/ICNN.1995.488968

Kumar, S., & Aggarwal, A. (2023). Gene Expression based Blood Cancer Classification Model using Natural Computing along with Deep Learning. In *2023 International Conference on Communication, Security and Artificial Intelligence* (ICCSAI), pp. 292-297. https://doi.org/10.1109/ICCSAI59793.2023.10421507

Noonari, S., Memon, M.I.N., Solangi, S.U., Laghari, M.A., Wagan, S.A., Sethar, A.A., ... Panhwar, G.M. (2015) Economic implications of tomato production in Naushahroferoze district of Sindh Pakistan. *Res. Humanit. Soc. Sci.*, *5*(7), 158–170.

Sahoo, M. (2011). Biomedical image fusion and segmentation using glcm. In Proceedings of the 2nd *National Conference-Computing, Communication and Sensor Network* (CCSN), Orissa, India, pp. 29-30.

Singh, K., Malik, D., & Sharma, N. (2012). Evolving limitations in K-means algorithm in data mining and their removal. *International Journal of Computational Engineering & Management, 12*(1), 105-109.

Thangaraj, R., Anandamurugan, S., Pandiyan, P., & Kaliappan, V. K. (2022). Artificial intelligence in tomato leaf disease detection: a comprehensive review and discussion. *Journal of Plant Diseases and Protection, 129*(3), 469-488. https://doi.org/10.1007/s41348-021-00500-8

Tian, K., Li, J., Zeng, J., Evans, A., & Zhang, L. (2019). Segmentation of tomato leaf images based on adaptive clustering number of K-means algorithm. *Computers and Electronics in Agriculture, 165*, 104962. https://doi.org/10.1016/j.compag.2019.104962

Ulutaş, H., & Aslantaş, V. (2023). Design of Efficient Methods for the Detection of Tomato Leaf Disease Utilizing Proposed Ensemble CNN Model. *Electronics* (Switzerland), *12*(4). https://doi.org/10.3390/electronics12040827

Umamageswari, A., Bharathiraja, N., & Irene, D. S. (2023). A Novel Fuzzy C-Means based Chameleon Swarm Algorithm for Segmentation and Progressive Neural Architecture Search for Plant Disease Classification. *ICT Express, 9*(2), 160–167. https://doi.org/10.1016/j.icte.2021.08.019

Mishra, V., Mishra, M., Tamrakar, A., Srikanth, T., Kumar, T., & Kumar, A. (2024). Pneumonia Detection through Deep Learning: A Comparative Exploration of Classification and Segmentation Strategies. *International Journal of Experimental Research and Review, 40*(Spl Volume), 41-55. https://doi.org/10.52756/ijerr.2024.v40spl.004

Upadhyay, S., Jain, J., & Prasad, R. (2024). Early Blight and Late Blight Disease Detection in Potato Using Efficientnetb0. *International Journal of Experimental Research and Review, 38*, 15-25. https://doi.org/10.52756/ijerr.2024.v38.002

Venkatasubramanian, S. (2021). A Chaotic Salp Swarm Feature Selection Algorithm for Apple and Tomato Plant Leaf Disease Detection. *International Journal, 10*(5). https://doi.org/10.30534/ijatcse/2021/161052021

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