Iran University of Science and Technology

Iranian Journal of Electrical and Electronic Engineering

Journal Homepage: ijeee.iust.ac.ir

FirePSOSA: A Hybrid Metaheuristic Approach for Enhanced Segmentation of Maize Leaves

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Abstract: The potential adverse effects of maize leaf diseases on agricultural productivity highlight the significance of precise disease diagnosis using effective leaf segmentation techniques. In order to improve maize leaf segmentation, especially for maize leaf disease detection, a hybrid optimization method is proposed in this paper. The proposed method provides better segmentation accuracy and outperforms traditional approaches by combining enhanced Particle Swarm Optimisation (PSO) with Firefly algorithm (FFA). Extensive tests on images of maize leaves taken from the Plant Village dataset are used to show the algorithm's superiority. Experimental results show a considerable decrease in Hausdorff distances, indicating better segmentation accuracy than conventional methods. The proposed method also performs better than expected in terms of Jaccard and Dice coefficients, which measure the overlap and similarity between segmented sections. The proposed hybrid optimization method significantly contributes to agricultural research and indicates that the method may be helpful in real scenarios. The performance of proposed method is compared with existing techniques like K-Mean, OTSU, Canny, FuzzyOTSU, PSO and Firefly. The overall performance of the proposed method is satisfactory.

Keywords: Maize leaf, Optimization, PSO, SA, Firefly, Segmentation.

1 Introduction

OVER the years, maize growing in India has risen significantly, becoming a vital sector of the nation's agricultural sector. Favourable climatic conditions and vast agricultural expertise have facilitated the spread of maize agriculture in several locations. Due to flexibility and excellent yield potential of maize, farmers in India have embraced it, which has increased productivity and enhanced food security. In addition to providing rural populations with economic possibilities, expanding maize growth also helps the country's overall agricultural development. The agricultural sector and farmers stand to gain a lot from the automated disease identification in maize leaves [1]. The automated detection system uses cutting-edge technology and image-processing techniques to quickly and precisely identify diseases that damage maize plants [2]. Because of the early discovery, farmers can move quickly to stop the disease's spread by implementing specific treatments and preventive measures. Automatic disease identification has advantages beyond individual farms since it reduces crop losses and prevents broad outbreaks [3]. Ultimately, the automated diagnosis of maize leaf diseases improves agricultural productivity and efficiency, resulting in healthier harvests and protecting farmer's livelihoods [4]

Many diseases, such as common rust, grey leaf spot, and northern corn leaf blight, can affect maize plants. The output of maize is significantly hampered by these three diseases on a global scale [5]. To reduce the effects of these diseases on maize productivity, integrated disease management techniques, such as timely fungicide treatments and resistant maize types, must be used. Numerous critical phases are involved in plant disease detection [6]. The general health and look of the

Iranian Journal of Electrical & Electronic Engineering, 2024.
Paper first received 11 October 2023 and accepted 27 March 2024.
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plant must first be carefully observed. This entails looking for any indications of discolouration, lesions, or abnormal development on the leaves, stems, and fruits. The second step is identifying each illness's precise signs and symptoms, such as spots, wilting, or abnormalities. Plant samples must then be gathered, inspected under a microscope, or tested in a lab for additional examination. These tests may use DNA-based methods, pathogen isolation, or serological assays to determine if a particular pathogen or illness is present. Additionally, cutting-edge technology like imaging methods or remote sensing can help in disease identification by taking and examining plant leaf images. Finally, a disease must be correctly diagnosed and identified before effective treatment and preventative actions may be taken to lessen its effects on plant health and crop yield [7].

Techniques based on image processing provide a valuable method for various applications, such as disease detection in plant leaves [8]. The following actions must be taken to use these approaches for leaf analysis. First, high-quality images of the plant leaves are obtained using cameras or other imaging equipment. The visual traits and patterns linked to illnesses or anomalies on the leaf's surface are depicted in these images [9]. Second, to enhance the quality, isolate the target leaf region, and eliminate any background interference, preprocessing techniques such as image enhancement, noise reduction, and leaf segmentation are used [10]. Thirdly, elements, including leaf texture, colour, form, and vein patterns, are extracted using feature extraction algorithms from the segmented leaf images [11].

These characteristics are used as inputs by algorithms for categorization or detection. The system may then learn and recognize patterns and categorize leaf pictures into healthy or unhealthy categories by utilizing machine learning or deep learning methods to train models using labelled datasets. Then the images are used to test and evaluate the trained model’s accuracy in identifying disease. The researchers and farmers can monitor the health of leaves and conduct prompt treatments by utilizing effective and non-invasive disease detection approaches based on image processing and targeted at leaf analysis [12]. In many image processing applications, such as disease detection, segmentation is crucial. The segmentation of skin lesions is done using an automated learning technique. In this method first of all skin cancer images are pre-processed to minimise artefacts, and then segmentation is done using this improved filtered image. K-mean clustering with an optimised FFA method is used to accomplish this segmentation [13].

By removing noise, unimportant components, and differences in illumination, this method ensures that the extracted features and examined patterns accurately reflect the traits of the leaf. Additionally, segmentation permits a more specific localization of disease-related signs like spots, lesions, or discolouration, facilitating the classification and identification of illnesses that affect plant leaves.

1.1 Motivation

The dire need to improve disease identification and classification in agriculture led to the developing of a hybrid optimization algorithm to segment maize leaves. One of the most important staple crops in the world, maize, is plagued by various diseases that can result in significant output losses and food shortages. For farmers to efficiently execute appropriate control measures and secure their crops, accurate and prompt disease identification is crucial. But manually segmenting maize leaves for disease categorization takes time, is arbitrary, and is prone to mistakes. So, by automating this process, its accuracy and efficiency in identifying the leaf areas of interest can be ensured using the proposed hybrid optimization method. The suggested method can potentially revolutionize disease diagnosis in maize crops by providing farmers with a quick and accurate tool for early disease detection. The ultimate goal of this work is to improve crop health, boost agricultural output, and improve food security for populations that depend on maize as a primary food source.

1.2 Contribution of this paper

The main focus of this work is to propose a hybrid optimization algorithm to improve the segmentation in maize leaf for the application of maize leaf disease detection. Following are a few of the contributions of this paper:

- The main contribution is the algorithm developed using a hybrid combination of optimization algorithms that use enhanced PSO and firefly algorithms.
- The paper's second contribution is the implementation and testing of the proposed method as well as other methods of segmentation using a dataset of maize leaves from the Plant Village dataset.
- The third key addition of this paper is a complete comparison evaluation in which all stated methodologies are applied to identical datasets with uniform scales. This is supplemented by a thorough review based on a wide variety of performance criteria designed expressly for segmentation. This methodology not only emphasises the relative strengths and limitations of each method under consistent settings, but it also gives a distinct perspective

that contributes to the area of segmentation analysis.

This paper discusses the existing literature on the segmentation problem for maize and other plant leaves. Further, it deliberated the design and process of the proposed hybrid algorithm, followed by experimentation and result analysis. Finally, results are evaluated and elaborated based on the experimentation data, and concluding remarks are presented with their future scope.

2 Related Work

This section discusses existing segmentation approaches developed for maize leaf disease detection and other plant disease detection systems to identify the current challenges and considerations. Plant disease detection is a significant concern in the agriculture field, where computer vision provides fast and better solutions for the same. Before detection, segmenting the region to attain better outcomes is essential. Earlier, a simple method like binarization was used to separate the region as foreground and background [14], and further, only the foreground area was used for the classification or identification of disease in maize plants. Sukmana et al. [15] also utilized binarization after converting RGB samples to CIElab to enable the approach with different devices for segmentation. Sibiya and Sumbwanyambe [16] proposed a fuzzy inference-based approach for image segmentation specially designed for maize leaves. Firstly, the colour threshold method is used and then found the infected area using a fuzzy approach. After segmentation, they also defined some rules to identify the severity of the disease based on the area covered by the infected area. Another corn leaf segmentation method used colour and spatial properties of the pixels, the algorithm first trained two classic maize leaf segmentation models. Then segmented image is improved using spatial structure analysis [17].

Other approaches like canny edge detection and machine learning-based k-nearest neighbour (KNN) and K-mean [18] were also used to segment corn, tomato, and potato leaves. The analysis shows that the canny edge detection performance is better for corn leaves, but tomato and potato leaves were segmented well with k-mean based method. K-mean was further enhanced with HSV alteration to accurately segment pepper bell and tomato plant leaves [19]. A simple linear iterative clustering method is also proposed [20] for superpixel region generation and segmentation. Nowadays, deep learning-based automated segmentation is also in a trend where different models were proposed for this aim. Divyanth et al. [21] designed a two-stage deep learning model, UNet-DeepLabV3+, where the model is trained with ground truth masks based on which the predicted mask is generated to segment the region of interest. Another DCNN model, GoogleNet, is implemented [22] to segment maize leaf with northern corn leaf blight samples. Furthermore, a texture and contrast-based GrabCut segmentation method was proposed [23] for a deep learning system. The approach is tested on six different crop data and provides an efficient result. Another improved version of GrabCut [24] describe segmenting maize leaves for further identification of diseases. Histogram-based method to compute threshold and perform segmentation is also utilized with a deep learning model [25]. Furthermore, the channel-based histogram approach was also designed for segmentation in a deep learning-based classification system [26].

Apart from this, metaheuristic approaches are also utilized to segment the image samples. Different optimization algorithms, including Genetic Algorithm (GA), Ant Colony Optimization (ACO), PSO, etc., are part of this. Singh [27] worked on detecting sunflower leaf disease, where PSO was selected as a segmentation method which helped improve the detection system's accuracy. Moreover, Fast fuzzy c-mean with Otsu threshold performed well [28]. Another leaf disease segmentation model utilizes an active contour model with a fruitfly optimization algorithm to improve segmentation for plant leaves [29]. The given literature on plant disease detection and image segmentation exhibits some limitations. Early methods like binarization may oversimplify complex leaf structures, leading to less reliable results. Fuzzy inference approaches depend on manual rules and may need to generalize better to various plant diseases. Handcrafted feature-based techniques might need help to capture all relevant information. Some methods are specific to certain plant species or diseases, limiting their broader applicability. Optimization algorithms, though promising, can be computationally expensive and require careful parameter tuning. Deep learning models demand large annotated datasets and might vary in performance based on data quality. Addressing these limitations could lead to improved and more robust plant disease detection and segmentation methods with broader agricultural impact.

3 FirePSOSA- Hybrid Approach

This section of the paper deliberates the hybrid optimization approach proposed for segmentation. In this hybrid approach, two different metaheuristic approaches, the firefly algorithm and enhanced particle swarm optimization, are combined to derive better and optimum results. Both of these algorithms are well-renowned algorithms and are used in various applications for distinct purposes. Here, it is designed to select an optimum threshold for image segmentation, specifically for maize leaf to separate the region in the leaves and identify the region of interest for further disease identification.

3.1 Firefly Algorithm

The Firefly Algorithm (FFA) is a metaheuristic optimization algorithm inspired by nature that uses flashing fireflies as its model. Bioluminescence is a form of communication and mate attraction used by fireflies. The method simulates this behaviour by mimicking the movement of fireflies in a search space to solve optimization issues. The brightness of a firefly corresponds to its fitness value in the Firefly Algorithm, where brighter fireflies are regarded as better answers. Each Firefly represents a potential solution to the optimization issue. By iteratively adjusting the placements of fireflies depending on their brightness and the attraction between them, the programme seeks to discover the best answer [30]. Each Firefly indicates a potential region or segment inside the image when using the Firefly Algorithm to segment images. The brightness of a firefly is related to its fitness, which is determined by how well the segment matches the target item or location. Brighter fireflies signify more promising segments that more closely resemble the properties of the sought item. Fireflie's brightness and spatial proximity in the image affect how appealing they are to one another. Just as brighter fireflies in nature draw other fireflies towards them, so do fireflies with increasing brightness. This property encourages fireflies to migrate to brighter areas, representing better segmentation outcomes and assisting the algorithm's convergence towards more ideal image segments [31]. The Firefly Algorithm is highly suited for image segmentation tasks because it can balance exploration and exploitation. Better segmentation outcomes are obtained due to efficient exploration of the search space for potential picture segments and exploiting prospective regions with many bright fireflies. Up to convergence, the algorithm iteratively segments the image's objects and areas with accuracy and precision.

3.2 Enhanced Particle Swarm Optimization Simulated Annealing (PSOSA)

The social behaviour of fish schools or bird flocks served as the basis for the well-known and effective metaheuristic optimization technique, PSO. It searches the search space for the best answer to a given issue by moving a population of potential solutions or particles. While maintaining its location and speed and acting as a possible solution, each particle learns from its own experiences and those of its neighbours. The global best position (gbest), the best solution found by every particle in the population, and a particle's historical best position (pbest), which is the best solution a particle has encountered thus far, determine how a particle will travel. Particles work together to cooperatively explore and exploit the search space to converge towards the best solution by continually altering their locations and velocities depending on these best solutions [32].

Each particle in PSO-based segmentation indicates a possible area or segment inside the image. Particles are led by their pbest and gbest, representing the best segmentation outcomes each particle and the whole population have experienced, respectively. Particles jointly explore and utilize the search space to move towards the best segmentation by iteratively modifying their locations and velocities depending on these best solutions. The PSO-based segmentation method aims to identify the best sections in the image that match the objects or regions of interest. The best pixel values or borders representing the segmented items are chosen to divide these areas from the backdrop. The best segmentation is discovered by updating particle locations and speeds until convergence [32].

Further, Simulated Annealing (SA) is fused to improve and strengthen PSO, forming a hybrid algorithm PSOSA [33]. PSO uses particles to represent alternative solutions and travel around the search space. However, SA principles also have an impact on how the particles travel. SA is an optimization method that draws inspiration from the metallurgical annealing procedure, in which a material is progressively cooled to a low-energy state. It entails accepting less-than-ideal answers with a predetermined probability in the optimization context, enabling search space exploration to bypass regional optima. When PSO and SA are combined, particles can use the most incredible solutions thus far while sometimes exploring less-than-ideal areas to avoid being trapped in local optima. The technique is more suited for difficult, multimodal optimisation problems because of the harmony between exploration and exploitation.

3.3 Proposed method (FirePSOSA)

A highly effective hybrid metaheuristic optimisation technique the result of merging PSOSA and FFA is FirePSOSA, an algorithm that makes use of the benefits of all other algorithms. This hybridization attempts to improve the separate algorithm's efficiency, resilience, and convergence capabilities so that they may be used for various challenging multimodal optimization issues. Particles indicate possible image segments in the FirePSOSA technique for segmentation, and fireflies signify additional segment candidates. Particles can travel across the search space using the PSOSA component, altering their locations as per PSO principles and occasionally accepting less-than-ideal solutions using SA. With the help of this feature, the algorithm may investigate various segmentation options and avoid local optima, improving its ability to do global searches. The FFA also stimulates particle movement towards brighter fireflies, serving as alluring areas representing ideal image segments. This cooperative behaviour makes it easier to effectively explore and utilize the segmentation space, producing more accurate and exact segmentation results. The pseudo-code of the proposed FirePSOSA algorithm is given in Fig1.

```
Algorithm 1: FirePSOSA-based segmentation
Input: Image Sample
Output: Segmented regions
Start
Initialize PSO particles and fireflies randomly
Initialize gbest with the best particle position and temp for SA
For iterations ≤ maximum iterations
    For each PSO particle
        Evaluate the fitness of the particle based on segmentation quality
        Update pbest if necessary
        Update gbest if the current particle position is better than gbest
        Update particle velocity
        Move the particle to the new position based on the updated velocity
        Start SA
            If pbest, gbest, and temp is matched with an acceptance criterion
                Move particle to the accepted new position based on SA
            End of if
        End
    End of for
    For each Firefly
        Evaluate the fitness of the Firefly based on segmentation quality
        Update Firefly brightness based on the fitness
        Move fireflies towards brighter fireflies based on the FFA update rule
    End of for
    Return gbest
End of for
End
```

Fig. 1 Pseudocode of proposed method (FirePSOSA)

4 Materials and Methods

The main focus of this work is to propose an optimized segmentation method using the features of an improved PSO and firefly optimization algorithm. This integration provides an efficient way to select and segment the areas based on fitness criteria. The proposed approach is designed specifically for maize leaf segmentation to identify the diseased areas, which can be utilized further to classify disease in the maize leaf. This section describes the dataset and approaches used in this work.

4.1 Dataset

This work mainly focuses on maize leaf disease, so an image dataset of maize leaves is taken from the plant village dataset [34]. The Plant Village dataset is well-known and often used in plant pathology and computer vision. It is intended for the creation and assessment of algorithms for the identification and categorization of plant diseases. The photos in the collection were taken under controlled settings to guarantee consistency and dependability and represent diverse plant species afflicted by various illnesses. The photos depict a variety of plant ailments, such as gray leaf spots, Northern corn leaf blights, and common rust. Researchers and developers can train and test machine learning models for illness diagnosis since each image is labelled with the appropriate disease category. The PlantVillage dataset of maize includes images of various common diseases affecting maize crops, including Gray Leaf Spot, Common Rust, Northern Corn Leaf Blight, and healthy maize leaves. The distribution of the data for maize leaves which is used in this work is represented in the Fig. 2.

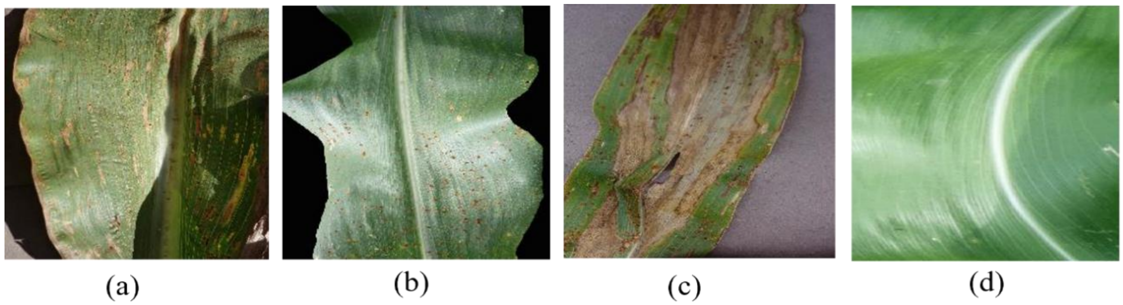

Fig. 2 Dataset distribution used for (a) Gray Leaf Spot (b) Common Rust (c) Northern Corn Leaf Blight and (d) Healthy maize leaves

4.2 Proposed method

The automatic leaves disease detection systems depend heavily on segmentation. For effective disease treatment in plant pathology, precisely identifying and localizing the damaged plant leaf areas is crucial. By segmenting the plant leaves into sick and healthy regions, the specific portion of the plant leaves can be separated and examined that displays disease, such as spots, lesions, or discolorations. This segmentation stage enables automated and trustworthy plant disease detection systems by laying the groundwork for later disease categorization and quantification. Subtle changes in leaf form, colour, and texture are frequent symptoms of plant diseases. Therefore, proper segmentation becomes difficult due to changes in leaf appearance, lighting circumstances, and overlapping symptoms. An efficient segmentation algorithm enables disease detection systems to concentrate on the regions of interest and eliminate unnecessary background information, producing more precise and understandable findings. Additionally, by processing just the segmented zones, segmentation reduces computing overhead, essential for real-time or extensive applications in precision agriculture.

Conventional segmentation techniques, including K-Mean clustering, OTSU thresholding, and Canny edge detection, are frequently employed in image processing [18]. While K-Mean segmentation is straightforward and computationally efficient, it may need help to handle complicated leaf shapes, yielding less accurate results. Bimodal leaf images benefit from OTSU thresholding since it works well for images with clear foreground-background separation. Still, it may be better when the background and foreground could be better divided. Although canny edge detection is great for recognizing leaf contours, comprehensive region segmentation could need other procedures [18]. Researchers have looked at cutting-edge methodologies such as fuzzy logic and metaheuristic algorithms to remedy the shortcomings of conventional methods. To handle uncertain areas more effectively and support partial memberships, fuzzyOTSU blends fuzzy logic with OTSU thresholding. When dealing with overlapping disease symptoms, this is advantageous [28]. PSO [27] and Firefly [35] are two effective examples of metaheuristic algorithms that may be used for optimization-based segmentation. They help understand complex leaf disease patterns because they can identify the best segmentations while considering numerous regions of interest.

Further, the combination of PSOSA leverages the global search capability of PSO and the local search finesse of SA, providing a balance between exploration and exploitation in the search space. However, while PSOSA shows considerable efficacy, it occasionally falls short in terms of convergence speed and escaping local optima in more complex segmentation tasks. So, there is a scope of improvement for which this work integrates the PSOSA with Firefly Algorithm and proposed FirePSOSA. The rationale behind this integration is as follows:

- Diversity and flexibility: The Firefly algorithm brings a new level of diversity and flexibility to the search process. Its distinctive attraction-based movement, driven by the brightness intensity notion, enables a more dynamic search. This can be especially useful for exploring complicated environments and preventing premature convergence, which we saw with PSOSA in some circumstances.
- Complementary Strengths: The Firefly algorithm enhances PSOSA by adding its expertise in tackling multimodal optimisation challenges. This is critical in image segmentation, as the objective function landscape might be quite multimodal. By merging both technologies, we hope to capitalise on their respective strengths: PSOSA's powerful search skills and the Firefly algorithm's increased exploring abilities.

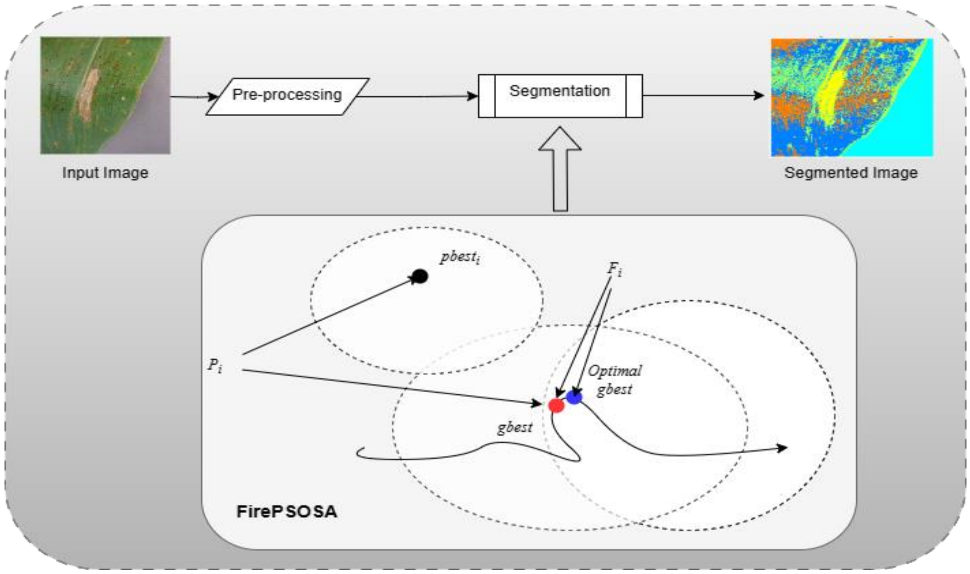

Fig. 3 The proposed method (FirePSOSA)

This proposed FirePSOSA is a hybrid optimization technique for maize leaf segmentation. It effectively explores the solution space to precisely partition disease-affected regions by combining the Firefly Algorithm (FA) and improved Particle Swarm Optimization (PSO) strengths. Like, the Fig. 3 demonstrates the segmentation process and highlights how FirePSOSA selects the best values for region selection to segment the image and identify different areas. This process starts with PSO, and its initial point is P_i; further, in each iteration best solution is found, like highlighting a $pbest_i$ in i^{th} iteration. After all iterations, the best solution will be selected as the *gbest*, but here SA plays its role in selecting the *gbest* solution. After this, FFA takes this *gbest* as its initial point F_i and starts finding the other solutions in different iterations. Finally, based on the fitness score, an *optimal gbest* solution will be selected as the final solution for FirePSOSA. So, the performance of FirePSOSA for segmentation is improved because of the social behaviour of PSOSA and the multimodal optimization of FFA. Because of its adaptive parameter adjustment, it can handle a variety of maize leaf images with different disease patterns while also improving convergence speed. FirePSOSA advances automated plant disease diagnostics and sustainable crop management by supporting early disease identification and targeted responses. It is essential to conduct additional validation on real-world datasets to evaluate its efficacy across various plant species and disease kinds. Therefore, in the next section, the performance of the proposed method is tested using a publicly available dataset of maize leaf images based on different performance metrics.

5 Experimentation and Result Analysis

This work proposes FirePSOSA, a hybrid optimized segmentation method. The performance of this proposed method is analyzed using a MATLAB simulator, and the comparison is also made by implementing other state-of-the-art methods. The existing methods like K-Mean [18], OTSU [36], Canny [18], FuzzyOTSU [28], PSO [27], and Firefly [31] are also implemented with the same parameters. After using K-Mean, OTSU, Canny, FuzzyOTSU, PSO, Firefly, and proposed method (FirePSOSA), the segmented images infected with gray leaf spot, common rust, northern leaf blight, and healthy leaves, respectively, are shown in Fig. 4.1, 4.2, 4.3, and 4.4.

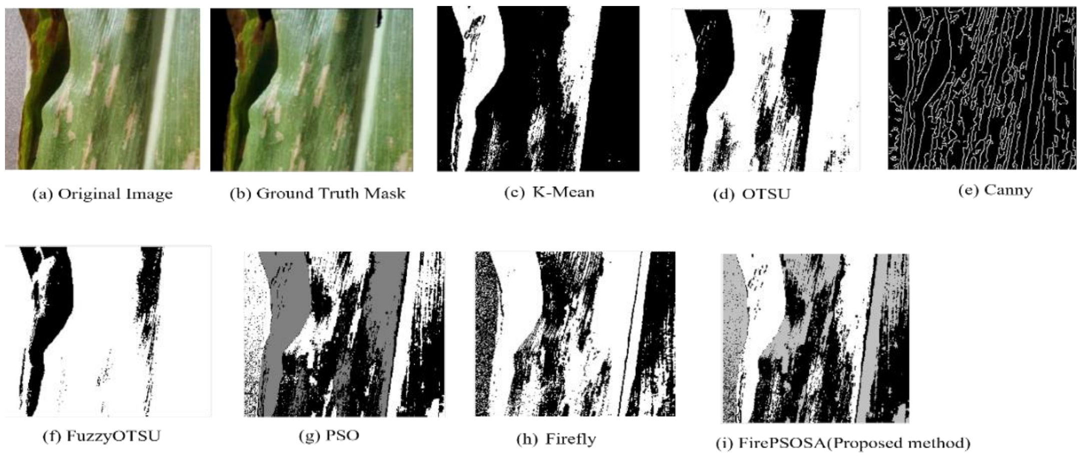

Fig. 4.1 Segmentation results of gray leaf spot maize leaves sample using different methods (a) Original image (b) Ground truth mask (c) K-Mean (d) OTSU (e) Canny (f) FuzzyOTSU (g) PSO (h) Firefly and (i) Proposed method (FirePSOSA).

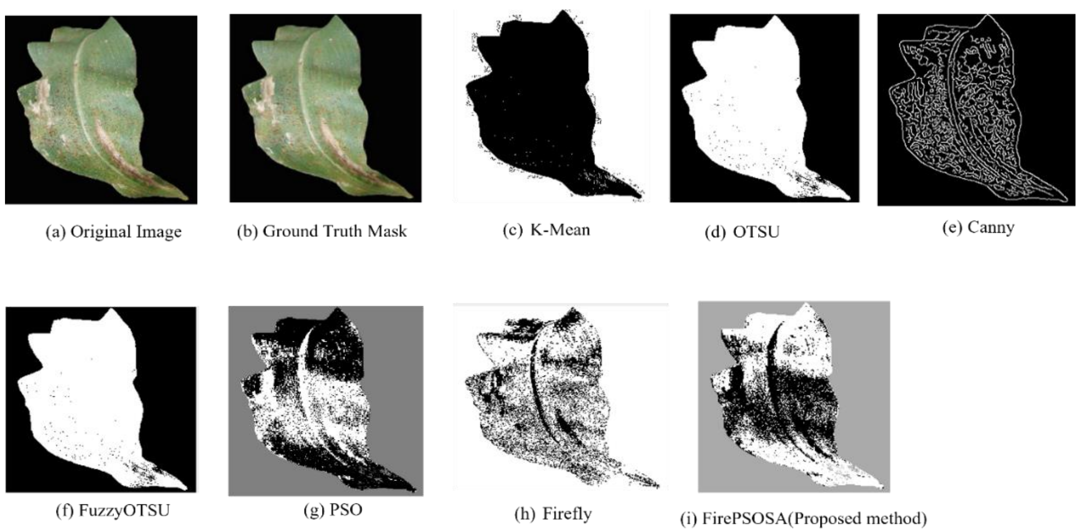

Fig. 4.2 Segmentation results of common rust maize leaves sample using different methods (a) Original image (b) Ground truth mask (c) K-Mean (d) OTSU (e) Canny (f) FuzzyOTSU (g) PSO (h) Firefly and (i) Proposed method (FirePSOSA).

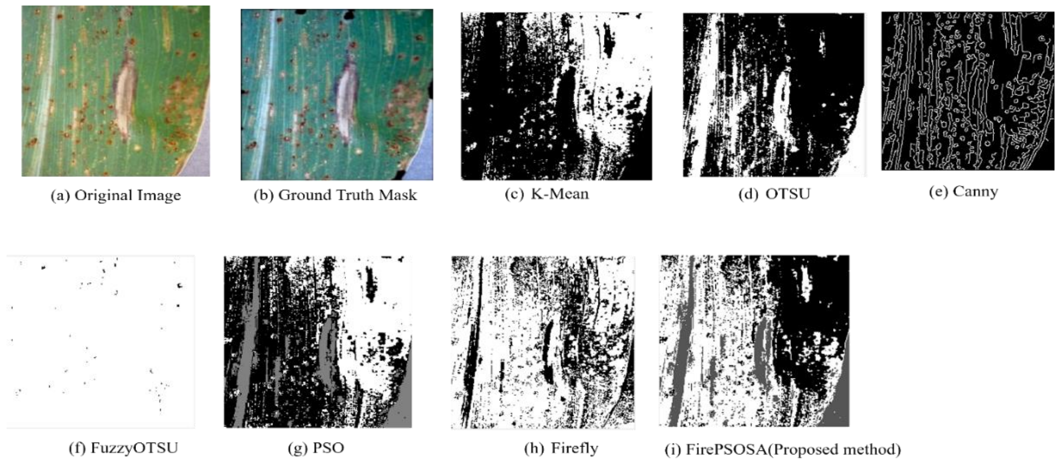

Fig. 4.3 Segmentation results of northern corn leaf blight maize leaves sample using different methods (a) Original image (b) Ground truth mask (c) K-Mean (d) OTSU (e) Canny (f) FuzzyOTSU (g) PSO (h) Firefly and (i) Proposed method (FirePSOSA).

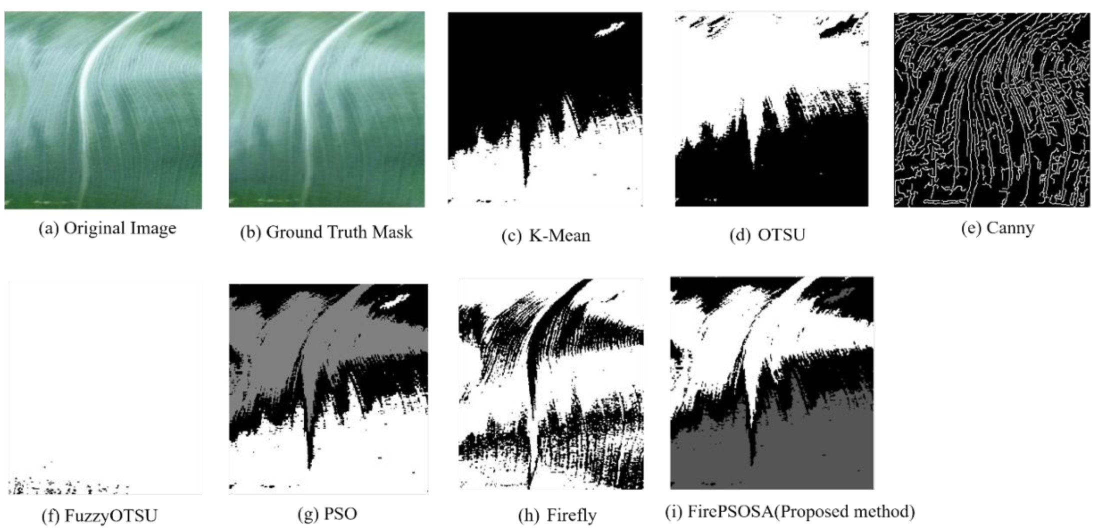

Fig. 4.4 Segmentation results of healthy maize leaves sample using different methods (a) Original image (b) Ground truth mask (c) K-Mean (d) OTSU (e) Canny (f) FuzzyOTSU (g) PSO (h) Firefly and (i) Proposed method (FirePSOSA).

The segmentation performance is described in terms of Hausdorff distance, Jaccard coefficient, and dice coefficient for quantitative analysis. The Hausdorff distance quantifies the separation between matching points in two sets and illustrates how the expected segmentation differs from the actual segmentation [36]. The Jaccard Coefficient (Intersection over Union) measures how closely the predicted segmentation matches the disease areas by calculating the overlap between the segmentation and the actual data [21]. Moreover, by computing the ratio of overlap of two sets to their average size, the Dice Coefficient assesses how similar two sets are [37]. The results presented in the graphs elaborate the effectiveness of the proposed method based on maize leaf images, including both healthy and diseased.

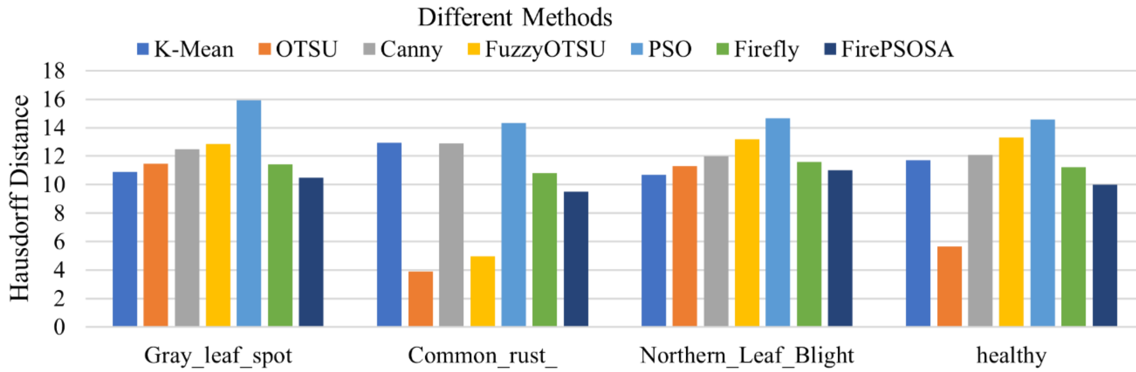

Fig. 5 Performance comparison based on Hausdorff Distance for Gray leaf spot, Common rust, Northern corn leaf blight and healthy images of maize plant leaves for K-Mean, OTSU, Canny, FuzzyOTSU, PSO, Firefly and Proposed method (FirePSOSA).

The Fig.5 compare segmentation performance using Hausdorff distance and indicates better segmentation accuracy by lower Hausdorff distance values in most of the cases. Regarding these outcomes, the algorithm FirePSOSA consistently performs good, obtaining the smallest Hausdorff distance values for gray leaf spot images. It outperforms other algorithms, such as K-Mean, OTSU, Canny, FuzzyOTSU, PSO, and Firefly, demonstrating its potency in precisely segmenting the various disease zones in the maize leaf images. In some instances, the K-Mean and Firefly algorithms also produce competitive results, offering comparatively smaller Hausdorff distances for particular disease classes. In terms of total segmentation accuracy across all classes, FirePSOSA outperforms them. The segmentation results produced by the OTSU, Canny, FuzzyOTSU, and PSO algorithms, on the other hand, show greater Hausdorff distances and are thus less accurate. Further, Jaccard coefficient-based performance comparison is illustrated in Fig.6.

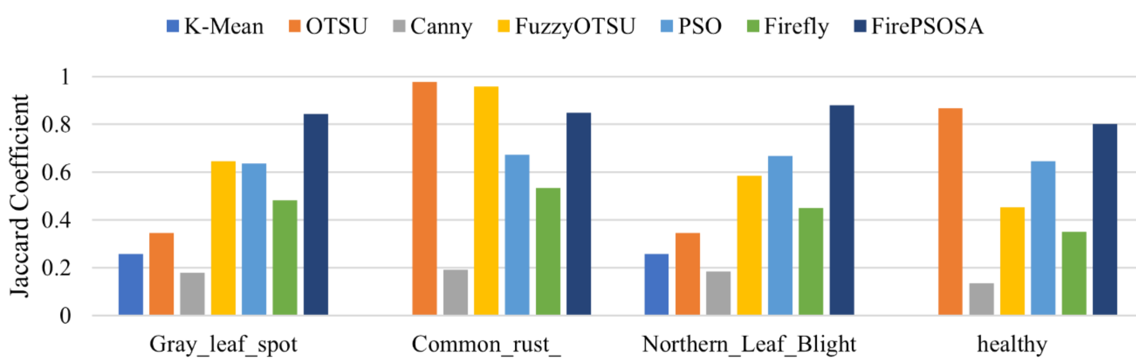

Fig. 6 Performance comparison based on Jaccard Coefficient distance for Gray leaf spot, Common rust, Northern corn leaf blight and healthy images of maize plant leaves for K-Mean, OTSU, Canny, FuzzyOTSU, PSO, Firefly and Proposed method (FirePSOSA).

The results in Fig.6 shows and contrast the effectiveness of various segmentation techniques with a suggested technique based on the Jaccard coefficient. Perfect overlap is represented by a Jaccard Coefficient of 1, whereas no overlap is represented by a value of 0. When the extracted results are analyzed, FirePSOSA regularly outperforms all classes and achieves the highest Jaccard Coefficient values. It shows that FirePSOSA delivers segmentation results that most closely match the ground truth regions in the images of maize leaves, demonstrating great accuracy in identifying the disease areas. The FuzzyOTSU and PSO algorithms also produce competitive results, offering Jaccard Coefficient values generally high for most classes. These algorithms are excellent at accurate segmentation because they can catch significant overlaps with the actual disease zones. Lower Jaccard Coefficient values for the K-Mean, Canny, and Firefly algorithms show less overlap with the actual illness zones and substantially less accurate segmentation. Complex leaf structures and disease-region changes may be intricate for these algorithms, resulting in less accurate

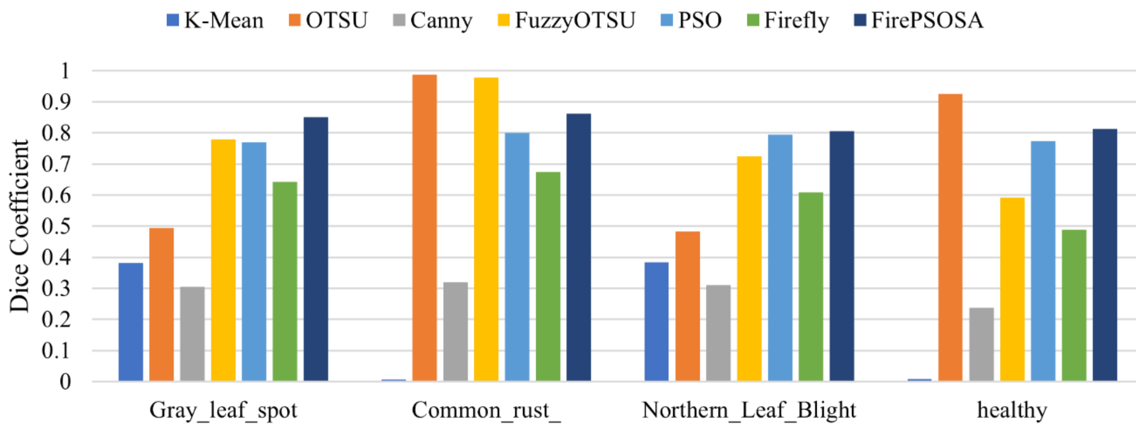

Fig.7 Performance comparison based on Dice Coefficient Distance for Gray leaf spot, Common rust, Northern corn leaf blight and healthy images of maize plant leaves for K-Mean, OTSU, Canny, FuzzyOTSU, PSO, Firefly and Proposed method (FirePSOSA)

segmentations. While the OTSU method achieves high Jaccard Coefficient values for Common Rust and healthy plants, it achieves comparatively lower values for Gray Leaf Spot and Northern Leaf Blight classes. It shows that while OTSU could be effective for some disease groups, it might not be as effective across the board. The Fig.7 demonstrates the performance of the methods based on the dice coefficient. According to the Dice Coefficient, which gauges the similarity between two sets, the figure above assessed the findings to compare the segmentation performance. Based on the findings above, it can be concluded that the FirePSOSA consistently performs the best across all classes, attaining the highest Dice Coefficient valu:es. Its value of 1 denotes perfect overlap, while 0 indicates no overlap. It presents that FirePSOSA generates segmentation results that closely resemble the real, showing the significant overlap between the projected segmentations and the actual areas in the maize leaf images. The FuzzyOTSU and PSO algorithms also produce competitive results, offering Dice Coefficient values that are generally high for most classes. Lower Dice Coefficient values for the K-Mean, Canny, and Firefly algorithms show less overlap with the actual areas and comparatively less accurate segmentation. The OTSU method achieves high Dice Coefficient values for Common Rust and healthy plant classes, while Gray Leaf Spot and Northern Leaf Blight achieve comparatively lower values. It shows that while OTSU could be effective for some disease groups, it might not be as effective across the board. The performance of the proposed method is compared with existing techniques in the table 1.

Table 1. Overall Performance Analysis of and Proposed method (FirePSOSA) with K-Mean, OTSU, Canny, FuzzyOTSU, PSO, Firefly in terms of average Hausdorff Distance, Jaccard Coefficient, Dice Coefficient.

Name of algorithm	Hausdorff Distance	Jaccard Coefficient	Dice Coefficient
K-Mean [18]	11.55215	0.130707	0.194758
OTSU [36]	**8.07982**	0.634104	0.722416
Canny [18]	12.36247	0.172823	0.29292
FuzzyOTSU [28]	11.08654	0.66099	0.768025
PSO [27]	14.87842	0.655298	0.783786
Firefly [31]	11.26527	0.454313	0.602975
Proposed method (FirePSOSA)	10.24157	**0.844585**	**0.832071**

The data in table 1 shows the outcomes of several segmentation methods used for maize leaf diseases with assessments based on the Hausdorff Distance, Jaccard Coefficient, and Dice Coefficient. Compared to the other studied approaches, FirePSOSA regularly outperforms them on all criteria. It gets the lowest Hausdorff Distance, showing the segmentation finding's closest approach to the disease areas. The maximum Jaccard Coefficient and Dice Coefficient are also attained by FirePSOSA, demonstrating significant overlap with the actual disease zones and precise segmentation. FuzzyOTSU and OTSU perform admirably, offering precise segmentations with strong Jaccard and Dice Coefficients. On the other hand, k-Mean, Canny, and PSO exhibit considerably greater Hausdorff Distances and less exact segmentations. In comparison to other techniques, Firefly performs around average. FirePSOSA is the most efficient technique for accurate and trustworthy segmentation of maize leaf diseases, with excellent potential for real-world agricultural applications.

6 Conclusion

In order to improve maize leaf segmentation for maize leaf disease detection, this research concludes by presenting a hybrid optimization strategy FirePSOSA. The outcomes of rigorous testing using a collection of maize leaves from the Plant Village dataset show that the FirePSOSA algorithm performs better than traditional segmentation techniques K-Mean, OTSU, Canny, FuzzyOTSU, PSO and Firefly. The FirePSOSA algorithm significantly decreased the Hausdorff distance to 10.24, which indicates better accuracy in identifying diseased areas in maize leaves. The algorithm's outstanding Jaccard coefficient, and Dice coefficient values of 0.84 and 0.83 also showed higher overlap and similarity between the segmented sections. These findings highlight the algorithm's ability to precisely identify and isolate disease-infected regions inside maize leaves, an essential step in the early diagnosis and control of maize leaf diseases. Farmers and researchers may greatly benefit from the improved segmentation accuracy provided by FirePSOSA in helping them make wise decisions to lessen the impact of diseases on agricultural production and crop harvests. The effectiveness of the FirePSOSA algorithm is evidence of hybrid optimization approaches to improve disease detection procedures in agriculture. This method gets over the drawbacks of conventional segmentation techniques and offers a viable option for precision farming by combining enhanced Particle Swarm Optimisation and Firefly algorithms.

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