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Implementing PSO-based Image Segmentation for Detecting Sweet Potato Leaf Disease

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Abstract

Sweet potato (Ipomoea batatas) is an important global crop, but its production is threatened by various leaf diseases, requiring accurate and efficient disease detection methods. Traditional manual inspection is labor-intensive and error-prone, making automated image processing techniques a promising alternative. This study implements Particle Swarm Optimization (PSO)-based image segmentation to detect diseased leaf regions by optimizing threshold selection in HSV color space. In the classification phase, leaves are classified into healthy and diseased classes using a Euclidean distance-based classifier. The proposed method achieved an average classification accuracy of 88.1%, with an accuracy of 95.8% for diseased leaves and 80.4% for healthy leaves, demonstrating its effectiveness in discriminating infected regions. The results confirm that PSO is a robust and efficient segmentation technique that improves the accuracy of disease detection. This research highlights the potential of PSO-based segmentation in smart agriculture, enabling early disease detection to help farmers take timely action and minimize crop losses. Compared to traditional methods, PSO reduces computational complexity while maintaining high segmentation accuracy, making it a valuable tool for agricultural disease monitoring. Future work can integrate deep learning models to refine disease classification and expand datasets to improve system performance under different environmental conditions.

Keywords: image segmentation, particle swarm optimizer, Ipomoea Batatas, Leaf Diseases, Image Processing.

Introduction

Sweet potato (*Ipomoea batatas*) is a globally significant crop, widely consumed for its nutritional value and bioactive compounds, earning it the title of a "Superfood" by the Centre for Science in the Public Interest (CSPI), USA (Behera et al., 2022). Ranked as the sixth most important food crop worldwide and seventh in terms of production volume, sweet potato holds a vital position in agriculture, particularly in India, where it is considered a major tuber crop (Behera et al., 2022; Ogero & van der Vlugt, 2023). However, its cultivation faces challenges due to varying cropping systems and disease prevalence, which differ between temperate and tropical regions (Ogero & van der Vlugt, 2023). Traditional methods of disease detection, reliant on manual inspection, are not only time-consuming and labor-intensive but also susceptible to human error (Fang & Ramasamy, 2015). To address these limitations, automated image processing techniques have emerged as a promising solution, offering accurate and efficient disease identification, thereby enhancing crop management and productivity (Ngugi et al., 2021).

Early disease detection is of paramount importance in effective crop management, allowing for early intervention, reduced crop losses, and enhanced food security. It plays a crucial role in preventing crop loss and improving agricultural productivity (Kadel, 2023). The symptoms of plant diseases often appear first on leaves in the form of color changes, spots, or lesions. Identifying these symptoms at an early stage allows farmers to take timely corrective actions, such as applying appropriate fungicides, adjusting irrigation, or isolating infected plants (Ogero & van der Vlugt, 2023). Advanced computer vision and image processing techniques have enabled automated disease detection by analyzing leaf characteristics, reducing dependence on human expertise, and increasing efficiency in large-scale farming (Nerkar, 2022; Ngugi et al., 2021).

Modern techniques for detecting plant diseases rely on image processing, pattern recognition, and automated classification tools, which are increasingly helping farmers improve crop quality and yield. Plant diseases can quickly spread, impacting stems, leaves, and fruits. Detecting these diseases involves identifying the infected parts, extracting relevant features, and classifying the disease to facilitate timely action. Among the various image segmentation methods, Particle Swarm Optimization (PSO), a part of swarm intelligence, has emerged as a promising approach due to its efficiency in optimizing threshold selection or clustering pixel intensities (Singh, 2019). Inspired by the collective behavior of birds and fish, PSO uses particles (candidate solutions) to navigate an optimization space, delivering precise segmentation outcomes (Ren et al., 2024).

PSO is particularly advantageous for image segmentation due to its computational efficiency, robustness, and accuracy. Unlike traditional segmentation techniques, PSO requires fewer parameters and can quickly converge to an optimal solution, making it well-suited for processing large datasets or real-time applications (Chen et al., 2019). Additionally, PSO performs effectively in complex imaging environments, handling variations in lighting, noise, and background complexity, which are common challenges in plant disease detection. By optimizing segmentation parameters, PSO enhances the precision of distinguishing between healthy and diseased leaf regions, leading to more reliable disease detection and classification (Singh, 2019). In this study, PSO is applied to segment diseased leaf regions from sweet potato images, enabling accurate and efficient detection of affected areas.

This research focuses on the practical implementation of PSO-based image segmentation for detecting sweet potato leaf diseases. The study explores how PSO can be used to provide a robust approach for identifying diseased leaf regions in images. By leveraging

PSO, this study aims to contribute to the development of efficient, and accurate leaf disease detection systems that can assist farmers and researchers in early disease diagnosis and crop management.

Literature Review

The rapid spread of plant diseases poses a significant threat to global agricultural productivity, leading to substantial economic losses and reduced crop yields. Traditional disease detection methods, which rely on manual inspection, are often inefficient, labor-intensive, and prone to human error, making them unsuitable for large-scale farming. As a result, researchers have increasingly turned to computer vision and machine learning techniques to develop automated plant disease detection systems (Nerkar, 2022). Among these approaches, Particle Swarm Optimization (PSO) has emerged as a powerful tool for image segmentation, feature extraction, and classification, significantly improving the accuracy and efficiency of disease identification.

One of the critical applications of PSO in agriculture is rice leaf disease detection, where early diagnosis is essential to maintaining crop health and preventing large-scale yield losses. To address the limitations of manual inspection, researchers have developed PSO-based image segmentation techniques to detect and classify common rice leaf diseases, including bacterial leaf blight, brown spot, leaf smut, blast, sheath rot, and leaf scald. By integrating PSO with a minimum distance classifier, this approach optimizes feature extraction and clustering, achieving a high classification accuracy of 98.28% on a large dataset comprising 40,880 training images and 3,589 validation images. These results highlight PSO's effectiveness in automating disease recognition and classification, offering a scalable solution for rice disease management (Kavitha & Sirisha, 2021).

Beyond rice crops, PSO has also been successfully applied to sunflower leaf disease detection, where traditional methods struggle due to the complexity of symptoms and variations in environmental conditions. Researchers have implemented PSO-based segmentation techniques to enhance classification accuracy and efficiency. The methodology involves preprocessing images, optimizing segmentation parameters using PSO, and extracting relevant disease features. Experimental evaluations demonstrate that this approach achieves an average classification accuracy of 98.0%, outperforming existing state-of-the-art methods with accuracy rates of 97.6% and 92.7%. These findings further reinforce PSO's potential in agricultural image processing by ensuring precise and consistent disease detection (Singh, 2019).

Research Method

This study focuses on the implementation of Particle Swarm Optimization (PSO)-based image segmentation for detecting diseases in sweet potato leaves. The methodology involves several key steps, including image acquisition, preprocessing, segmentation using PSO, and evaluation. The proposed system is designed to efficiently identify and segment diseased leaf regions and enabling precise disease detection.

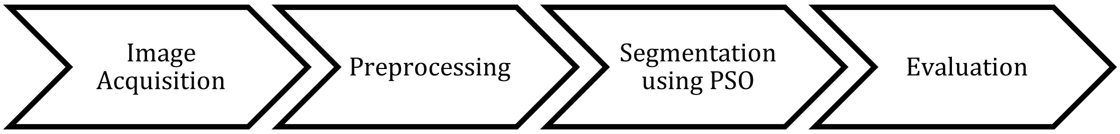

Figure 1. Research Method

1. Image Acquisition

The dataset was collected using a high-resolution digital camera under controlled lighting conditions to ensure consistency and quality. Images were taken from top angles, various rotations, and various distances to provide different representations of leaf structure and increase the robustness of the dataset. To improve segmentation accuracy, all images were taken against a white background, which minimized noise and allowed for clear differentiation between the leaf and its surroundings. The dataset comprises a total of 750 images, including 250 healthy leaf images and 500 diseased leaf images. The diseased images cover a range of conditions such as Cercospora leaf spot, and brown lesions, offering a comprehensive representation of common sweet potato leaf diseases. The sweet potato leaf dataset used in this research was collected by Suhendar et al. (2023). This diverse and well-structured dataset serves as a valuable resource for developing and testing automated disease detection systems.

2. Image Preprocessing

To enhance the accuracy of leaf disease detection, the collected images undergo a systematic preprocessing pipeline consisting of several key steps. The first step is background removal, where the white background is eliminated to ensure that only the leaf region remains in the image. This process minimizes noise and prevents unwanted pixels from affecting the segmentation accuracy. By isolating the leaf from its surroundings, the system can focus solely on analyzing disease symptoms (Kc et al., 2021). Next, the cropping process is applied to adjust the image boundaries so that they align with the shape of the leaf. This step ensures that unnecessary empty spaces around the leaf are removed while preserving all critical parts of the leaf, including potential disease-affected areas. Proper cropping helps maintain consistency across all images in the dataset. After cropping, the images are resized to 50% of their original dimensions to optimize computational efficiency. Reducing the image size decreases processing time and memory usage while retaining important visual details. This step is crucial for ensuring a balance between accuracy and performance, especially in large-scale datasets. Once the images are resized, contrast enhancement is applied to improve the visibility of diseased regions. This technique adjusts the brightness and contrast levels to make subtle discolorations, lesions, and disease patterns more distinct. By enhancing the contrast, the segmentation process can more effectively differentiate between healthy and affected areas (Maharana et al., 2022; Nerkar, 2022).

Masking is performed in the HSV (Hue, Saturation, and Value) color space to differentiate between diseased and healthy regions. By applying specific thresholds to the HSV components, the model can effectively segment disease-affected areas based on their distinct color properties. The HSV color space is utilized during the preprocessing stage before implementing Particle Swarm Optimization (PSO). Unlike the Red-Green-Blue (RGB) color model, which is highly sensitive to lighting variations, HSV separates color information (hue) from intensity (value), making it more effective for identifying disease symptoms. In this process, saturation (S) and value (V) components are analyzed to isolate diseased areas from healthy regions (Purnama & Syukriyah, 2024). PSO is then applied to optimize threshold selection within the HSV domain, ensuring precise segmentation of affected leaf regions based on color differences. This combined approach enhances robustness against lighting variations and significantly improves disease detection accuracy (Kuarkamphun & Ratanavilisagul, 2022).

3. Segmentation using PSO

This program uses the Particle Swarm Optimization (PSO) method to segment images of disease-infected leaves based on brown color in the HSV color space. This approach does not require mask annotation, making it more flexible in handling unlabeled datasets. Images are converted to HSV, then segmentation is performed by thresholding using HSV lower and upper bounds optimized by PSO (Naderi Boldaji & Hosseini Semnani, 2022). In PSO optimization, each potential solution (called a particle) moves in the search space of HSV parameters. Each particle has a position (HSV value) and a velocity that is updated at each iteration based on its own best experience (personal best) and the best experience of the entire population (global best)(Singh, 2019). Each particle in the population has its position and velocity updated at each iteration. The particle position $X_k(i)$ represents the HSV parameter value being tested for brown color segmentation in leaf images. The particle velocity $V_k(i)$ determines how much the particle position changes in the next iteration. The equation is used to update the position of the particles (Jain et al., 2022):

$$V_k(i+1) = w.V_k(i) + c_1.r_1\left(p_{best,i}^{k} - X_k(i)\right) + c_2.r_2\left(p_{best,i} - X_k(i)\right)$$

In this equation, w is an inertia factor that controls the influence of the previous velocity on the current velocity. A large value of www makes the particle explore more of the search space, while a smaller value makes it focus more on exploiting the best area found. c_1 and c_2 are acceleration coefficients that govern how much the particle is attracted to its own best position and the best position in the population. Two components in the equation that affect the direction of particle motion are $p_{best,i}^{k} - X_k(i)$ and $p_{best,i} - X_k(i)$. The first component refers to the distance between the particle's current position and its personal best. The second component refers to the distance between the particle's current position and the best position found by the entire population (global best). These two components are multiplied by random values r_1 and r_2 (with values between 0 and 1) provide variation in the particle's motion, thus avoiding the trap of local solutions.

Once the velocity has been updated, the position of the particle is updated using the equation below:

$$X_k(i+1) = X_k(i) + V_k(i+1)$$

This equation shows that the new particle position is the result of updating the previous position with the newly calculated velocity. In this way, each particle gradually moves toward the optimal HSV parameter value for brown color segmentation. This process is repeated for several iterations until the best HSV parameter value is found.

4. Evaluation

In this phase, the segmentation results are evaluated by extracting and comparing the co-occurrence features of the segmented leaf regions with precomputed feature values stored in the feature dataset. These extracted features, which include color, texture, and shape descriptors, are used for classification to determine whether a given leaf is healthy or diseased. To achieve this, a Minimum Distance Classifier (MDC) is employed, which assigns an unknown test image to the class with the closest feature representation in the multi-feature space. The classifier operates by computing the Euclidean distance between the feature vector of a test image and the parameter sets representing different disease classes. This distance serves as an index of similarity, where a smaller distance indicates a higher similarity between the test image and a particular disease category. The training dataset is used to determine the optimal feature space, while the testing dataset is utilized to evaluate the classifier's performance (Elen & Avuçlu, 2021). The Euclidean distance between a feature vector x and a reference feature vector $c_{i,j}$ for class i is calculated using the following equation:

$$D_i(x) = \sqrt{\sum_{j=1}^{n} (x_j - c_{i,j})^2}$$

$D_i(x)$ is the Euclidean distance between the feature vector of test image x and the feature vector of class c_i, where x_j represents the j feature of the test image, $c_{i,j}$ is the j feature of class i, and n is the total number of features used for classification. The test samples are classified by calculating $D_i(x)$ for each class, and the class with the minimum Euclidean distance is selected as the final classification result. This approach ensures accurate and efficient segmentation evaluation, which contributes to a reliable disease detection system.

Classification output is determined based on the minimum Euclidean distance computed for each test sample. The class with the smallest distance is considered the most similar to the test image, and the leaf is classified accordingly. This ensures that the segmented regions are assigned to their respective disease categories with high accuracy. Once the Minimum Distance Criterion is applied for classification, the performance of the classification model is assessed using classification gain, which measures the effectiveness of the classification process (Joshi et al., 1997). The classification gain (CG) is calculated using the following equation:

$$CG = \left(\frac{N_c}{N_t}\right) \times 100$$

CG represents the classification gain (%), where N_c is the number of correctly classified images, and N_t is the total number of test images. A higher classification gain indicates better segmentation and classification performance, demonstrating the effectiveness of the PSO-based segmentation approach in accurately detecting leaf diseases. This metric ensures that the classification model is evaluated objectively, providing insights into its accuracy and reliability in agricultural disease detection.

Result

The proposed PSO-based image segmentation method was evaluated using a dataset of sweet potato leaf images captured with a white background. The effectiveness of the segmentation process was assessed based on the accuracy of disease detection and classification performance. After applying background removal, cropping, resizing, contrast enhancement, and HSV-based masking, the segmented leaf regions were analyzed to distinguish between healthy and diseased areas. The preprocessing steps, as illustrated in Figure 2, demonstrate the systematic enhancement of leaf images.

Figure 2. Preprocessing process

The final masking result, shown in Figure 3, segmented outputs, effectively isolating diseased regions. The extracted features from these segmented images are then utilized to differentiate various disease types, enabling accurate identification and classification.

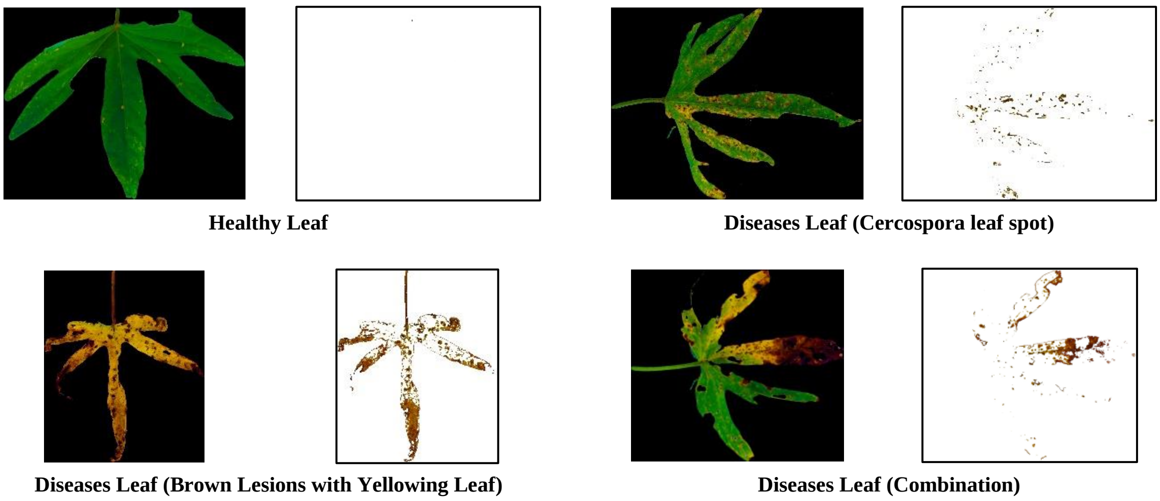

Figure 3. Segmented image output suggested algorithm leaf images

The classification process categorizes the segmented leaf images into two main classes: healthy leaves and diseased leaves. Healthy leaves exhibit a uniform color and texture, while diseased leaves display irregular patterns, spots, or discoloration caused by infections such as Cercospora leaf spot and brown lesions.

Table 1. Proposed method classification results per class

Classification	Healthy Leaf	Disease Leaf	Accuracy
Healthy Leaf	221	49	80.4
Disease Leaf	21	479	95.8
Average			88.1

The classification process categorizes the segmented leaf images into two main classes: healthy leaves and diseased leaves. Healthy leaves exhibit a uniform color and texture, while diseased leaves display irregular patterns, spots, or discoloration caused by infections such as Cercospora leaf spot and brown lesions. Based on the classification results presented in Table 1, the proposed method achieved an accuracy of 80.4% for healthy leaf classification and 95.8% for diseased leaf classification, with an overall average accuracy of 88.1%. These results demonstrate the effectiveness of the approach in distinguishing between healthy and diseased sweet potato leaves.

Discussion

The findings of this study demonstrate the effectiveness of PSO-based image segmentation in detecting sweet potato leaf diseases. With an average classification accuracy of 88.1%, the proposed method successfully differentiates between healthy and diseased leaves, showing a particularly high accuracy of 95.8% for disease detection. These results align with previous studies that highlight the efficiency of swarm intelligence in optimizing image segmentation tasks (Behera et al., 2022; Ren et al., 2024). Compared to conventional thresholding and clustering approaches, PSO enhances segmentation precision by adaptively selecting optimal parameters, reducing the impact of noise and variations in leaf texture.

The high classification accuracy, particularly in detecting diseased leaves, reinforces the importance of intelligent segmentation in agricultural disease monitoring. Prior research on PSO-based segmentation for plant disease detection has reported competitive accuracy rates, but most focus on common crops such as rice and sunflower. This study extends the application of PSO to sweet potato leaf diseases, confirming its adaptability across different plant species. Additionally, the use of the HSV color space for feature extraction aids in distinguishing diseased regions more effectively, as it isolates color variations linked to infections.

Despite its success, the method has certain limitations. The classification accuracy for healthy leaves (80.4%) is lower than for diseased leaves, possibly due to similarities between healthy leaf textures and early-stage infections. Furthermore, segmentation performance varies depending on the disease type. Cercospora leaf spot, characterized by circular brown lesions with yellow halos, is segmented with high precision due to its distinct contrast against the healthy leaf background. In contrast, chlorotic symptoms, which cause a gradual yellowing of leaf tissues, present a challenge for segmentation, as their color variations blend with normal leaf discoloration. Addressing these challenges in future research could involve integrating hybrid approaches, such as combining PSO with deep learning-based classification, to refine disease-specific segmentation. Additionally, increasing dataset diversity with various environmental conditions could improve robustness. These enhancements would strengthen the practical applicability of the proposed system in real-world smart agriculture settings.

Conclusion

This study presents an effective method for segmenting and classifying sweet potato leaf diseases using Particle Swarm Optimization (PSO). The proposed approach successfully distinguishes between healthy and diseased leaves, achieving an average classification accuracy of 88.1%. The method demonstrates high accuracy in detecting diseased leaves (95.8%), confirming the reliability of PSO in optimizing image segmentation and classification. The segmentation results highlight the effectiveness of HSV-based feature extraction in isolating infected regions, particularly for diseases such as Cercospora leaf spot and brown lesions. Despite its effectiveness, the model encounters challenges in differentiating early-stage infections and chlorotic symptoms, which affect classification accuracy for healthy leaves. Future work could enhance the system's robustness by incorporating hybrid techniques, such as deep learning integration, and expanding the dataset with diverse environmental conditions. Overall, the findings support the potential of PSO-based segmentation in smart agriculture applications, enabling early disease detection to improve crop health and yield.

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References

Behera, S., Chauhan, V. B. S., Pati, K., Bansode, V., Nedunchezhiyan, M., Verma, A. K., Monalisa, K., Naik, P. K., & Naik, S. K. (2022). Biology and biotechnological aspect of sweet potato (Ipomoea batatas L.): a commercially important tuber crop. In *Planta* (Vol. 256, Issue 2). Planta. https://doi.org/10.1007/s00425-022-03938-8

Chen, X., Miao, P., & Bu, Q. (2019). Image Segmentation Algorithm Based on Particle Swarm Optimization with K-means Optimization. *2019 IEEE International Conference on Power, Intelligent Computing and Systems, ICPICS 2019*, 156–159. https://doi.org/10.1109/ICPICS47731.2019.8942442

Elen, A., & Avuçlu, E. (2021). Standardized Variable Distances: A distance-based machine learning method. *Applied Soft Computing*, *98*, 106855. https://doi.org/10.1016/j.asoc.2020.106855

Fang, Y., & Ramasamy, R. P. (2015). Current and prospective methods for plant disease detection. In *Biosensors* (Vol. 5, Issue 3, pp. 537–561). Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/bios5030537

Jain, M., Saihjpal, V., Singh, N., & Singh, S. B. (2022). An Overview of Variants and Advancements of PSO Algorithm. In *Applied Sciences (Switzerland)* (Vol. 12, Issue 17, p. 8392). Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/app12178392

Joshi, R. L., Jafarkhani, H., Kasner, J. H., Fischer, T. R., Farvardin, N., Marcellin, M. W., & Bamberger, R. H. (1997). Comparison of different methods of classification in subband coding of images. In *IEEE Transactions on Image Processing* (Vol. 6, Issue 11, pp. 1473–1486). https://doi.org/10.1109/83.641409

Kadel, R. (2023). Implication of a Smart Farming System for Disease Detection and Crop Protection in Nepalese Agriculture. *Journey for Sustainable Development and Peace Journal*, *1*(02), 198–219. https://doi.org/10.3126/jsdpj.v1i02.58277

Kavitha, D., & Sirisha, J. (2021). PARTICLE SWARM OPTIMIZATION BASED RECOGNITION AND CLASSIFICATION OF RICE LEAF DISEASES. *Juni Khyat (UGC Care Group I Listed Journal)*, *11*(01), 282–287.

Kc, K., Yin, Z., Li, D., & Wu, Z. (2021). Impacts of background removal on convolutional neural networks for plant disease classification in-situ. *Agriculture (Switzerland)*, *11*(9), 827. https://doi.org/10.3390/agriculture11090827

Kuarkamphun, T., & Ratanavilisagul, C. (2022). Face recognition using Skin Color Segment and Modified Binary Particle Swarm Optimization. *ICSEC 2022 - International Computer Science and Engineering Conference 2022*, 66–71. https://doi.org/10.1109/ICSEC56337.2022.10049354

Maharana, K., Mondal, S., & Nemade, B. (2022). A review: Data pre-processing and data augmentation techniques. *Global Transitions Proceedings*, *3*(1), 91–99. https://doi.org/10.1016/j.gltp.2022.04.020

Naderi Boldaji, M. R., & Hosseini Semnani, S. (2022). Color image segmentation using multi-objective swarm optimizer and multi-level histogram thresholding. *Multimedia Tools and Applications*, *81*(21), 30647–30661. https://doi.org/10.1007/s11042-022-12443-9

Nerkar, B. (2022). Application of Image Processing in Plant Leaf Disease Detection. In *Advanced Sensing in Image Processing and IoT* (pp. 319–336). CRC Press. https://doi.org/10.1201/9781003221333-17

Ngugi, L. C., Abelwahab, M., & Abo-Zahhad, M. (2021). Recent advances in image processing techniques for automated leaf pest and disease recognition – A review. In *Information Processing in Agriculture* (Vol. 8, Issue 1, pp. 27–51). Elsevier. https://doi.org/10.1016/j.inpa.2020.04.004

Ogero, K., & van der Vlugt, R. (2023). *Diseases of Sweetpotato* (pp. 1–59). Springer, Cham. https://doi.org/10.1007/978-3-030-35512-8_29-1

Purnama, A., & Syukriyah, Y. (2024). *Plant Disease Identification in Ipomoea Batatas Leaf Images Using Color Space Features*. 255–265. https://doi.org/10.2991/978-94-6463-

618-5_27

Ren, Y., Xu, Z., Zhao, J., Liu, J., Liu, Y., & Cheng, J. (2024). Collective Foraging Mechanisms and Optimization Algorithms: A Review. *Lecture Notes in Electrical Engineering*, *1203 LNEE*, 123–135. https://doi.org/10.1007/978-981-97-3324-8_11

Singh, V. (2019). Sunflower leaf diseases detection using image segmentation based on particle swarm optimization. *Artificial Intelligence in Agriculture*, *3*, 62–68. https://doi.org/10.1016/j.aiia.2019.09.002

Suhendar, S., Purnama, A., & Fauzi, E. (2023). Deteksi Penyakit Pada Daun Tanaman Ubi Jalar Menggunakan Metode Convolutional Neural Network. *Jurnal Ilmiah Informatika Global*, *14*(3), 62–67. https://doi.org/10.36982/jiig.v14i3.3478