Potato powdery scab segmentation using improved GrabCut algorithm

Rui Liu, Tong Zhu, Jiawei Wu, Jingtao Li

Faculty of Information, Engineering and Automation, Kunming University of Science and Technology, Kunming, Yunnan, China

Abstract

Potato powdery scab is a serious disease that affects potato yield and has widespread global impacts. Due to its concealed symptoms, it is difficult to detect and control the disease once lesions appear. This paper aims to overcome the drawbacks of interactive algorithms and proposes an optimized approach using object detection for the GrabCut algorithm. We design a YOLOv7-guided non-interactive GrabCut algorithm and combine it with image denoising techniques, considering the characteristics of potato powdery scab lesions. We successfully achieve effective segmentation of potato powdery scab lesions. Through experiments, the improved segmentation algorithm has an average accuracy of 88.05%, and the highest accuracy can reach 91.07%. This is an increase of 46.28% and 32.69% respectively compared to the relatively accurate K-means algorithm. Moreover, compared to the original algorithm which could not segment the lesions independently, the improvement is more significant. The experimental results indicate that the algorithm has a high segmentation accuracy, which provides strong support for further disease analysis and control.

Correspondence: Jingtao Li, Kunming University of Science and Technology, Kunming, Yunnan, China.
E-mail: ljteducontact@163.com

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Introduction

Powdery scab, caused by infection of potato tubers by *Spongospora subterranea* f.sp. Subterranea (Harrison *et al*., 1997),which often occurs during potato growth. Potato powdery scab mainly affects the tubers and roots of potatoes and is a common disease in temperate regions. Powdery scab generally occurs early in the field, and its occurrence is closely related to climatic conditions. The disease mainly affects the quality of potatoes, especially for fresh-eating potatoes (Zhao *et al*., 2021). It has been reported that potato powdery scab is more severe in countries such as the United States, Israel, the United Kingdom, and Switzerland; in China, it is mainly distributed in Yunnan, Gansu, Inner Mongolia, and other places (Li *et al*., 2019), causing significant economic losses to farmers when it occurs. Segmenting diseased crops and extracting lesions from images is an important step in the process of disease detection and identification. Therefore, achieving segmentation of potato powdery scab lesions is helpful to assessing the severity and scope of the disease and helps to take preventive measures to curb the spread of the disease. Traditional disease detection methods require manual inspection, which is time-consuming, labor-intensive, and has limited accuracy. Most lesion recognition methods currently use machine learning or deep learning methods to achieve lesion detection. There are already many studies on leaf lesion recognition for potato late blight and early blight Johnson *et al*. (2021) used an automated system based on the Mask R-CNN architecture and residual network to achieve a detection accuracy of 98% for late blight lesions on potato leaves. Afzaal *et al*. (2021) compared the recognition effects of GoogleNet, VGGNet, and EfficientNet on early, middle, and late stages of potato early blight. Deep learning-based methods require a large number of data samples for training. Tang *et al*. (2023) improved the YOLOv4-tin model and proposed a method for fruit detection and localization in complex orchard environments. Arshaghi *et al*. (2023) used deep learning to detect common scab disease on potato tubers.

Deep learning-based methods require a large number of data samples for training. Usually, thousands or even tens of thousands of images are needed as training samples to obtain relatively accurate results. For example, the large model Segment Anything Model used efficient models in data collection cycles to build the largest segmentation dataset to date with over 11 million licensed and privacy respecting images (Kirillov *et al*., 2023). However, there is still little research on detecting powdery scab lesions, and related image data is limited. It is not possible to directly achieve disease recognition and classification through neural network models while ensuring high accuracy. Related research shows that each category requires 150-500 images to achieve reasonable classification accuracy for the model (Shahinfar *et al*., 2020). However, the data we collected related to potato powdery scab

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was extremely limited. Isolating images with powdery scab lesions and using data augmentation to train models still did not produce relatively accurate detection results. Training neural networks with small datasets can lead to low accuracy, slow convergence, and severe overfitting.

Image segmentation algorithms divide images into different parts to extract interesting information. Singh *et al*. (2017) successfully achieved segmentation of lesions on multiple plants using image segmentation technology. Gu *et al*. (2019) successfully achieved segmentation of corn disease images based on the GrabCut algorithm. However, potato powdery scab lesions near the potato fibrous roots are similar in color to normal tissues, making accurate segmentation difficult with conventional image segmentation methods alone. Therefore, segmenting potato powdery scab lesions with limited data samples poses a challenge. Deep learning and traditional image segmentation approaches have proven effective for related applications. Wu *et al*. (2023) designed a combined deep learning and classic image processing approach for banana fruit detection, using classical algorithms for image enhancement, banana hand segmentation, and centroid extraction to enable accurate counting under complex conditions. Zhou *et al*. (2022) employed a fusion of YOLOv7 and classical image processing for adaptive localization of tea fruit, with classic methods providing a basis for final centroid positioning. Thus, combining neural networks and image segmentation algorithms can enable effective image segmentation given limited data.

The main contributions of this study are: i) Use of YOLOv7 object detection to identify regions with lesions and provide these marked images as input to GrabCut segmentation, optimizing the interactive portion to remove complex backgrounds without manual labeling. ii) Applying traditional grayscale transformation and thresholding to increase lesion contrast, followed by morphological transforms to reduce noise, ultimately achieving powdery scab lesion segmentation. The primary aim of this experiment was to propose a simple yet effective algorithm for segmenting potato powdery scab lesions.

Materials and Methods

Dataset construction

The potato leaf images were collected at the potato experimental base of Yunnan Agricultural University in China, using a camera to take pictures of the leaves. Diseased plants were photographed from multiple angles using a mobile phone camera under natural light (time period: 10:00-16:00). Imaging under natural light is more conducive to capturing key characteristics of crop lesions, such as texture, color, and shape, and more closely represents real conditions. The camera was set to auto mode with automatic adjustment of focus, aperture, and white balance. Images were captured vertically at a distance of approximately 20-40 cm from diseased plants. The acquired images had a resolution of 3904 × 2928 pixels. For experimental convenience, the images were cropped to 640 × 640 pixels. In this study, a total of 337 original images were obtained, including normal plants and various diseases such as late blight, early blight, powdery scab, etc., as personal data sets, and the public data PlantDoc containing 2598 images was downloaded. The two were used together as the data set for this experiment.T he data is labeled by IabelImg and converted into a YOLO format data set. Some materials are shown in Figure 1.

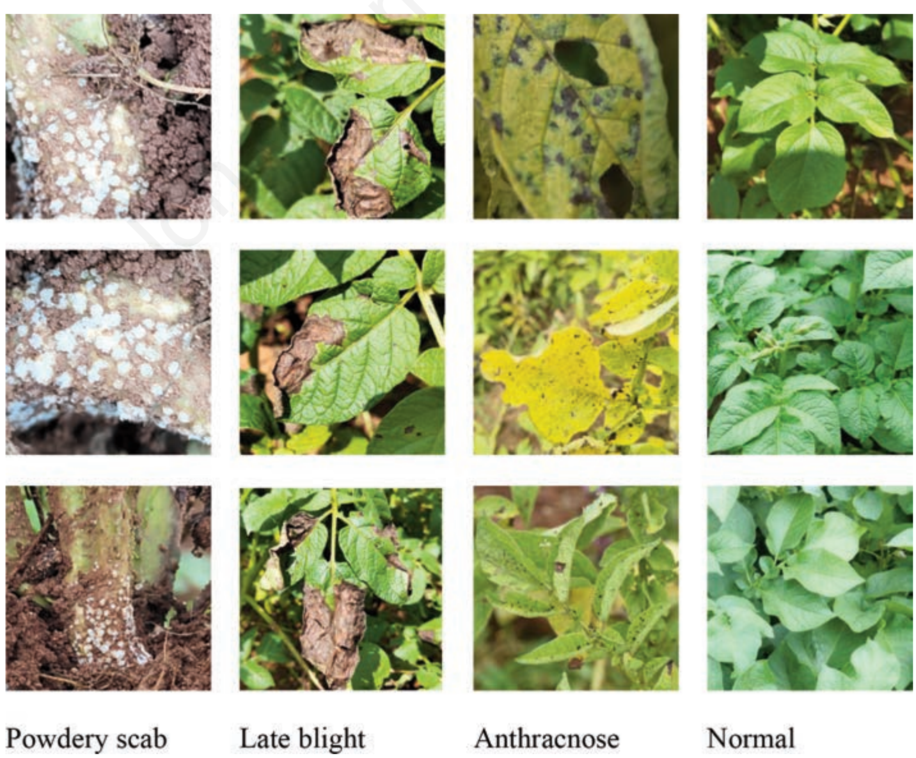

Figure 1. Part of the data set picture.

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Experimental design

The secretions produced by the pathogen usually cause the surface of the lesion to be covered with a gray-white, powdery substance, creating a high contrast between the lesion and the surrounding environment. The GrabCut algorithm has a better segmentation effect for high-contrast regions, so the GrabCut algorithm is used as the basis, and its interactive part is improved to achieve more efficient automatic labeling and lesion area segmentation. In addition, methods such as gray level adjustment, threshold segmentation, and dilation and erosion are used to remove the remaining noise.

Improved GrabCut algorithm for removing complex background

GrabCut algorithm

Rother *et al*. (2004) proposed an image segmentation method called GrabCut. It can estimate the color distribution of the target and the background by the bounding box of the target area specified by the user and use the Gaussian mixture model to construct an energy function, and then segment the target and the background by minimizing this energy function. The energy function E can be expressed by Formula 1.

$$E(\alpha, k, \beta, s) = U(\alpha, k, \beta, s) + V(\alpha, s) \quad (1)$$

Where α and s are in the range of {0,1}, representing pixel labels and gray array ; k = {k1, k2,... kN}, Kn {1,... K}.
U and V are the region term and the boundary term, respectively, where the region term U and the boundary term V are expressed by Formula 2 and Formula 3.

$$U(\alpha, k, \beta, s) = \sum_n D(\alpha_n, k_n, \beta, s_n) \quad (2)$$

$$V(\alpha, s) = \gamma \sum_{(m,n)\in C} [\alpha_n \neq \alpha_m] \exp - \lambda \| s_m - s_n \|^2 \quad (3)$$

The D in the regional term U formula is obtained by Formula 4.

$$D(\alpha_n, k_n, \beta, s_n) = -\log \pi(\alpha_n, k_n) + \frac{1}{2} \log \det \Sigma(\alpha_n, k_n) + \frac{1}{2}[s_n - \mu(\alpha_n, k_n)]^T \Sigma(\alpha_n, k_n)^{-1} [s_n - \mu(\alpha_n, k_n)] \quad (4)$$

In addition, the GMM model parameter β can be represented by Formula 5.

$$\beta = \{\pi(\alpha, k), \mu(\alpha, k), \Sigma(\alpha, k), \alpha = \{0,1\}, k = 1, \dots, K\} \quad (5)$$

Finally, according to the final probability value, divide the image into two parts: foreground and background, iterate and optimize to smooth the image edge, and output the result. In general, the GrabCut algorithm is an iterative optimization algorithm that continuously updates the image model by minimizing the energy function, thereby obtaining a more accurate segmentation result.

YOLOv7 model

YOLO is a target detection algorithm that has evolved from YOLOv1 first proposed by Joseph Redmon in 2015 to YOLOv7 used in this study, with each version improving detection accuracy and speed while introducing new network architectures and optimization techniques. The most widely used are YOLOv3 and YOLOv5; the former improved the backbone network and the latter was re-implemented in PyTorch with better performance than YOLOv4. YOLOv6 incorporated mixed precision training, further enhancing its capabilities.YOLOv7 is a deep learning model for realtime object detection, which has higher accuracy and faster speed than YOLOv5 under the same volume according to the official release.YOLOv7 surpasses all known object detectors in both speed and accuracy in the range from 5 FPS to 120 FPS and has the highest accuracy 56.8% AP among all known realtime object detectors with 30 FPS or higher on GPU V100 (Wang *et al*., 2023). The YOLOv7 network consists of three modules: input, backbone, and head. The YOLOv7 network model is shown in Figure 2.

The performance of YOLOv7 with different models on the COCO dataset (Wang *et al*., 2023) is shown in Table 1.

Interactive-free GrabCut algorithm guided by YOLOv7

The GrabCut algorithm can segment some larger individual lesions, however potato powdery scab lesions are more diffusely distributed with smaller individual lesion areas. Using GrabCut alone cannot segment most lesions, and the initialization step of the algorithm requires manual labeling, which can cause issues. For example, providing more input and output to create an interactive interface increases the program's burden and algorithm complexity. The manual labeling process also reduces execution efficiency, and errors during labeling lower user productivity and satisfaction. Therefore, to address these problems, this study optimized the initialization process and proposed a YOLOv7-guided interactive-free GrabCut as an optimization to GrabCut for segmenting potato scab lesions. The idea for improving the GrabCut initialization in this experiment is as follows: first train the dataset with the YOLOv7 network to obtain a trained model, then use object detection to detect and label powdery scab lesion regions, and finally use the labeled images as GrabCut input to achieve

Table 1. Comparison of different versions of YOLOv7.

Model	Test size	AP^{test}	AP_{50}^{test}	AP_{75}^{test}	batch 1 fps	batch 32 average time
YOLOv7	640	51.4%	69.7%	55.9%	161fps	2.8ms
YOLOv7-X	640	53.1%	71.2%	57.8%	114fps	4.3ms
YOLOv7-W6	1280	54.9%	72.6%	60.1%	84fps	7.6ms
YOLOv7-E6	1280	56.0%	73.5%	61.2%	56fps	12.3ms
YOLOv7-D6	1280	56.6%	74.0%	61.8%	44fps	15.0ms
YOLOv7-E6E	1280	56.8%	74.4%	62.1%	36fps	18.7ms

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interaction-free implementation. The workflow of the YOLOv7-guided interactive-free GrabCut algorithm is:

1. Construct dataset, train model with YOLOv7 for inferring lesion regions.
2. Read in output images from inference, obtain lesion regions from YOLOv7 detection.
3. Create target and background GMM models.
4. Establish energy function and solve it.
5. Iterate solving and adjust GMM parameters until energy function minimized or max iterations reached.
6. Output segmentation result.

Compared to the original algorithm, the improved algorithm omits the manual labeling process, greatly reducing labeling time when processing large batches of images. Combined with subsequent noise reduction algorithm, the lesion it will segmentation can be realized.

Multi-algorithm noise reduction for lesion segmentation

Grayscale piecewise linear transformation and threshold segmentation

To maximize the preservation of the lesion areas in the image below, it is necessary to further enhance the contrast of the lesion area. After segmenting the foreground and background, the image is processed in grayscale and then threshold segmented to remove some of the background unrelated to the lesions. The transformation relationship is shown in Figure 3. After the above changes, the threshold segmentation is performed, as shown in Formula 6, where f(x, y) is the pixel value of the point (x, y), g (x, y) is the segmented image, and T is the global threshold.

$$g(x,y) = \begin{cases} 1 & ,f(x,y) > T \\ 0 & ,f(x,y) \leqslant T \end{cases} \tag{6}$$

Noise removal by morphological transform

After GrabCut algorithm, grayscale transformation and threshold segmentation, most of the complex background in the lesion image has been removed. However, erosion and dilation algorithms in morphological image processing are still needed to remove remaining normal tissue portions from the image, making the lesions more distinct. Formula 7 is used to represent the expansion treatment.

$$A \oplus B = \{z \mid (B)_z \cap A \neq \Phi\} \tag{7}$$

Erosion can be seen as the dual operation of dilation. Formula 8 is used to represent the expansion treatment.

$$A - B = \{\mathbf{x} \mid B_x \subseteq A\} \tag{8}$$

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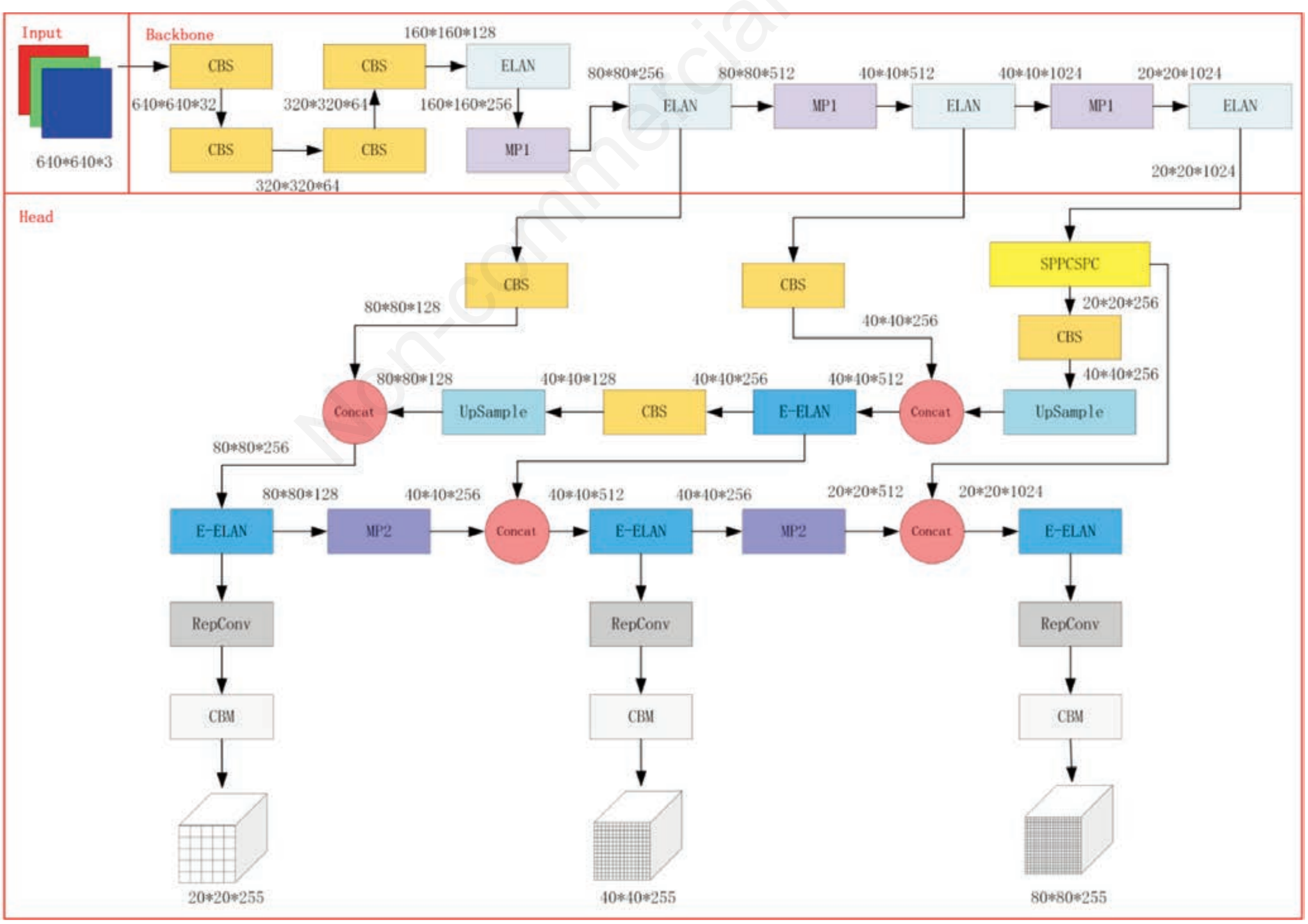

Figure 2. YOLOv7 network model.

Results

Using the improved GrabCut algorithm

The lesion area of powdery scab can be marked by using the trained model and object detection method of YOLOv7, and then the marked area can be read by GrabCut algorithm to achieve segmentation of lesion area. The specific effect is shown in Figure 4.

Residual noise removal

After the improved GrabCut algorithm, most of the complex background can be removed, but there are still irrelevant noises such as soil and roots in the remaining lesion area, which need to be gray-scale linearly transformed and threshold segmented, and then the noise can be eliminated by dilation and erosion, highlighting the lesion area. Figure 5 shows the comparison of results after noise removal.

Comparison of erosion and dilation convolution kernels

In order to obtain the most suitable convolution kernel size, erosion and dilation both use different sizes of convolution kernels for comparison experiments, and the comparison effect is shown in Figure 6. To evaluate the accuracy of the algorithm, it is necessary to manually label the diseased areas of the image and compare the labeled areas with the segmentation results of the algorithm. The accuracy rate is calculated using Formula 9, and the accuracy rate table is shown in Table 2.

$$\mathrm{ACC} = \left(1 - \frac{|X_1 - G|}{X_1}\right) \times 100\% \quad (9)$$

Where G is the algorithm output segmentation of the actual lesion area, and X_1 marks the reference area of the original lesion.

Comparative experiments

To verify the effectiveness of the algorithm in this paper, four other image segmentation algorithms are used for comparison: the GrabCut algorithm, OTSU algorithm, OTSU + morphological denoising algorithm (hereinafter referred to as OTSU-md), and the K-means algorithm. The comparison images are shown in Figure 7, and the accuracy is shown in Table 3.

As can be seen from Figure 7, the direct use of the GrabCut algorithm cannot effectively segment the lesion area separately. The effect of direct use of the OTSU algorithm is too poor, with an average accuracy rate of less than 20%, so the accuracy rate of these two algorithms is no longer calculated. Considering that there is too much noise using OTSU, morphological transformation denoising was added, but the OTSU+md algorithm still has serious over-segmentation. The reason is that this algorithm cannot achieve accurate segmentation in areas with low contrast. The segmentation effect of the K-means algorithm is better than the first three algorithms, but there is still over-segmentation. The improved GrabCut algorithm proposed in this paper can achieve an average accuracy rate of 88.05%, which has the highest accuracy rate in comparison.

The final segmentation result

inally, synthesize the original image with the image after lesion segmentation to get the final segmentation effect, as shown in Figure 7.

Result analysis

The computer software configuration used in this experiment was: Windows 11, 64-bit operating system, CUDA version 11.5, and PyTorch framework based on Python. The hardware was configured with an NVIDIA GeForce RTX 3060 Laptop GPU and an AMD Ryzen 9 5900HX processor. By comparing different convolution kernels, it can be concluded that when erosion uses a 3×3

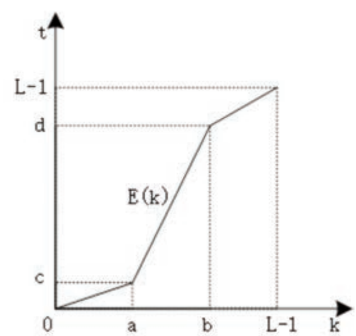

Figure 3. Transformation relationship.

Table 2. Accuracy table.

Example	Accuracy			
	3×3 Erosion 3×3 Dilation	3×3 Erosion 5×5 Dilation	5×5 Erosion 3×3 Dilation	5×5 Erosion 5×5 Dilation
Example 1	79.59%	85.43%	78.46%	71.47%
Example 2	84.37%	91.07%	72.92%	70.98%
Example 3	81.15%	87.67%	71.38%	73.08%

Table 3. Accuracy comparison of different algorithms.

Example	Accuracy		
	OTSU+md	K-means	Improved GrabCut
Example 1	29.21%	68.63%	85.43%
Example 2	26.75%	59.72%	91.07%
Example 3	32.37%	52.24%	87.67%

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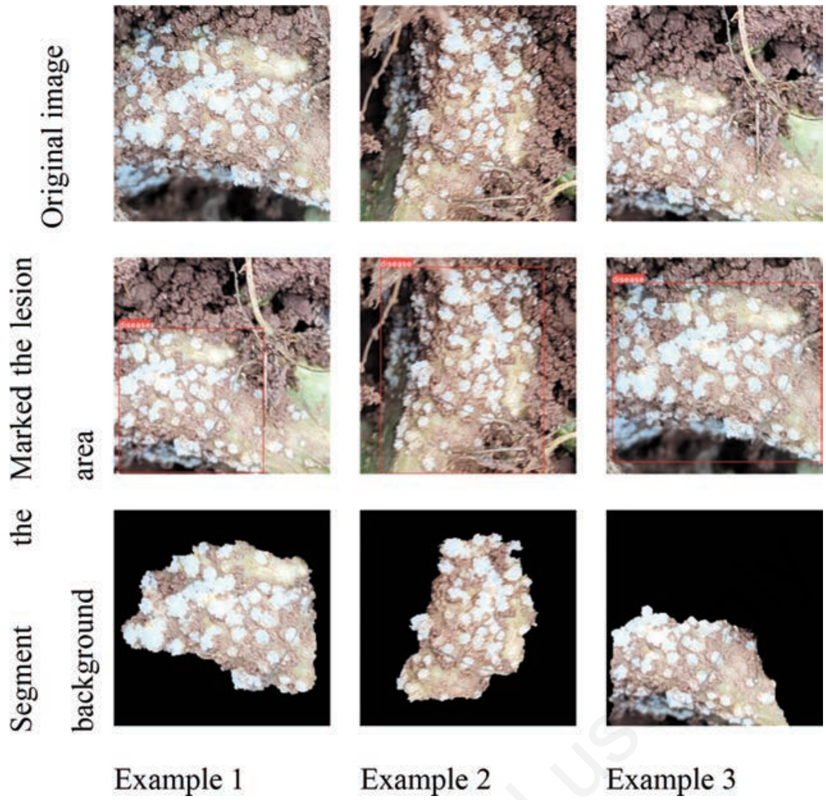

Figure 4. The effect of background segmentation.

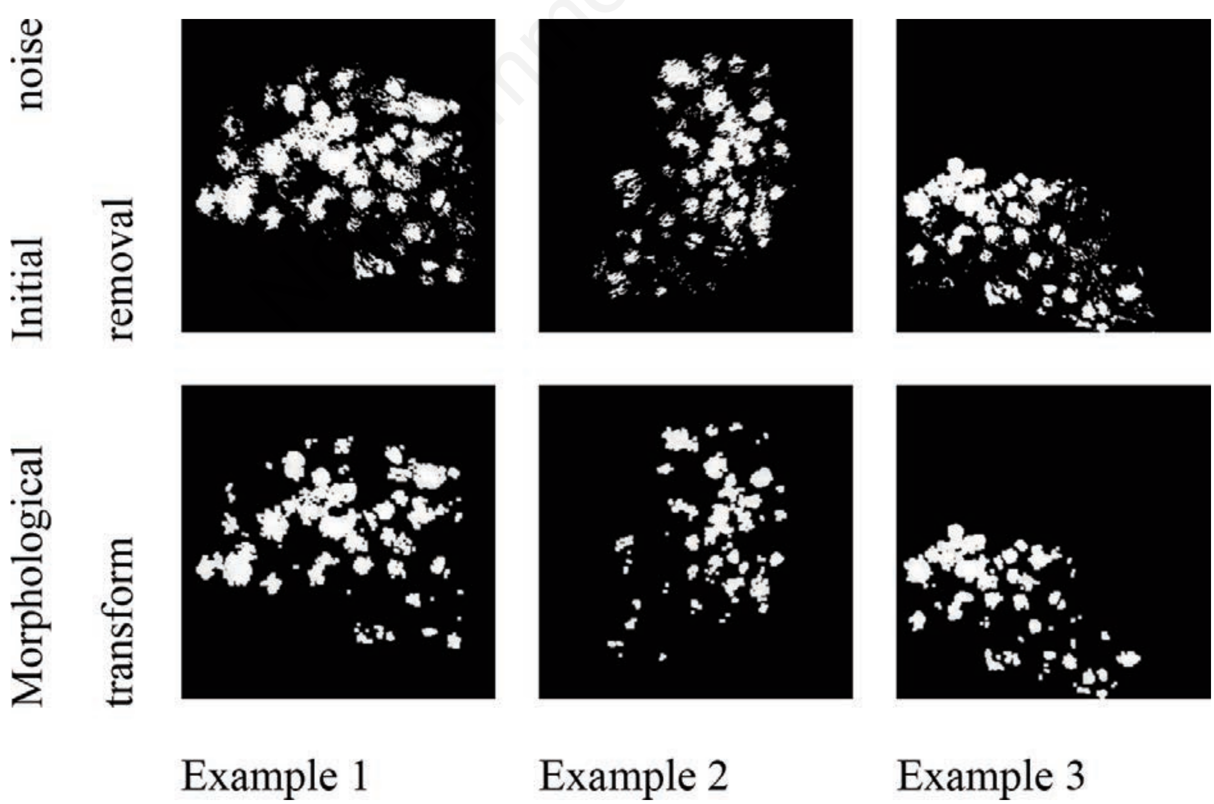

Figure 5. The effect picture after noise removal.

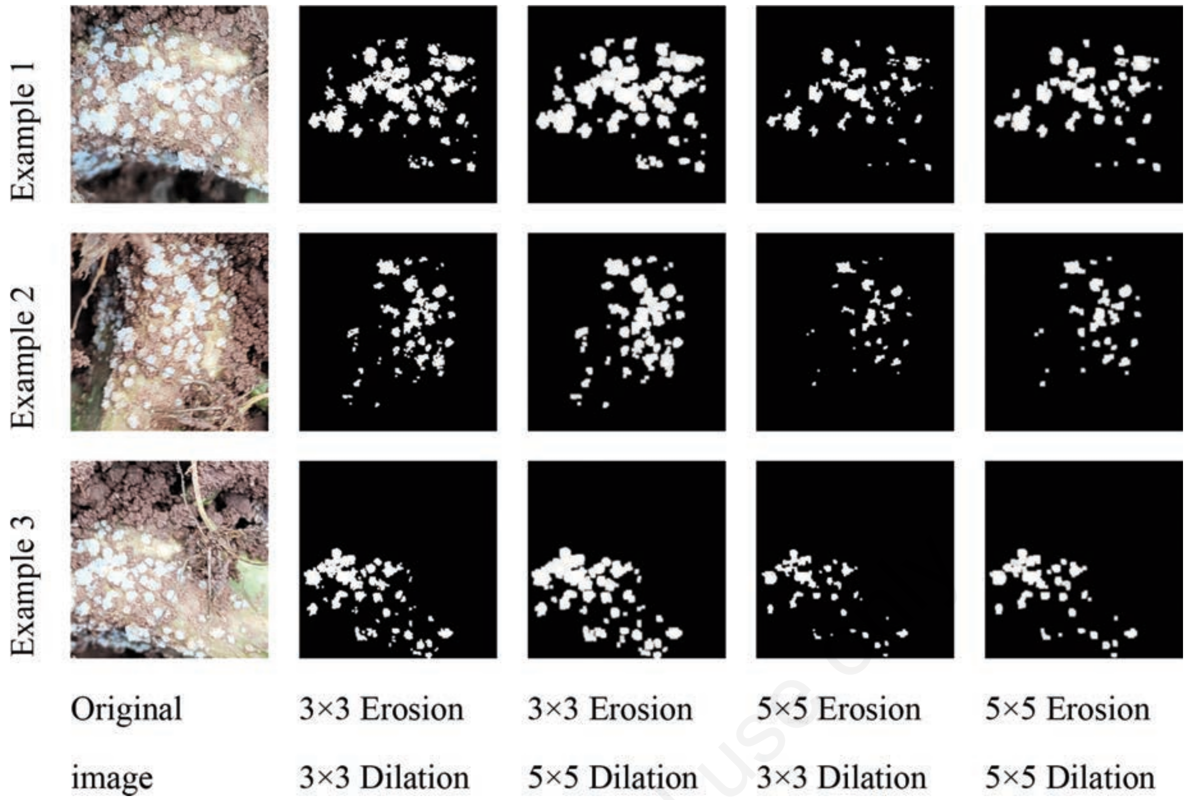

Figure 6. Comparison of using different convolution kernels.

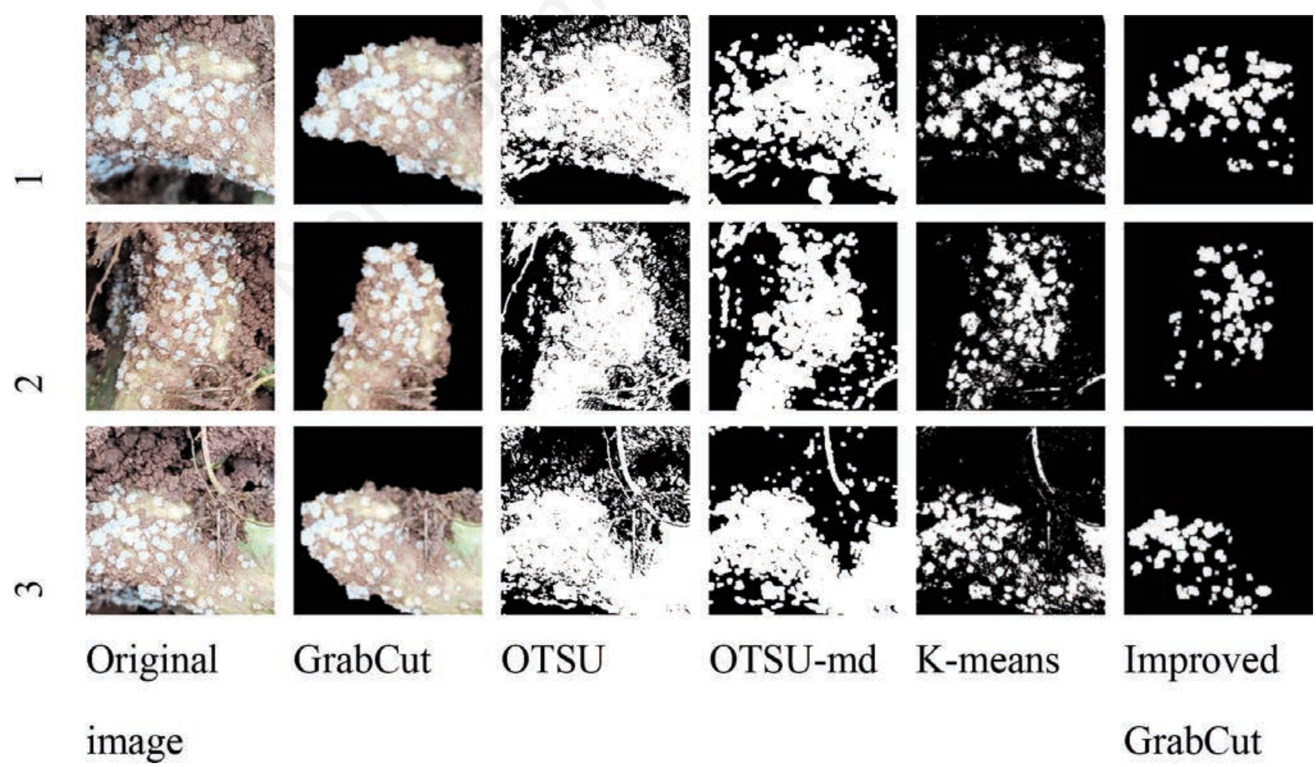

Figure 7. Comparison of different algorithm.

convolution kernel and dilation uses a 5×5 convolution kernel, the highest accuracy is achieved. The comparative experiments show that the traditional GrabCut algorithm and OTSU algorithm basically cannot segment lesions alone. The OTSU+md algorithm and K-means algorithm exhibit over-segmentation to varying degrees, with average accuracies of 29.44% and 60.20% respectively, and maximum accuracies of 32.37% and 68.63% respectively. The improved GrabCut algorithm proposed in this paper achieves an average accuracy of 88.05% and maximum of 91.07%. Compared to the relatively accurate K-means among the other four algorithms, the average and maximum accuracies increased by 46.28% and 32.69% respectively, significantly outperforming the other four algorithms. Manual labeling is time-consuming, error-prone, and directly impacts segmentation performance. Using the YOLOv7 model for object detection can automatically label lesion regions, avoiding the limitation of manual interactive labeling in traditional GrabCut, greatly improving the automation and accuracy of labeling. The image denoising techniques used in this paper, including grayscale transformation, thresholding, and morphological transforms, can effectively eliminate background noise and better highlight lesion regions, providing critical support for accurate lesion segmentation. Experiments compared morphological transforms with different kernel sizes, finding optimal combinations through repeated experiments to further eliminate residual noise points on lesion boundaries while preserving the edges. Compared to other segmentation algorithms, the improved method in this study demonstrates clear advantages in accuracy. However, some mis-segmentation still occurs in regions where lesion contrast is weaker, primarily because the color difference between lesions and normal tissue is less distinct, increasing segmentation difficulty. Additionally, small diffuse lightly colored lesions can be mistaken for noise and removed, reducing accuracy. Future work should focus on improving segmentation of low contrast lesions.

Conclusions

This paper proposes a potato powdery scab lesion image segmentation method based on YOLOv7 object detection and the GrabCut algorithm. This method utilizes the YOLOv7 model to automatically locate lesion regions as initialization input for GrabCut, avoiding manual interactive labeling and greatly simplifying the workflow. Meanwhile, combining grayscale transformation, thresholding segmentation, and morphological transforms removes noise from the complex background, enhancing lesion segmentation. Experimental results show this method can effectively segment potato powdery scab lesions, achieving an average accuracy of 88.05% and maximum of 91.07%. The proposed approach has broad application prospects. Segmented images can be used to compute lesion area in the future to assess disease severity and enable automated powdery scab detection. Further improving the algorithm's ability to segment low contrast lesions and small spots will provide powerful technical support for automated plant disease detection and control. This research provides an effective approach for segmenting plant disease lesion images with small datasets.

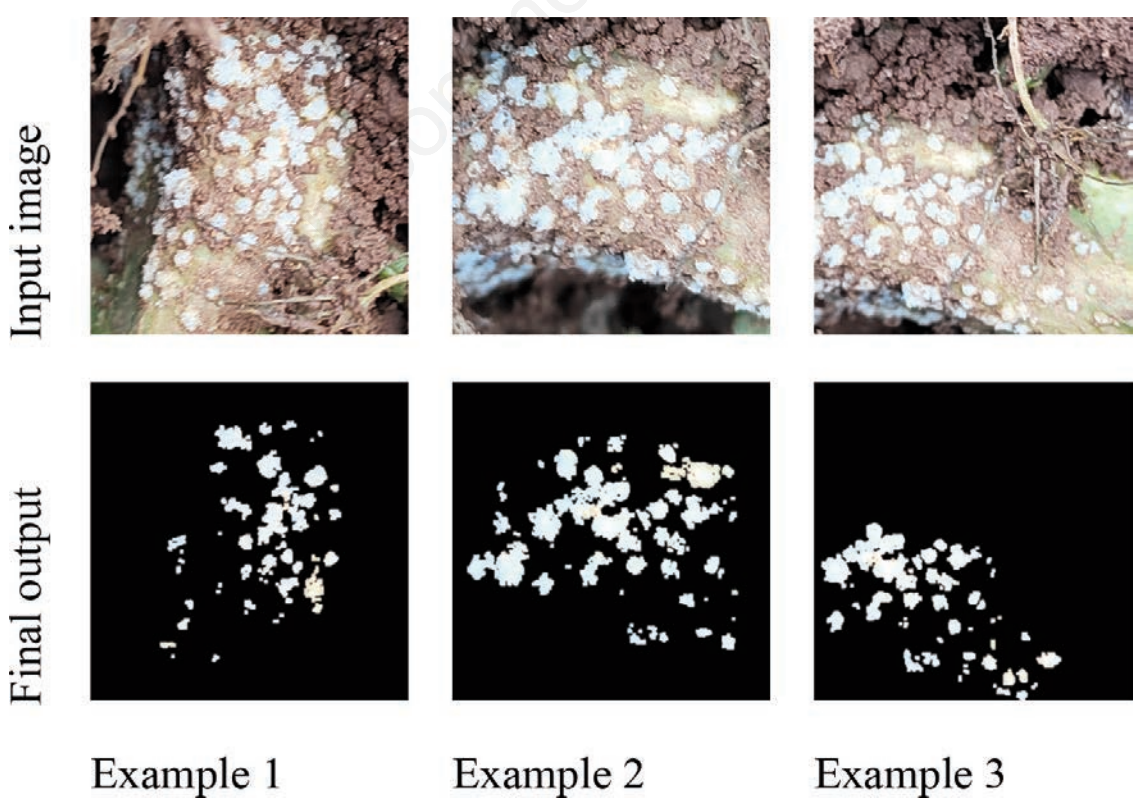

Figure 8. Comparison of the final segmentation results..

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