Deep Learning for Recognition and Classification in Soybean Leaf Image Data Management (Postprint)

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Abstract

[目的/意义]To improve the classification accuracy and efficiency of soybean leaf images and further facilitate their storage and management.

[方法/过程]This paper proposes an automatic classification method based on deep learning for soybean leaf image data, which exhibits low accuracy in visual observation and significant variation in classification results among different individuals. This study first delineates the Region of Interest (ROI) of soybean leaves, then extracts the leaf regions using the watershed segmentation method, and finally achieves efficient and accurate classification and recognition of soybean leaves through deep learning.

[结果/结论]By analyzing the characteristics of soybean leaf morphological images, this research conducted a study on the classification and recognition of soybean leaf morphology based on deep learning, achieving high recognition accuracy.

Full Text

Preamble

Deep Learning-Based Recognition and Classification of Soybean Leaf Image Data Management

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Abstract: [**Purpose/Significance**] To improve the classification accuracy and efficiency of soybean leaf images and facilitate their storage and management, this study proposes an automatic classification method for soybean leaf image data using deep learning techniques. Manual observation suffers from low accuracy and significant inter-observer variability. [**Method/Process**] This research first delineates regions of interest (ROI) for soybean leaves, then employs watershed segmentation for leaf extraction, and finally achieves efficient and accurate classification and recognition of soybean leaves through deep learning. [**Results/Conclusions**] Through analysis of soybean leaf morphological image characteristics, this study conducted classification and recognition research based on deep learning, achieving high recognition accuracy.

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1 Introduction

Although numerous studies indicate that the organization of Chinese agricultural data remains in its infancy [1], the application of data science and computer technology has become increasingly widespread and intensive. Over the past decade, image processing and computer vision methods have been extensively applied to plant disease detection and classification. Domestic researchers have achieved successful applications of deep learning in plant phenotypic data processing, with deep learning playing a crucial role in both text and image data recognition and classification. In large-scale sample analysis, deep learning has replaced traditional machine learning methods, employing unsupervised learning approaches. For instance, Weng et al. [2] conducted a review of deep learning applications in agricultural plant phenotyping, while Cen et al. [3] explored the current status and prospects of deep learning in plant phenotyping research. Yuan et al. [4] achieved variety identification of chrysanthemum flowers using convolutional neural networks, and Wu et al. [5] extracted apple tree crown information from remote sensing imagery using deep learning, enabling growers to dynamically monitor orchard tree growth. Numerous similar datasets for plant disease detection have been established, such as the citrus fruit PlantVillage dataset and Kaggle datasets. Many studies on plant image classification based on deep learning have emerged, including MAYRA et al. [6], who used 3D-CNN to generate wall-to-wall tree species maps for entire research areas, with improved tree species classification benefiting sustainable forestry and biodiversity conservation. MADS et al. [7] demonstrated weed classification using deep convolutional neural networks for plant species classification. Deep learning applications in agricultural science data management have primarily focused on image recognition and classification of plants and plant phenotypes at scale, agricultural pest and disease detection, crop and weed detection and classification, and crop yield prediction [8]. Pests, diseases, and various pathogens in food crops severely impact production and cause significant global economic losses, making crop health monitoring and early disease diagnosis critical tasks for sustainable agriculture. Existing automatic detection and classification methods for grain plant diseases remain in their infancy, necessitating novel fully automated tools. Correctly acquiring soybean leaf image data and improving the accuracy of deep learning classification and recognition while enhancing model generalization capability are essential for avoiding field measurement errors.

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2 Deep Learning-Based Recognition and Classification of Agricultural Scientific Image Data

2.1 Data Preparation

2.1.1 Characteristics of Soybean Leaf Data Soybean leaf morphology is defined by the shape of the terminal leaflet in the plant's trifoliate leaves, which can be categorized into four forms: lanceolate, ovate, elliptic, and round, as shown in [Figure 1: see original paper]. The data exhibit several key characteristics. First, inter-class differences are subtle: variations between different soybean leaf forms are smaller than those between distinct plant species, making classification more challenging. Second, intra-class variation is substantial: morphological features within the same leaf type vary considerably, complicating manual differentiation. Third, leaves are often curled and uneven, lacking typical morphology that can affect visual judgment. For soybean leaf image data classification and recognition, several difficulties arise: image distortion due to non-perpendicular photography, target occlusion as leaves overlap in field conditions, significant background noise affecting classification results, and poor generalization of methods effective only on single datasets. Based on these characteristics, this study employs image processing techniques for ROI division and leaf extraction to avoid nonlinear distortion and enhance convolutional neural network generalization.

2.1.2 Image Acquisition The dataset used in this study was collected from soybean plants in the experimental fields of the Heilongjiang Academy of Agricultural Sciences. During the soybean flowering period, mature trifoliate leaves from the middle and upper portions of plants from different varieties were randomly sampled to reduce potential morphological differences between varieties and improve recognition accuracy. A total of 3,200 soybean leaf groups were sequentially placed in a closed dark box for image acquisition. The technical flow chart is shown in [Figure 2: see original paper]. Using marker-based watershed segmentation, each captured soybean leaf image containing a complete trifoliate leaf was processed. The leaf mask created during watershed segmentation was used to cover the background and other leaflets in black, displaying only the terminal leaflet of the trifoliate leaf. This process yielded 3,200 individual soybean leaf images across four categories. The dataset was split into training and test sets at a 7:3 ratio, with 2,240 images for training and 960 for testing. Additional data augmentation through flipping and random rotation of the training set expanded it to 15,680 soybean leaf images.

2.2 Experimental Methods

The methodology involves three main stages: ROI division, leaf extraction, and deep learning classification. The process flow is illustrated in [Figure 2: see original paper].

2.2.1 ROI Division OpenCV, a cross-platform computer vision library developed by Intel for real-time image processing and pattern recognition, was used for batch image processing. The process involves grayscale conversion and Gaussian filtering to remove noise, followed by binarization and contour detection to find the minimum bounding rectangle of the leaf. Based on the four vertices of this rectangle, the ROI is delineated. Cropping according to the ROI removes background effects from the dark box, isolating the extracted leaf.

2.2.2 Leaf Extraction Marker-based watershed segmentation was employed for soybean leaf image segmentation. This algorithm improves upon traditional watershed segmentation by using morphological transformations to define foreground and background regions. The process treats the grayscale image as a topological surface where high grayscale values represent peaks and low values represent basins. Opening operations remove the leaf stem, erosion defines foreground regions, and dilation defines background regions. Each region is labeled sequentially, and as "water levels rise," different labels are separated by dams, segmenting the complete trifoliate leaf into three individual leaflets. The terminal leaflet is displayed while other leaflets are masked with the background, avoiding over-segmentation caused by minor grayscale variations in traditional watershed algorithms. The leaf extraction process is shown in [Figure 3: see original paper], and segmentation results in [Figure 4: see original paper].

Following segmentation, OpenCV detects contours and iterates through them to identify the minimum bounding quadrilateral. The image is then cropped to a square by extending 200 pixels in each direction from the center, using the maximum of the vertical and horizontal lengths as the standardized dimension. All images are uniformly resized to 224$×$224 pixels for deep learning input, ensuring position independence and improving training accuracy and generalization.

2.3 Feature Extraction and Recognition

2.3.1 Network Model Structure This study employs the DenseNet network model for deep feature extraction and morphological recognition of soybean leaves. DenseNet's key characteristic is creating direct connections between all layers to maximize information flow while ensuring layer-to-layer transmission. Each layer receives input from all preceding layers, enabling more effective feature utilization and allowing training of deeper networks with fewer parameters. The network structure primarily consists of four Dense Blocks, each containing six Bottleneck layers (48 layers total). Each Bottleneck layer follows the structure BN-ReLU-Conv(1\$$\times 1) - BN - ReLU - Conv(3\times 3), maintainingconsistentfeaturedimensionswithineachDenseBlock.EachBottlenecklayeroutputs4$ average pooling to reduce dimensionality and feature map size. The network model parameters and structure are shown in [Figure 6: see original paper] and [Figure 7: see original paper], respectively.

2.3.2 Network Training Process To train DenseNet for soybean leaf classification, preprocessed 224\$$\times 224imagesareinputintothenetwork.Theinitialconvolutionlayercontains96filterso$ max pooling with stride 2. Features then pass through four Dense Blocks connected by Transition layers. The final BN layer flattens the output into a 2,208-dimensional fully connected layer, using softmax to classify into four categories: lanceolate, ovate, elliptic, and round. DenseNet employs the ReLU activation function for fast convergence and sparse activation. The loss function uses Cross Entropy Loss, which provides more effective penalty objectives for CNN training. The Momentum optimizer (with learning rate α=0.9 and momentum =0.9) updates weights based on physics principles of energy conversion between potential and kinetic energy, helping parameters escape local minima and preventing divergence.

2.4 Experimental Results and Analysis

2.4.1 Experimental Environment The experiments were conducted on a Windows 7 64-bit system with a GeForce GTX 1070Ti GPU, Intel Core i5-8400 processor, and 8GB RAM. Visual Studio 2015 and the OpenCV library were used for image preprocessing, while the PyTorch framework with Jupyter Notebook and Python was employed for training the DenseNet model and testing predictions.

2.4.2 Evaluation Criteria For soybean leaf morphological classification, this study first applied traditional machine learning methods (Support Vector Machine and Random Forest) for recognition, then compared classic AlexNet and popular ResNet networks against the proposed DenseNet approach. Accuracy for each leaf type is calculated as shown in the formula, where pi=1 indicates correct identification and M represents the number of test samples. Recognition accuracy results for different soybean leaf shapes are presented in , and comparative results across methods in .

2.4.3 Comparison and Analysis of Different Algorithms The DenseNet network achieved an average recognition accuracy of 0.94 across four soybean leaf types, meeting practical requirements. Traditional machine learning algorithms (SVM and RF) require manual feature extraction of morphological, texture, and color features (14 features total), which is labor-intensive and susceptible to subjective factors and environmental conditions, resulting in lower accuracy. While AlexNet and ResNet directly use images as input, their accuracy remains lower than DenseNet. AlexNet's Dropout regularization randomly ignores neurons, causing feature loss and performing well only on easily classified lanceolate leaves. ResNet's short connections between early and late feature layers mitigate gradient vanishing but are less effective than DenseNet's dense connections. DenseNet's Bottleneck layers use 1$×1*convolutionbefore*3×$3 convolution to reduce input features, fuse cross-channel features, and decrease computational cost, making the network narrower while enabling more effective feature and gradient propagation.

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3 Conclusion

This study systematically demonstrated the complete process of agricultural data classification and recognition using deep learning, taking soybean leaf morphology from experimental fields in Heilongjiang as an example. DenseNet achieved 94% recognition accuracy, offering optimal performance with minimal storage requirements, though with longer training time. The approach successfully addressed the time-consuming, inefficient, and low-accuracy limitations of traditional methods in soybean leaf image classification, meeting the practical needs of agricultural image data classification. Future research should focus on collecting larger, more diverse datasets to advance soybean leaf recognition studies, developing reliable background removal techniques, and incorporating additional data modalities to improve system accuracy and reliability.

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Note: Figure translations are in progress. See original paper for figures.