Postprint: Deep Learning-Based Recognition of Garlic Clove Orientation

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Abstract

To address the challenges that current garlic automatic planters face in achieving upright sowing and the excessive complexity of existing garlic clove bud orientation recognition algorithms, a deep learning-based method is proposed to solve the garlic clove bud orientation recognition problem. This method eliminates the need for deliberately extracting contour features of garlic cloves or calculating the positions of the clove tip and centroid. Instead, it directly takes garlic clove images as input, enabling the model to automatically extract image features and implicitly learn from the training data to recognize garlic clove bud orientation. Experimental results show that when using 1,700 garlic clove images as the training set, the model achieves a recognition accuracy of 97.5% on an independent test set composed of 400 images. This method is simple, efficient, and reliable, providing a novel solution to the problem of garlic upright sowing, while also being applicable to other pattern recognition tasks such as agricultural seed selection.

Full Text

Preamble

Title: Identifying Bulbil Direction of Garlic Based on Deep Learning

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Abstract: To address the challenge of upright sowing in automated garlic planting machines and the excessive complexity of existing bulbil orientation recognition algorithms, this paper proposes a novel deep learning-based approach for identifying garlic bulbil direction. This method eliminates the need for explicit extraction of garlic clove contour features or calculation of tip and centroid positions. Instead, it uses raw clove images as direct input, allowing the model to automatically extract image features and implicitly learn from training data to recognize garlic bulbil orientation. Experimental results demonstrate that when trained on 1,700 garlic clove images, the model achieves 97.5% recognition accuracy on an independent test set of 400 images. This simple, efficient, and reliable method provides a new solution for garlic upright sowing and can be extended to other pattern recognition applications such as agricultural seed selection.

Keywords: algorithm; deep learning; garlic bulbil direction; pattern recognition

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0 Introduction

Garlic is widely consumed globally for its nutritional and medicinal properties. China is the world' s largest garlic producer, with approximately 11 million mu (about 733,000 hectares) under cultivation, accounting for roughly three-quarters of global output. Currently, garlic planting relies almost entirely on manual labor, which is labor-intensive, inefficient, and costly. Consequently, there is an urgent need to develop automated garlic planters that can operate at high speed with uniform spacing for large-scale cultivation. Since garlic growth occurs around the bulbil, ensuring the bulbil faces upward during planting is critical for seedling emergence and the development of both garlic scapes and bulbs. Controlling bulbil orientation represents a key challenge in garlic planter research.

Previous approaches have significant limitations. Guo Yingfang et al. extracted shape features using edge detection and applied the SUSAN corner detection algorithm for tip identification, but this method could only locate the garlic tip without determining precise bulbil orientation, and failed when the garlic skin had sharp protrusions resembling the clove tip. Wu Xian et al. used morphological processing with observation windows to locate tip positions and calculate orientation angles relative to the centroid. Yang Qingming et al. designed orientation recognition models through image transformation, segmentation, and dilation based on clove shape characteristics. All these methods require explicit feature extraction—such as contour extraction, tip localization, and centroid calculation—followed by feature reconstruction, resulting in complex designs with suboptimal performance.

In recent years, image processing technology has been widely applied in agriculture, including crop area statistics, weed identification, pest assessment, quality evaluation, and seed classification. With the rise of artificial intelligence, deep learning has attracted considerable attention, particularly convolutional neural networks (CNNs), which demonstrate strong advantages in image recognition. CNNs can directly accept raw images as input, integrating feature extraction into multi-layer perceptrons through structural reorganization and weight reduction. This eliminates the complex feature extraction and reconstruction processes of traditional methods, instead implicitly learning image features—including color, texture, shape, and topological structure—from training data. CNNs exhibit excellent robustness and computational efficiency for two-dimensional image problems, particularly in applications requiring invariance to translation, scaling, and other distortions. They can handle complex environmental information with unclear background knowledge and ambiguous reasoning rules, demonstrating strong adaptability.

Since garlic bulbil orientation recognition depends heavily on contour features, and local pixel correlations are strong while distant correlations are weak, global image perception is unnecessary. Only local feature perception is required, with global information synthesized at higher layers. CNNs are naturally suited for this "local perception" approach and excel at object contour recognition. After examining common CNN architectures, we found that even simple combinations of convolutional and pooling layers can effectively extract garlic contour features and achieve high recognition accuracy. This study employs a CNN-based deep learning method using Python and the Keras framework to automatically recognize garlic bulbil orientation, enabling planting machines to automatically determine whether bulbil orientation meets cultivation requirements.

1.1 Image Acquisition

We separated cloves from 10 kg of garlic and randomly selected 2,100 large cloves (width > 20 mm) as samples to ensure each image was unique. Following previous research recommendations, we used a dark matte background—a dark blue wooden board fixed horizontally. During image acquisition, cloves were placed on the board with the camera lens perpendicular to the surface. We captured 1,050 images of cloves with upward-facing bulbils (meeting planting requirements) and 1,050 images with random orientations (not meeting requirements) using a Nikon Coolpix A10 digital camera. Since original photos were too large for our experimental setup, we used Meitu Xiuxiu batch processing software to resize all images to 150×150 pixels while preserving aspect ratios and maintaining JPG format. Sample images are shown in [Figure 1: see original paper].

1.2 Training and Test Sets

The training set (Training_1,700) comprised 850 upward-facing and 850 random-orientation images. The test set (Testing_400) contained the remaining 200 upward-facing and 200 random-orientation images. Since all images came from different cloves, no duplicates existed, which helped prevent overfitting and improved model generalization. Commonly used convolution kernel sizes in CNNs are 3×3, 5×5, or 7×7; we employed 3×3 kernels due to our relatively small image dimensions.

1.3 Convolutional Neural Network Architecture

Bulbil orientation recognition is essentially a binary image classification problem. CNNs, as a cornerstone of deep learning, are designed as optimal models for "perception" tasks. They excel at image classification, learning features effectively even from limited data without manual feature engineering. CNNs process information from low-level to high-level features: initial kernels detect edges, corners, and curves, while deeper layers identify progressively complex features. Since garlic bulbil orientation depends largely on these shallow contour features, CNNs are naturally suited for this task.

To evaluate network depth impact, we performed five-fold cross-validation on Training_1,700 using models with 1–4 convolutional layers (each followed by a pooling layer). Accuracy distributions across 1–50 epochs are shown in [Figure 2: see original paper], with corresponding loss distributions in [Figure 3: see original paper]. All models performed well, but 3-layer (green line) and 4-layer (purple line) models achieved higher accuracy and lower loss than 1-layer (blue) and 2-layer (red) models, demonstrating that increased depth improves performance. However, the 4-layer model showed minimal improvement over the 3-layer version. To control network complexity, we adopted the architecture shown in [Figure 4: see original paper], featuring three convolutional layers interleaved with three pooling layers, followed by two fully connected layers. A Dropout layer (p=0.5) between fully connected layers prevented overfitting. All layers used ReLU activation except the final fully connected layer, which used Sigmoid. For this binary classification task, we selected 'binary_crossentropy' as the loss function and 'RMSprop' as the optimizer for its adaptive learning rate adjustment.

2.1 Relationship Between Model Accuracy, Loss, and Training Epochs

In deep learning, one epoch represents a complete forward and backward pass through all training samples with parameter updates. [Figure 5: see original paper] shows the relationship between epoch count and recognition accuracy, while [Figure 6: see original paper] illustrates the corresponding loss function behavior. When epochs exceeded 35, accuracy on both training and test sets stabilized, with test set accuracy reaching 95.5%-97.5% and loss steadily decreasing to 0.076–0.130, confirming the model' s effectiveness for bulbil orientation recognition.

2.2 Impact of Training Set Size on Model Performance

Like other non-linear machine learning models, deep learning typically performs better with larger datasets. To verify this, we trained models with varying sample sizes (100, 300, 500, 700, 900, 1,100, 1,300, 1,500, and 1,700 images) and evaluated them on the same test_400 set. Accuracy distributions across 1–50 epochs are shown in [Figure 7: see original paper], with loss distributions in

[Figure 8: see original paper]. Recognition accuracy improved consistently with increased training data (from ~0.5 to 0.97). Loss fluctuated significantly with 100–900 samples but decreased stably with 1,100–1,700 samples. summarizes maximum, average, and minimum accuracy for epochs 21–50 across different training set sizes. Despite limited experimental conditions restricting us to 1,700 training samples, the model achieved 97.5% accuracy; practical applications could utilize tens of thousands of images to further enhance performance.

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3 Conclusion

Leveraging CNNs' "local perception" advantage for object contour recognition, we proposed a deep learning-based algorithm for garlic bulbil orientation identification. Trained on 1,700 clove images and validated on a separate 400-image test set, the model achieved 97.5% accuracy, offering a novel solution for garlic upright sowing. Compared with traditional methods, our approach offers several advantages:

a) It eliminates the need for explicit contour extraction and calculation of tip/centroid positions, avoiding complex feature engineering and data reconstruction.

b) The algorithm is simple, efficient, and reliable. After 30–50 training epochs, model performance stabilizes with recognition accuracy exceeding 97%, improving further with larger datasets.

c) The method is highly generalizable and can be adapted for similar pattern recognition tasks such as crop seed selection and fruit quality assessment.

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