Postprint: Apple Phenological Stage Recognition in Natural Environments Based on an Improved ResNet50 Model

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Abstract

[Purpose/Significance] To address issues such as low accuracy and incomplete coverage of traditional methods in recognizing apple phenology images under natural environments, this paper proposes an apple phenology recognition method based on an improved ResNet50 model. [Method] By constructing a spherical camera system to acquire an apple image dataset under complex backgrounds, using ResNet50 as the base model, introducing the SE (Squeeze-and-Excitation Network) channel attention mechanism to enhance feature extraction capability for apple images, and combining it with the Adam optimizer utilizing cosine annealing learning rate decay, intelligent recognition of plateau Red Fuji apple phenology images under natural environments is achieved. [Results] Experiments were conducted on a dataset comprising 32,000 apple tree images. The results demonstrate that the improved ResNet50 model for apple phenology image recognition achieves a validation set accuracy of 96.35% and a test set accuracy of 91.94%, with an average detection time of 2.19 ms. Compared with AlexNet, VGG16, ResNet18, ResNet34, ResNet101, and the classic ResNet50 model, the optimal validation set accuracy is improved by 9.63%, 5.07%, 5.81%, 4.55%, 0.96%, and 2.33%, respectively. [Conclusion] The improved ResNet50 can achieve effective recognition of apple phenology. This research can provide a reference for orchard phenology recognition and, through integration into an intelligent monitoring and production management platform for fruit tree growth stages, enable intelligent management and control of apple orchards.

Full Text

Apple Phenological Period Identification in Natural Environment Based on Improved ResNet50 Model

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Abstract

[**Objective**] Aiming at the problems of low accuracy and incomplete coverage in traditional methods for identifying apple phenological periods from natural environment images, this study proposes an improved ResNet50 model for apple phenological period recognition.

[**Methods**] Spherical cameras were deployed to acquire apple image datasets under complex natural backgrounds. Using ResNet50 as the baseline architecture, the Squeeze-and-Excitation (SE) channel attention mechanism was introduced to enhance feature extraction capabilities for apple images. Combined with the Adam optimizer employing cosine annealing learning rate decay, the model achieved intelligent recognition of plateau Red Fuji apple phenological period images under natural conditions.

[**Results**] Experiments conducted on 32,000 apple tree images demonstrated that the improved ResNet50 model achieved 96.35% accuracy on the validation set and 91.94% on the test set, with an average detection time of 2.19 ms. Compared with AlexNet, VGG16, ResNet18, ResNet34, and ResNet101 models, the optimal validation set accuracy improved by 9.63%, 5.07%, 5.81%, 4.55%, and 0.96%, respectively.

[**Conclusions**] The improved ResNet50 model can effectively identify apple phenological periods. These research results provide a reference for orchard phenological period recognition and enable intelligent management and control of apple orchards when integrated into an intelligent monitoring and production management platform for fruit tree growth periods.

Keywords: apple; residual network; ResNet50; phenological period recognition; smart orchard

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1 Introduction

Apple is an important economic crop in China and one of the most widely cultivated fruits, occupying a significant position in domestic agricultural production. The annual growth cycle of apple trees typically involves multiple phenological stages including bud stage, flowering stage, young fruit stage, fruit expansion stage, fruit ripening stage, and others, each requiring different cultivation management practices. Effective identification of apple tree phenological periods can guide growers to timely implement pruning, irrigation, fertilization, bagging, and harvesting measures, providing an effective basis for scientific orchard management.

Traditional methods for identifying fruit tree phenological periods rely on historical data estimation or manual observation, which suffer from large errors and low efficiency when apple orchards are located in remote areas or regions with complex microclimates. In recent years, with the continuous development of deep learning in artificial intelligence, computer vision technology guided by deep learning theory has been widely utilized in agriculture, advancing research on intelligent recognition of crop phenological periods to a new stage.

Li et al. proposed a rapeseed phenological period identification method based on time-series fully polarimetric synthetic aperture radar data combined with a decision tree model, achieving relatively accurate results for rapeseed phenological period recognition. Wang et al. used convolutional neural networks to identify white tea phenological periods and then fused meteorological features to optimize the recognition performance, obtaining a high-accuracy white tea phenological period recognition model. Tan et al. constructed a field rice panicle detection and growth stage recognition model based on RiceRes2Net, achieving recognition accuracies of 99.83%, 99.34%, and 94.59% for the booting, heading, and filling stages of rice, respectively. Li et al. proposed a wheat growth stage recognition model and dynamic transfer algorithm based on deep reinforcement learning, demonstrating high recognition accuracy for wheat seedling, tillering, overwintering, regreening, and jointing stages. Aguiar et al. achieved automatic detection of grape growth stages using deep learning quantized models combined with cameras mounted on mobile robots. Tian et al. proposed an improved YOLOv3 model utilizing dense connection methods to process low-resolution feature layers for discriminating apple growth stages including young fruit, expansion, and maturity stages. Xu et al. improved the existing Tiny-YOLOv3 model by combining ResNet and DenseNet methods to enable real-time detection of apple young fruit, fruit expansion, and fruit ripening stages.

Although researchers both domestically and internationally have achieved certain results in crop phenological period recognition using modern deep neural network technologies, deep neural networks are difficult to apply in actual agricultural environments due to limited computational resources and restricted network conditions in remote areas. Phenological period identification in modern orchards still relies heavily on manual observation. Furthermore, current research on apple phenological period recognition is mostly combined with the objective of automatic fruit harvesting, focusing more on identification during the young fruit and ripening stages, with limited research on full life-cycle phenological period recognition for apple trees.

This study selected Red Fuji apple trees in the Sichuan plateau region as the research object, using an improved ResNet50 model as the backbone network.

By introducing attention mechanisms and the Adam optimizer to fuse feature information from apple phenological period images, this research aims to achieve precise monitoring of the complete life-cycle phenological periods of plateau Red Fuji apple trees, providing scientific guidance and decision-making support for intelligent management and control of apple orchards.

2 Materials and Methods

2.1 Data Collection

Apple tree image data were collected from the Western Sichuan Plateau Comprehensive Experimental Station of the National Apple Industry Technology System. Located in Yanyuan County, Liangshan Prefecture, Sichuan Province, on the southeastern edge of the Tibetan Plateau on the west bank of the lower Yalong River at an altitude of 2500 m, the station has a subtropical monsoon climate. Plateau Red Fuji apple trees undergo eight phenological stages throughout the year: bud stage, flowering stage, young fruit stage, fruit expansion stage, fruit coloring stage, fruit ripening stage, defoliation stage, and dormancy stage. Images of apples at different phenological periods are shown in [Figure 1: see original paper].

To reflect the characteristics of apple tree images from different time periods and angles, three sets of spherical network cameras (Hikvision) were installed at the experimental station as acquisition devices, consisting of dome cameras, poles, and equipment boxes as shown in [Figure 2: see original paper]. The dome cameras were mounted on top of the poles, and after capturing images, they were transmitted to the target server via 4G network modules in the equipment boxes. The server stored the daily captured images to form a phenological period image dataset.

To capture images reflecting different time periods and angles, movement trajectories were set for the cameras, and images were collected during three time periods: morning, noon, and evening (no collection at night). Three images were collected per time period, totaling nine images per day. The three camera sets collected approximately 9800 original images from April 2022 to March 2023. The camera shooting parameters are set as shown in .

The 9800 original images were labeled by fruit tree professionals: images with obvious phenological period characteristics were directly labeled. If individual images contained features of multiple phenological periods, they were comprehensively determined based on the image collection time and the phenological characteristics of other fruit trees at the same time according to the mid-to-late maturing apple tree growth stage classification standards. For example, if an image was collected on October 29 and the fruit tree was shedding leaves while a few unharvested fruits remained, referencing the mid-to-late maturing apple tree growth stage classification standards, this period was determined to be the defoliation stage. Since other fruit trees also exhibited leaf-shedding characteristics during this period, the image was still labeled as defoliation stage despite the presence of a few unharvested fruits.

2.2 Image Preprocessing

All experimental images were automatically collected by the spherical cameras at the experimental station under natural environments. Due to the complexity and uncertainty of field conditions, the collected images suffered from issues such as object occlusion, overexposure, poor focus, and target deviation, requiring preprocessing of the original image dataset. First, the 9800 images collected throughout the year were screened through data cleaning to remove invalid image data, retaining 8000 images with better imaging quality. Second, since the duration of each apple phenological period varies, resulting in differences in collection quantities, data augmentation was performed through random cropping, random rotation, horizontal flipping, and brightness adjustment to avoid accuracy degradation caused by quantity imbalance, as shown in [Figure 3: see original paper]. The 8000 original images were expanded to 32,000 images, improving model generalization while balancing quantity differences among phenological periods. Third, the augmented dataset of 32,000 images was divided into training set (25,600 images), validation set (3200 images), and test set (3200 images) at a ratio of 8:1:1.

2.3 Model Architecture

2.3.1 ResNet50 Model Traditional convolutional neural networks experience accuracy degradation as network depth increases during model training. In 2015, He et al. proposed the ResNet model, which establishes residual mapping to train deep networks and effectively solves the problems of gradient vanishing and gradient explosion in deep neural networks. The core of the ResNet model lies in the proposed shortcut connections structure, as shown in [Figure 4: see original paper]. The output value x enters the first weight layer to obtain the residual mapping F(x). While passing through the ReLU activation function into the second weight layer, the identity mapping of input x is added to obtain the ideal mapping F(x)+x. The advantage of the residual structure is making the transmission between shallow input value x and F(x)+x more sensitive.

ResNet18, ResNet34, ResNet50, ResNet101, and ResNet152 are available variants, among which ResNet18 and ResNet34 are shallow networks while the latter three are deeper networks. ResNet50 has a deeper network structure compared to ResNet18 and ResNet34, offering greater advantages in feature extraction for image classification. Although ResNet101 and ResNet152 have greater depth advantages, their execution efficiency is lower than ResNet50, and their actual image classification performance is not significantly different from ResNet50. After comprehensive consideration of the experimental platform performance indicators and the complexity of apple tree phenological period recognition under natural environments, this study selected the ResNet50 model as the baseline for improvement.

2.3.2 SE Attention Mechanism Since all plateau apple tree images in this experiment were collected from naturally growing fruit trees under complex environments rather than independent target objects, the model could not autonomously determine whether extracted features belonged to background data. Attention mechanisms, inspired by human visual selective mechanisms, concentrate attention on information with obvious features while selectively ignoring secondary information to achieve optimal recognition performance. Attention mechanisms include channel attention and spatial attention mechanisms. This study added the SE (Squeeze-and-Excitation Network) channel attention mechanism to the ResNet50 model to improve feature extraction capabilities for plateau apple tree images. The network structure of the channel attention mechanism is shown in [Figure 5: see original paper].

The SE module mainly contains three steps. First, a feature map X is processed through Ftr convolution to obtain a feature map U of size H×W×C. Feature map U undergoes Fsq compression to produce a 1$×1×$C output, which compresses the two-dimensional features of each channel into a real number through global average pooling, expressed as formula (1).

Second, the activated 1$×1×$C matrix from Fex is treated as z, enabling each channel to obtain different weights. The z matrix passes through a fully connected layer that compresses the dimension to C/r (where r is the scaling parameter), then through a ReLU activation function, followed by another fully connected layer that restores the dimension to C, maintaining consistent input and output channels. Finally, the sigmoid function produces the output, expressed as formula (2).

Third, the output s from the previous step is multiplied with the original feature data to achieve weighted calibration of the original channel data features, expressed as formula (3).

2.3.3 Adam Optimizer During model training, the loss value is obtained through forward propagation, and parameter gradients are obtained through backpropagation. The optimizer's role is to use gradients to update parameters and continuously reduce the loss. The Adam (Adaptive Moment Estimation) optimizer combines the advantages of adaptive learning rate gradient descent and momentum gradient descent algorithms, adapting to sparse gradients while alleviating gradient oscillation problems. To better promote model convergence, this study introduced cosine annealing learning rate decay into the Adam optimizer of the improved ResNet50 model to enhance optimizer performance.

2.4 Phenological Period Recognition Model Architecture Based on the ResNet50 model, channel attention mechanism and Adam optimizer were integrated. SE channel attention was introduced at the end of each residual module group to improve the model's feature extraction capability for plateau apple tree images. To enable fast model convergence, ImageNet was selected as the pre-training model. The structure of the improved ResNet50 model is shown in [Figure 6: see original paper].

In the diagram, Conv represents the convolutional layer in the neural network, where ”Conv, 7$×7, 64"*indicatesaconvolutionallayerwithkernelsize*7×$7 and 64 channels. Max pool represents the max pooling layer, SE block represents the attention mechanism layer, Average pool represents the average pooling layer, and Softmax is the fully connected layer. The entire model contains 4 groups of building blocks with quantities of 3, 4, 6, and 3, respectively.

3 Results and Analysis

This study aimed to verify the effectiveness of the improved ResNet50 model for recognizing apple tree phenological periods from the self-built dataset and its performance superiority compared to other commonly used models through model parameter tuning, ablation experiments, performance comparisons, and confusion matrix analysis.

3.1 Test Platform

The experimental platform was based on the Pytorch deep learning framework using Python language, with Ubuntu 20.04 as the operating system. To ensure independence of the experimental environment, model training was conducted in a virtual environment configured by Anaconda. Detailed experimental environment configuration is shown in .

3.2 Evaluation Metrics

Classification task metrics including validation accuracy, test accuracy, average detection time, and confusion matrix were selected as evaluation indicators for the plateau Red Fuji apple tree phenological period classification and recognition model experiments.

3.3 Model Parameter Tuning

The initial learning rate of the Adam optimizer is typically set between 0.1 and 0.0001. To verify the improvement effect of different learning rate parameters on the improved ResNet50 model training, this study selected four learning rates (0.1, 0.01, 0.001, and 0.0001) to train the model with iteration epochs set to 30, 50, and 70. The plateau apple tree image training and validation sets used identical datasets. Taking iteration epoch 50 as an example, the impact of different learning rates on training results is shown in [Figure 7: see original paper].

The results indicated that when the Adam optimizer's initial learning rate was set to 0.0001, the test model's accuracy approached optimal and the loss value curve converged fastest. With initial learning rate set to 0.0001 and iteration epochs set to 30, 50, and 70, the model achieved optimal validation set accuracies of 0.9354, 0.9635, and 0.9528, respectively. Therefore, the improved ResNet50 model selected a learning rate of 0.0001 and iteration epochs of 50 as the Adam optimizer training parameters.

3.4 Ablation Experiments

To verify the effectiveness of model improvement methods, ablation experiments were conducted on different improved ResNet50 models under the same dataset. SE-ResNet50 represents the improved model with added SE attention mechanism; Adam-ResNet50 represents the improved model with added Adam optimizer; the improved ResNet50 model combines both SE and Adam improvement methods. Ablation experiment results are shown in .

The ablation experiment results showed that compared with the original ResNet50 model, the SE-ResNet50 model improved validation set accuracy by 0.8% and test set accuracy by 2.99%, indicating that the SE attention mechanism provided more significant improvement to test set accuracy. The Adam-ResNet50 model increased model convergence speed, improving validation set accuracy by 2.19% and test set accuracy by 1.42%. The improved ResNet50 model combining both methods improved validation set accuracy by 2.33% and test set accuracy by 3.65%, with minimal difference in average detection time. These results demonstrate that both improvement methods provide positive enhancements with significant performance improvements.

3.5 Comparison of Different Model Detection Results

To further verify the effectiveness of the improved ResNet50 model, comparative experiments were conducted with commonly used image classification models including AlexNet, VGG16, ResNet18, ResNet34, and ResNet101. Under the same training dataset and operating environment, models were evaluated from three aspects: validation accuracy, test accuracy, and average detection time. Comparative results of different classification models are shown in .

The results showed that the improved ResNet50 model improved validation set accuracy by 9.63%, 5.07%, 5.81%, 4.55%, and 0.96% compared with AlexNet, VGG16, ResNet18, ResNet34, and ResNet101 models, respectively. Test set accuracy improved by 12.31%, 6.88%, 8.53%, 8.67%, and 5.58%, respectively. Under execution on the RTX 4000 chip, the average detection time difference among all models was within 1 ms. The experimental results demonstrate that the improved ResNet50 model outperforms other commonly used classification models on the plateau apple tree self-built dataset.

3.6 Confusion Matrix of Apple Tree Phenological Period Recognition Model

The confusion matrix is an important indicator for evaluating image classification models. Due to the different durations of the eight phenological stages of Red Fuji apple throughout the year, there are significant differences in the quantity of test set data for different phenological periods. To objectively evaluate the recognition accuracy of the model for various phenological periods and improve the readability of the confusion matrix, this experiment selected 200 images from each of the eight phenological periods from the 3200 test set images as test data, with the resulting confusion matrix shown in [Figure 8: see original paper].

In the confusion matrix, the vertical axis represents the true labels of apple tree phenological period images, the horizontal axis represents model prediction labels, and the right side shows the prediction accuracy distribution heatmap. The main diagonal represents the number of correctly predicted samples, with darker colors indicating higher accuracy. The results showed that bud stage and dormancy stage had the lowest accuracy and high mutual misclassification probability, with test accuracies of 89.50% and 87.44%, respectively. The analysis revealed that bud stage and dormancy stage have similar macroscopic features, and the image acquisition equipment in this study observed from a relatively long distance, unable to capture subtle physiological features of the bud stage. Young fruit stage, fruit expansion stage, and fruit coloring stage also experienced occasional misclassification due to feature similarity between adjacent stages. Red Fuji apple trees have more obvious external characteristics during flowering and fruit ripening stages, with the model achieving the highest recognition rates for these stages, reaching 97.50% and 97.49% test accuracy, respectively.

3.7 Application of Apple Tree Phenological Period Recognition Model

Accurate identification of apple tree phenological periods can guide orchard managers in conducting agricultural activities during different phenological stages. The authors' team has developed an "Intelligent Monitoring and Production Management Platform for Fruit Tree Growth Period" based on the apple tree phenological period recognition model, with the platform interface shown in [Figure 9: see original paper]. The platform calculates daily water requirements and deficits for fruit trees based on apple tree phenological period water demand characteristics, comprehensively considering soil water holding characteristics, daily crop water consumption, weather precipitation forecasts, and irrigation points, thereby achieving precise irrigation through the control system.

Although the confusion matrix experiment results showed that the improved ResNet50 model achieved over 90% overall recognition rate for apple tree phenological periods, small probability misclassification still occurred. To reduce model misclassification probability, improve recognition accuracy, and ensure precise control of the platform over apple orchards, the platform backend adopted a maximum value method to reduce misjudgment probability. Specifically, three sets of cameras deployed in the apple orchard were set to capture motion trajectories with good imaging effects, collecting images during morning, noon, and evening periods. Three images were collected per period from each of the three camera sets, totaling 27 images per day. The model calculated recognition results for all 27 images and selected the category with the highest recognition count as the output result to update daily phenological period information. For example, if 22 of the 27 apple tree images were recognized as young fruit stage, 2 as flowering stage, 3 as fruit expansion stage, and 1 as unrecognizable due to occlusion interference, the platform would update the daily phenological period to young fruit stage based on the maximum value method. This approach corrects recognition rates and improves platform reliability.

4 Conclusions

This study proposes a method for identifying apple tree phenological periods in natural environments based on an improved ResNet50 model, focusing on eight phenological stages of Red Fuji apple trees in the Sichuan plateau region: bud stage, flowering stage, young fruit stage, fruit expansion stage, fruit coloring stage, fruit ripening stage, defoliation stage, and dormancy stage. Based on the classical ResNet50 model, SE attention mechanism, Adam optimizer, and cosine annealing learning rate decay were introduced to recognize the eight phenological stages of apple trees. The main conclusions are as follows:

1. When the improved ResNet50 model introduced the SE attention mechanism and Adam optimizer with an initial learning rate of 0.0001 and iteration epochs of 50, the optimal validation set accuracy reached 96.35%. Compared with AlexNet, VGG16, ResNet18, ResNet34, ResNet101, and the classical ResNet50 models, the optimal validation set accuracy improved by 9.63%, 5.07%, 5.81%, 4.55%, 0.96%, and 2.33%, respectively.

2. The confusion matrix was used to visualize apple tree phenological period classification results. The improved ResNet50 model achieved an overall test accuracy of 91.94%, with recognition rates above 90% for flowering stage, young fruit stage, fruit expansion stage, fruit coloring stage, fruit ripening stage, and defoliation stage, further verifying the effectiveness of the improved ResNet50 model for apple tree phenological period recognition.

Conflict of Interest Statement: This study has no conflicts of interest among researchers or with publicly disclosed research results.

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