

Peach Phenology Period Identification Method Based on Ensemble Learning

Xiaoyu Li, Aifeng Li*, Peng Lan*, Yaping Li, Dongyue Liang and Xiangqu Chen

Shandong Agricultural University, College of Information Science and Engineering, Tai'an, Shandong Province, China

Abstract

An ensemble learning-based algorithm for peach phenological stage recognition is proposed to address the problem that peach phenological stage recognition is susceptible to low accuracy due to interference from the complex environment of peach orchards. The model is trained on three networks, ResNet50, AlexNet and VGG-16, on the sample images to form a classification model. Attention mechanism was added to these three networks and the LRN layer was changed to BN layer in addition to the AlexNet improvement. Finally, the voting method of ensemble learning is used to improve the recognition ability of the model for images with complex background information. The experimental results show that the recognition accuracy of the algorithm is 99.3%, which can better achieve the accurate recognition of peach phenology with complex backgrounds.

Keywords

Voting method, Convolutional neural networks, Phenology identification

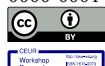
1. Introduction

The peach tree has many varieties and its fruits are delicious and loved by people for its adaptability, short growth cycle and nutritious fruits. At present, more than 70 countries around the world plant peach trees, and the planting range of peach trees in China is also very wide. In recent years, with the increasing demand for peaches, the planting area is also expanding, but the lack of labor has become a factor limiting the increase of peach production. In order to solve this problem of lack of labor to limit the production of agricultural products, unmanned orchards and unmanned farms have come into agricultural production. Unmanned orchards are a new production model that relies on a variety of new technologies such as the Internet of Things, big data, and artificial intelligence to complete all farming operations in accordance with the crop growth cycle by remotely controlling various machines [1]. Therefore, improving the recognition rate of peach phenological stages is the key to develop unmanned peach orchards.

At present, the main research on the phenological period in China and abroad are manual observation method, model simulation and remote sensing monitoring. Among them, Islam A S et al. constructed a potato phenology curve by extracting NDVI and LAI in potato fields, and this study showed that remote sensing data can show the growth of the crop [2]; Yang Q et al. used a UAV to collect high-resolution RGB images of rice for the detection of rice phenology by a two-branch CNN architecture [3]; Zhai Deli et al. used partial least squares to analyze the relationship between rubber tree phenology and climatic factors, and used environmental factors as variables to predict phenology [4]. Wang X A et al. proposed in the study of apple blossom phenology The new method of Deep Phenology and the method is commercially viable as it can evaluate both daytime and nighttime images [5]. At present, the research

ICBASE2022@3rd International Conference on Big Data & Artificial Intelligence & Software Engineering, October 21-23, 2022, Guangzhou, China

EMAIL: lxy18866856579@163.com(Xiaoyu Li); liaf@sdau.edu.cn(*Aifeng Li); lanpeng@sdau.edu.cn (*Peng Lan); 17862686709@163.com (Yaping Li); l411287204y@163.com(Dongyue Liang); ch_xiangqu@163.com(Xiangqu Chen)
ORCID:0000-0001-9699-4887(Xiaoyu Li);0000-0003-4427-4866(*Aifeng Li);
0000-0002-5492-524X(*Peng Lan);0000-0002-4256-1303(Yaping Li);
0000-0001-5785-6131((Dongyue Liang)); 0000-0002-3926-0390(Xiangqu Chen)



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CEUR Workshop Proceedings (CEUR-WS.org)

objects of the phenological period are mainly some economic crops such as corn, wheat and rice, and economic forest trees such as rubber trees, but the research on the phenological period of fruit trees such as peach is less. The problem of peach phenology identification is mainly to identify the phenology of flowers, buds and fruits of peach trees, so it is necessary to improve the model's ability to identify peach phenology images with complex background.

For the recognition of peach phenological period, this thesis analyzes 22686 peach images, we derive the results based on models such as AlexNet, ResNet50 and VGG16 then combine the results with ensemble learning methods to vote on the results and finally output the prediction results.

2. Materials and Methods

In order to improve the accuracy of peach season recognition, this paper uses a combination of deep learning and ensemble learning to build a season recognition model. The results are first trained by multiple convolutional neural networks and then voted by the ensemble learning method to get the best results.

The main improvement of AlexNet^[6] is to use BN layer instead of LRN layer, because the local response normalization layer is normalized locally, while BN layer is normalized for the whole batch. The BN^[7] layer is able to effectively converge the network quickly and reduce the number of iterations significantly, while also adding the coordinate attention mechanism after the fifth layer of convolution. The improvement for ResNet50^[8] and VGG-16^[9] is the addition of the coordinate attention mechanism, which is only added to the first and last layers of convolution. In VGG-16, the attention mechanism is placed at the last layer of convolution.

The majority voting method is chosen in this paper for the construction of the pooling strategy. Since the rejection of the prediction occurs in the standard absolute majority voting method, and the task of this paper is to require the output of the prediction, the majority voting method is chosen in this paper. For example, let the integrated model in this paper contain K base models $\{g_1, g_2, \dots, g_k\}$, the type set of all samples is $\{c_1, c_2, \dots, c_N\}$, the predicted output of the base model g_i on sample x is $(g_i^1(x); g_i^2(x); \dots; g_i^N(x))$, where $g_i^j(x)$ is the output of the base model g_i on type c_j , then the final discrimination result of the voting method is shown in Equation (1). In majority voting, the final predicted type is the type with the highest percentage of votes; If there is a type with the same percentage of votes, a type is randomly selected.

$$H(x) = c_{\arg \max \sum_{i=1}^K g_i^j(x)} \quad , \quad (1)$$

From the above, it can be seen that this paper uses ensemble learning^[10] for peach phenological stage identification, and its process is shown in Figure 1.

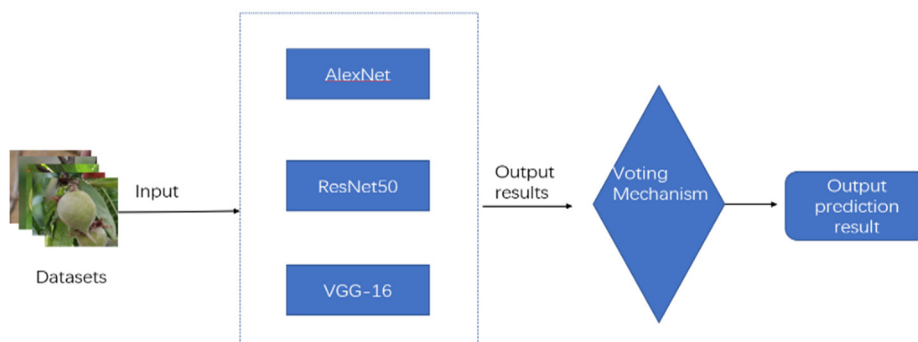


Figure 1: Peach phenological stage identification process.

3. Testing and Analysis

3.1. Data acquisition and preprocessing

The object of this paper is the various phenological stages of peaches, which are mainly distinguished according to the status of buds, flowers and fruits, and are divided into budding stage, flowering stage, young fruit stage, expansion stage, bagging stage and fruit ripening stage. The data in this paper are taken from the Science and Technology Innovation Park of Shandong Agricultural University. The data set has 22686 images, which are randomly selected and divided into training set and test set in the ratio of 8:2.

3.2. Test environment and analysis of results

The test environment is Windows 11 operating system, CPU is 12th Gen Intel(R) Core (TM) i7-12700H 2.70 GHz, graphics card is NVIDIA 3060, deep learning framework is Pytorch 1.12.0, and CUDA 11.6 and CUDNN 8.4.1 are also used to accelerate the computer's computational power. The initial learning rate was set to 0.0001; the optimizer was selected as Adam Optimizer.

The experiment in this paper is divided into 3 steps.

Step 1: The three models, AlexNet, Resnet50, and VGG-16, were trained on the prepared peach phenology dataset. The accuracy of these three models on the dataset was 96.8%, 97.9%, and 97.8, respectively. Then in the recognition of multi-model ensemble learning, the accuracy of integrated learning is 98.5% and the results are shown in Figure 2.

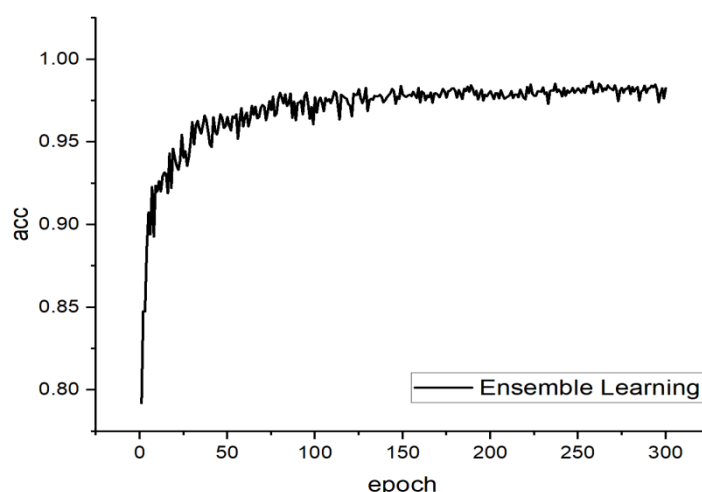


Figure 2: Accuracy of unimproved ensemble learning models.

Step 2: The AlexNet, Resnet50 and VGG-16 models were improved by adding an attention mechanism to each network model due to the characteristics of each weathering period of the studied peaches, and also by using the BN layer instead of the LRN layer in the improvement of AlexNet. The improvement process and recognition accuracy results are shown in Table 1.

Table 1: Individual model improvement process and recognition accuracy

Network Model	Attention Mechanism (Yes/No)	BN Layer (Yes/No)	Accuracy of the improved model
AlexNet	Yes	Yes	98.8%
ResNet50	Yes	No	98.7%
VGG-16	Yes	No	98.8%

From the above table, the test accuracy of AlexNet increased from 96.8% to 98.8% after adding the attention mechanism and BN layer, Resnet50 increased from 97.9% to 98.7%, and VGG-16 increased from 97.8% to 98.8%. This shows that adding the attention mechanism and BN layer can improve the recognition rate of the model for sample images with complex backgrounds.

Step 3: Perform multi-model integration learning using 3 models including AlexNet, Resnet50 and VGG-16 which have been improved.

The experiments of the algorithm in this paper were completed with the improved training and integrated learning of the models of AlexNet, Resnet50 and VGG-16, the ensemble learning with the unimproved models of AlexNet, Resnet50 and VGG-16 as the base models and the ensemble learning with the improved models of AlexNet, Resnet50 and VGG-16 as the base models of the recognition results are shown in Figure 3. The comparison of the experimental results of each model is shown in Table 2.

From Table 2, it can be seen that the LeNet model has the worst recognition effect of 94.7% in the individual model for peach phenological stage recognition. Then, after improving AlexNet, Resnet50 and VGG-16, the recognition accuracy increased by 2%, 0.8% and 1% respectively, which indicates that adding attention mechanism can improve the recognition accuracy of the model for images. From Figure 3, it can be seen that the fusion of multiple models under ensemble learning can also improve the recognition accuracy. At the same time, after improving the recognition accuracy of individual models, the accuracy of ensemble learning also increases from 98.5% to 99.3%, which means that improving the recognition accuracy of individual models is also beneficial to improve the recognition accuracy of multiple model fusion. In summary, the ensemble learning has good recognition effect for peach phenological stage.

Table 2: The comparison of the experimental results of each model

Network Model	Unchanged model into accuracy	Accuracy of the improved model
AlexNet	96.8%	98.8%
ResNet50	97.9%	98.7%
VGG-16	97.8%	98.8%
LeNet	94.7%	-
Vote-ensemble	98.5%	99.3%

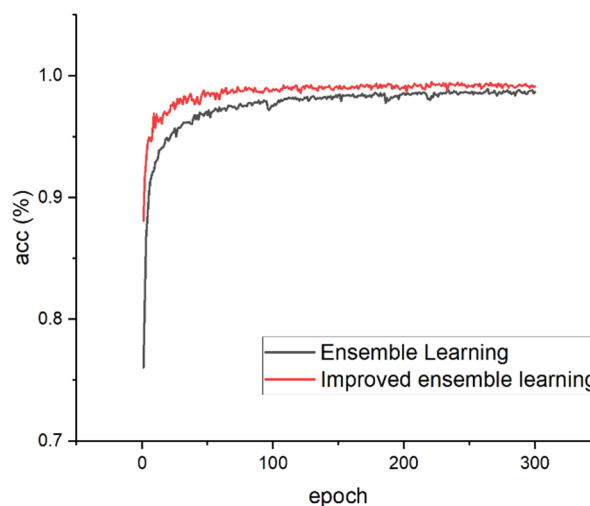


Figure 3: Accuracy comparison of integrated learning model before and after improvement

4. Conclusion

In this paper, we propose a method to identify the season of peach trees with high accuracy in complex environments, which further promotes the application of deep learning in agricultural production. In this paper, we use the data augmentation method to increase the number of sample images,

add the attention mechanism to AlexNet, and use BN layer instead of LRN layer to increase the convergence speed of the model. The attention mechanism is also added to ResNet50 and VGG-16, and the results show that the addition of the attention mechanism can effectively improve the recognition of the waiting period. Finally, using the ensemble learning model, it can be concluded that the ensemble model, without interfering with the results of the original model, uses the voting strategy to improve the image recognition accuracy significantly.

The learning rate used in this paper for image recognition using the integrated model is the same learning rate setting for all three models, and it is planned that different learning rates can be set for recognition in the future. Since this paper is mainly to solve the problem of low accuracy of peach season recognition, we ignore the problem of large size of the model used, so we should also consider reducing the size of the model and making it lighter in the future. While the model is lightweight, the accuracy of network model recognition should be kept constant or improved, so that the peach recognition model can be more effective and practical in agricultural production and contribute to agricultural development.

5. References

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