Identification of flowering rate of Litchi canopy based on UAV multispectral remote sensing images

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Abstract: The yield of litchi is closely related to the on-demand and precise operation of litchi trees. For litchi trees with different flowering rates, the quantity of fertilizer application may also vary from tree to tree. In order to reduce labor requirements and improve the efficiency of observing the flowering rate of the litchi canopy, this study combines multispectral remote sensing images with deep learning technology to achieve flowering rate recognition and modeling of the litchi tree canopy in large-scale orchards. This research proposes a technique for merging visible images with multispectral images. The five vegetation index images calculated from remote sensing images of five different wavelength bands were combined with visible three-channel images to derive the most favorable combination of vegetation index channels for identifying the flowering rate of the litchi canopy; the obtained multi-channel images were used as inputs for training, and the Vision Transformer neural network was used to construct a litchi canopy flowering rate recognition model with a normalization method to further improve the accuracy of the model. After normalization, the best results of litchi canopy flowering rate recognition were obtained when RGB was fused with OSAVI and NDVI vegetation indices. Compared with other models, the recognition model constructed based on Vision Transformer achieved an accuracy of 97.22%. This study can accurately identify the flowering rate of the litchi canopy under multispectral remote sensing images and direct the appropriate fertilizing or other production activities, which is helpful to realize the intelligent management of orchards.

Keywords: Multispectral remote sensing image; channel fusion; flowering rate recognition; deep learning
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1 Introduction

Lingnan has long been known for its production of litchi; in fact, the emperor once dispatched people thousands of kilometers away to send fresh litchi in an effort to ingratiate the concubine. Litchi has been grown in the Lingnan area for over a thousand years; It is the most blatant regional advantage, has the most distinctive variety, and is the largest fruit to be planted in Guangdong Province[1]. Guangdong Province litchi production has long been stable at about 1.31 million tons, with the cultivated area of about 4.1 million mu, production and area are ranked first in the country. Guangdong to achieve 1.165 million poor people all out of poverty in 2021, the bright achievements behind the "increase in production and income" of the litchi industry to support[2]. Guangdong's litchi industry has infused a consistent wellspring of essentialness for rustic renewal and destitution easing.

However, Guangdong litchi industry is hindered by some bottlenecks. The yield will be affected by climate, planting environment, fertilization, plant protection and so on. The precise control of farming operations can ensure the maximization of production and optimization of quality. During the flowering period, too little fertilizer application can easily lead to nutrient deficiency and yield reduction in litchi trees, and too much fertilizer application can easily lead to the coagulation of pistils and even soil caking. If more flowers bloom, the nutrition will not keep up and the yield will decrease. The type and amount of fertilizer to be applied is a challenge. This requires a more comprehensive production management system, through the observation of the litchi flowering rate, and thus provides more cutting-edge technical guidance on the amount of fertilizer applied to the litchi flowering period, to achieve real-time crop management and refinement. At present, the mainstream research method is to take images of litchi flowers at close range and use computer vision and machine learning methods for flowering recognition and diagnosis. However, for large-scale flowering rate identification in orchards the above methods are inefficient and require a lot of wasted material and financial resources. The use of artificial intelligence technology may a major key to solving the problems of the litchi industry.

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Currently, artificial intelligence techniques are widely used to implement smart orchards. For smart orchard for litchi, Xiong et al.[3] selected the YCbCr color model to judge three cases of immature, mature, and matured litchi fruits with decayed and deteriorated appearances, and established an intelligent system for litchi fruit quality identification with a correct rate of 93%. Jiang et al.[4] used high-resolution remote sensing images of litchi forest canopy information for extraction, and the final detection overall accuracy was 87.75%. Wang et al.[5] used a fully convolutional neural network for litchi epidermal defect extraction to improve the quality detection grading accuracy. Xiong et al.[6] proposed a deep semantic segmentation network to identify litchi flower and leaf pixels and segment them with a final recognition accuracy of 87%. Ye et al.[7] used a deep learning algorithm to achieve the identification of litchi pests with 95% accuracy. Lin et al.[8] used a multi-column convolutional neural network to estimate the amount of litchi flowers based on a density map by near ground observation and visible images. However, little research has been found to accurately determine the flowering rate of the litchi canopy from low altitude perspective, which can highly improve the efficiency of orchard patrol. As for the flowering rate of the other crops or spcecies, some exploration can be found in herbaceous plants such as rapeseed and mustard[9-10].

Crops in different states have different spectral information, so spectrum information has been widely adopted to discover the status of disease and growth of crops. Multispectral cameras use blue, green, red, red-edge and near-infrared bands to capture visible and invisible images of crops and vegetation[11]. These images are processed to provide farmers with timely and valuable information. Therefore, with the booming development of UAV remote sensing technology, more and more people are using UAVs with multispectral cameras, flying at low altitude to obtain efficient and high-resolution multispectral information, synthesizing and analyzing the obtained data[12], and then processing them through modeling, data analysis, and identification, which can realize applications such as farmland digitization and precision planting management, permitting farmers to save time and cost. Xiao et al.[13] took multispectral images of apple tree canopies by a UAV with a multispectral camera and estimated the flowering of apple trees using the grayscale values of R, G, and NIR as features, and the accuracy of the model reached 97%. Nogueira et al.[14] used a 5-band multispectral camera and a RGB camera to obtain crop canopy spectral information, and then used the coffee Maturity Index (CRI) and other five vegetation indices to complete the detection of coffee maturity. Deng et al.[15-17] and Lan et al.[18-19] used UAV hyperspectral and multispectral technology to detect citrus Huanglongbing disease with different machine learning algorithms and different vegetation indices. Ma et al.[20] calculated the non-healthy crop area and generated an agricultural monitoring report by color rendering the difference of NDVI index for each pixel point of the multispectral image map. Yang et al.[21] used the multispectral local R component as a spectral component for the ripeness determination of the Serpentine grape, and constructed a multispectral local R component and Serpentine grape ripeness relationship model with an average prediction error of ≤1.388% and a maximum prediction error of ≤4.6%. Zhang[22] proposed an end-to-end convolutional neural network spectral qualitative analysis model and applied it to the identification of 20 grape varieties, and the average classification accuracy of the model reached 87.81%. Using convolutional neural networks, Wu et al.[23] trained a recognition model to determine the nutritional status class of maize plants, in which the recognition verification set of color images reached 84.7% correct and the verification set of five-channel multispectral images reached 90.5% correct. Fabiano et al.[24] used images collected in the ultraviolet A region (365 nm) to classify the health status of rye seeds. The outcomes were quicker and more successful than conventional techniques. Fawakherji et al.[25] used generative adversarial networks (GANs) and RGB and NIR information to build a model that can generate 4-channel multispectral synthetic images of vegetation, further developing the segmentation performance of current semantic segmentation convolutional network. Multispectral remote sensing is an extremely powerful tool for analyzing plant growth conditions these days. The development of multispectral imaging technology has enabled researchers to no longer limit the spectral analysis of vegetation to the visible level, and multispectral data of vegetation has opened a new window. At the same time, more and more researchers have started to apply deep learning techniques to vegetation feature extraction, promoting the efficient and intelligent analysis of vegetation spectral information.

Summing up the past exploration results, it can be found that the effective use of vegetation spectral information by deep learning technology has extraordinary potential and attainability in vegetation growth monitoring. Therefore, in this study, we use the multi-spectral UAV to obtain the spectral information of litchi canopy, calculate various vegetation indexes, screen out the vegetation indexes that are conducive to distinguishing different flowering rates of litchi, and then use the neural network to establish a recognition model to estimate the flowering rate, which provides a basis for precise agricultural operations.

2 Materials and Methods

2.1 Overview of the test site

The experimental site for this study was located in a litchi orchard in Conghua District, Guangzhou City, Guangdong Province, China (23°35′11.98″N-113°36′48.49″E), with 141 litchi trees. The geographical overview of the orchard is shown in Figure 1.

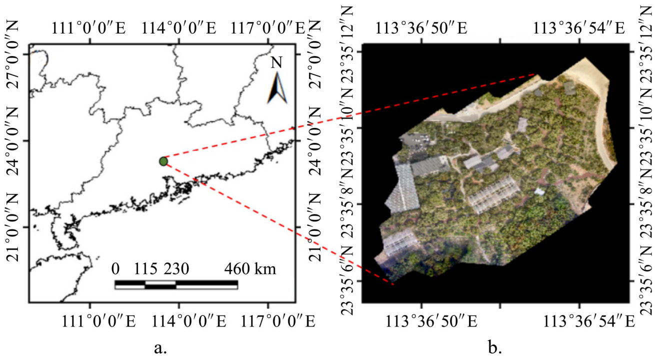


Figure 1 Geographical location of Litchi Orchard

2.2 Data acquisition equipment

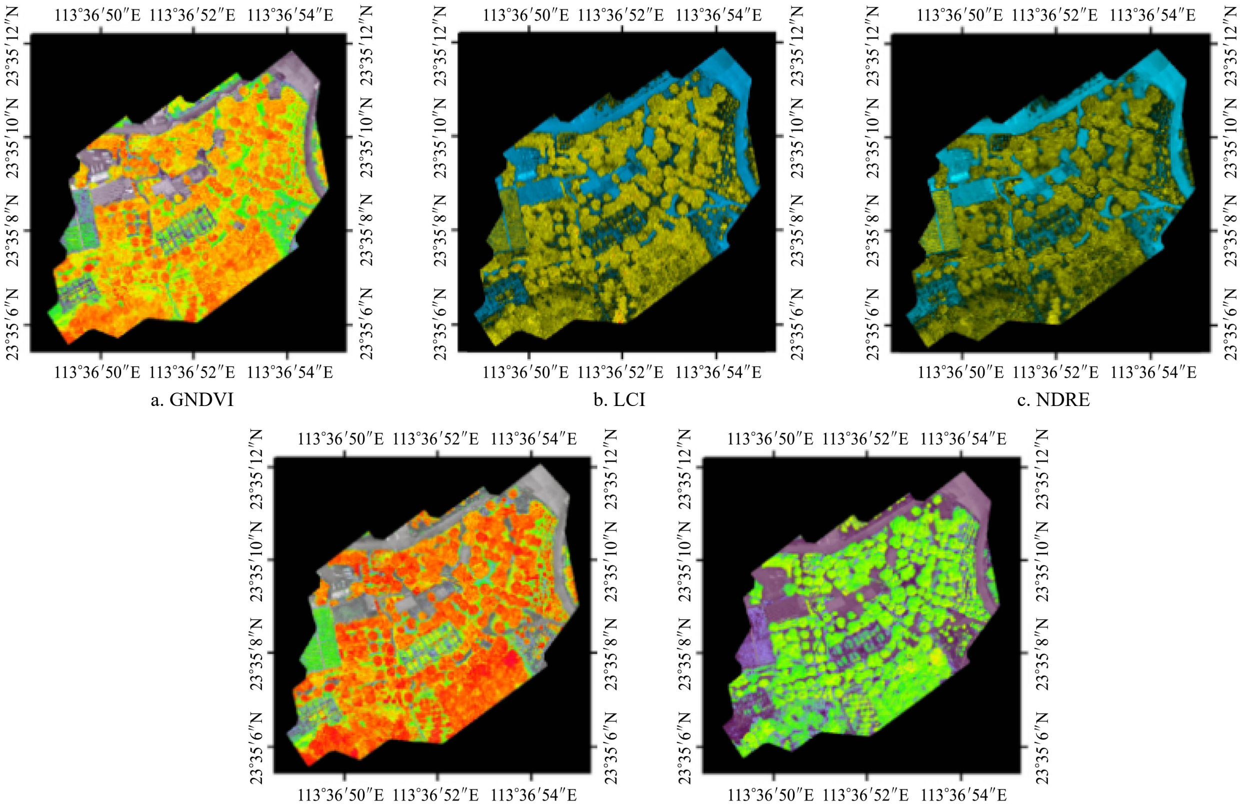
Multispectral images of the litchi canopy were obtained from aerial photography by a DJI Phantom 4 Pro multispectral version of the UAV. As shown in Figure 2, The UAV has a multispectral imaging system equipped with six 1/2.9″ image sensors, including a visible light sensor and five monochrome sensors: blue (450±16 nm), green (560±16 nm), red (650±16 nm), red edge (730±16 nm), and near-infrared (840±26 nm) for acquiring visible and multispectral images, respectively. It has a maximum flight time of about 30 minutes. The data collection dates are on February 20, March 1, March 17 and March 26, 2021. The UAV flied at an altitude of 45 meters.

Figure 2 DJI Phantom 4 Pro

2.3 Data pre-processing

2.3.1 Image stitching

The aerial images were stitched and processed by DJI Map software to obtain the panoramic visible images of the orchard and five vegetation index images generated based on monochromatic spectral data. The vegetation index images are shown in Figure 3, which are GNDVI[26], LCI[27], NDRE[28], NDVI[29], and OSAVI[30], the explanation of the five vegetation indices are shown in Table 1.



a. GNDVI b. LCI c. NDRE d. NDVI e. OSAVI

Figure 3 Vegetation index image

Table 1 The definition of five vegetation indices

Five vegetation index	Vegetation index meaning	Formula
GNDVI	GNDVI replaces the red light band in NDVI with the green light band and is a ground greenness index that characterizes the green plant canopy cover. It also reflects the decline in biomass after vegetation is subjected to water and plant stress or maturity.	GNDVI = (NIR – Green)/(NIR+Green)
LCI	LCI is an important indicator for assessing vegetation growth and yield. Chlorophyll content is one of the important indicators to evaluate plant nutrient stress, disease, growth and senescence. It is good for measuring chlorophyll nitrogen content in vegetation.	LCI = (NIR – RedEdge)/(NIR + Red)
NDRE	NDRE changes the red light band in NDVI to the red-edge band. The red-edge band is a spectral region in the transition from the red spectrum to the near-infrared spectrum. It is better for determining the chlorophyll content of non-primary crops.	NDRE = (NIR – RedEdge)/(NIR +RedEdge)
NDVI	NDVI is the most widely used indicator to measure the chlorophyll content of vegetation, which reflects the nutrient and growth information of vegetation and is suitable for monitoring the growth status of vegetation as well as the vegetation cover.	NDVI = (NIR – Red)/(NIR+Red)
OSAVI	OSAVI is based on NDVI and takes soil factors into account, which can effectively determine the chlorophyll content in the early stage of plant growth, while avoiding the complicated calculation of soil baseline parameters and better eliminating soil background and other interference.	OSAVI = (NIR – Red)/(NIR+Red+0.16)

2.3.2 Litchi canopy extraction method

The canopy of each litchi tree in the visible image was labeled using the LabelMe labeling tool. Since the canopy position information in the vegetation index image and the visible image is the same, according to the example segmentation method proposed by Mo et al.[31], the canopy coordinate file of the visible image can be used to crop out the litchi canopy in the five vegetation index images easily and quickly so that the corresponding coordinate files were generated. After cropping, a small number of Nan values which is the non-Litchi canopy area exists in the matrix of a small number of vegetation index canopy images. As most of the non-Litchi canopy area is soil and almost no plants exist, the Nan value in the non-Litchi canopy area was set to 0 in this study. The steps of canopy extraction are shown in Figure 4.

2.3.3 Data Enhancement

Deep learning requires a large amount of sample data to train a better model. To prevent overfitting of the model during training, this study enhances the image samples by image rotation based on the existing image data. All images in the training set were rotated by 90 degrees counterclockwise, flipped horizontally, rotated 90 degrees counterclockwise followed by flipped horizontally, and flipped horizontally followed by 90 degrees counterclockwise in four ways, which increased the amount of data by four times. The enhancement effect is shown in Figure 5.

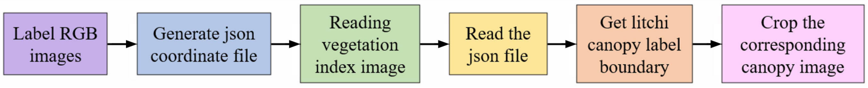
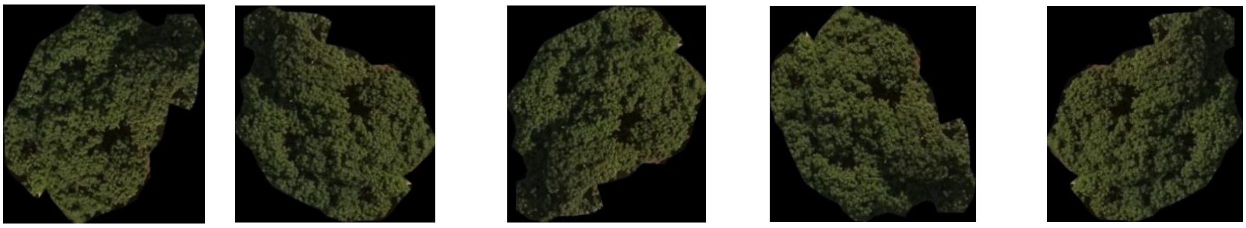


Figure 4 Steps of canopy extraction



a. Original b. Rotate 90 angle c. Rotate 90 angle and flip vertically d. Flip vertically e. Rotate 90 angle and flip horizontally

Figure 5 Data enhancement examples

After manually resolving the visible canopy images of each phase, the flowering rate of all canopies in each data set category was classified into 0%, 10%~30%, 40%~70%, and >80% in this study. The canopy samples were then divided into four categories according to the four intervals of 0%, 10~30%, 40~70%, and >80%. 80% of the samples in each category were randomly selected as the training set, 20% as the test set, and 10% of the training set as the validation set. The construction of the dataset was finally completed, as shown in Table 2.

Table 2 Division of datasets

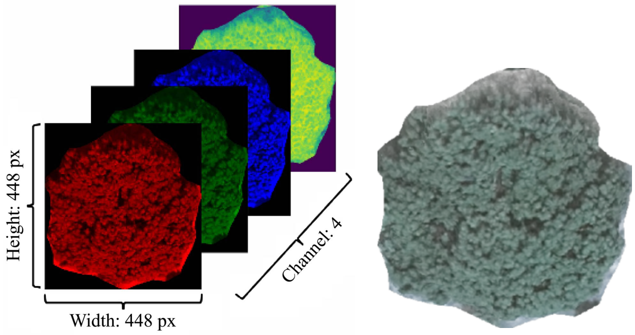
Flowering rate	Training set	Validation set	Test set	Total
0%	468	52	130	650
10%~30%	551	61	153	765
40%~70%	436	48	121	605
>80%	490	54	136	680

2.4 Selection method of the optimal channel combination

The definition of five vegetation indices of Table 1 shows that GNDVI mainly characterizes the canopy coverage of green plants, the larger the value is, the greater the vegetation density is; LCI has better effect on determining the chlorophyll nitrogen content in vegetation; NDVI reflects the chlorophyll content of vegetation. When NDVI is negative, the area is highly reflective such as water, building glass, etc., 0 means the area is rock or soil, etc., and positive values indicate vegetation cover; NDRE and OSAVI both measure chlorophyll content, but OSAVI takes soil factors into account based on NDVI, which can eliminate the influence of soil baseline parameters to determine the chlorophyll content in the early stage of plant growth.

Based on the characteristics of the five vegetation indices, this study inferred that there are vegetation indices among these five vegetation indices are favorable for the identification of flowering rate in the litchi canopy. To confirm our inference, the corresponding images were fused in this experiment. Based on the three channels R, G, and B of the visible image, five vegetation indices were synthesized as the fourth channel in this study, respectively, and the fused images of vegetation indices of the litchi canopy were synthesized as shown in Figure 6a. After selecting the vegetation index channels that are favorable to identify the flowering rate after fusion with RGB, further experiments were conducted to finally discover the most favorable band combination for canopy flowering rate identification.

Based on the canopy images from four aerial photographs, this study finally produced six datasets: RGB dataset, RGB-GNDVI dataset, RGB-LCI dataset, RGB-NDRE dataset, RGB-NDVI dataset, and RGB-OSAVI dataset, and 2700 litchi canopy images were obtained for each dataset. In order to verify that the vegetation index fusion images have better performance in model training, this study also produced a visible light canopy image dataset, five-channel vegetation index canopy image datasets, and an eight-channel canopy image dataset for experimental comparison.



a. RGB+GNDVI (4×448×448) b. Image of four bands

Figure 6 Fusion of multispectral images

2.5 Normalization

The values of vegetation indices are all between –1 and 1. In order to limit the value of each band of the fused vegetation index to a certain range, this study normalized the images after fusing the multispectral images. The mean and standard deviation of the canopy data of each band was calculated except for the non-litchi canopy image areas. Z-Score normalization was adopted as shown in the formula (1).

$$Value_{new}=(Num_i-Mean_i)/Std_i \quad (1)$$

where, $Value_{new}$ means the value after regulation; Num_i is the image canopy data of channel i; $Mean_i$ is the mean value of the image canopy data of channel i, and Std_i is the standard deviation of the image canopy data of channel i. The specific process is shown in Figure 7.

2.6 Model Building

2.6.1 ViT network

ViT (Vision Transformer), which apply the idea of NLP (Natural Language Processing) field to CV (Computer Vision) field[32], has a strong jumping connection mechanism and the ability to learn global features at a lower level, and has the ability to learn accurate position representation at a higher level. This behavior is very different from ResNet because global average pooling may blur location information. In this study, ViT was adopted as a deep learning neural network. The ViT network structure is shown in Figure 8 and the technical roadmap for this study is shown in Figure 9.

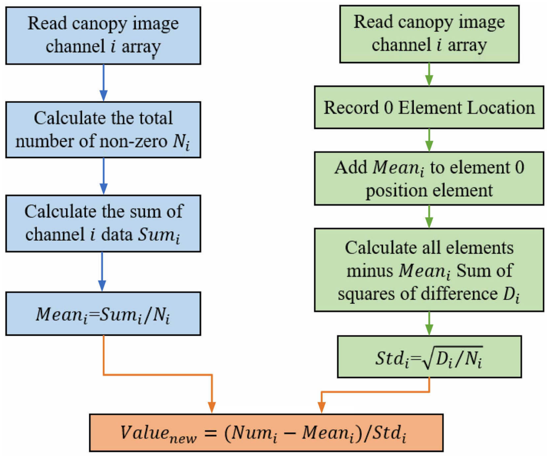


Figure 7 Normalization process

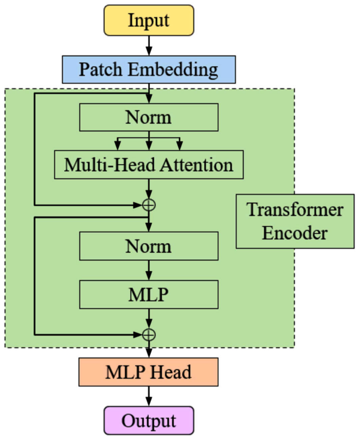


Figure 8 Vision Transformer Structure

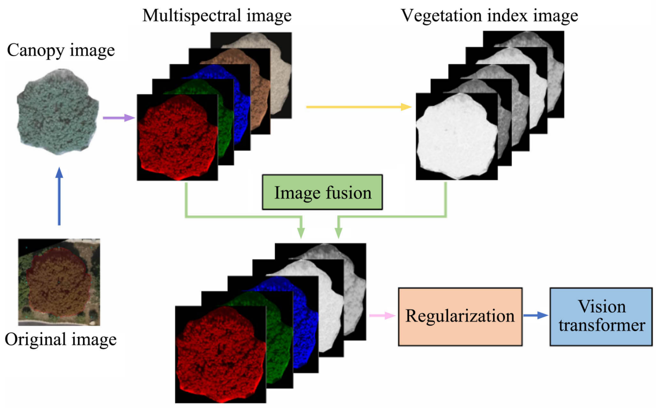


Figure 9 Technology Roadmap

In order to verify the advantages of the ViT neural network for litchi canopy flowering rate recognition, three mainstream neural networks, VGG16, ResNet50 (Residual Network 50), and MobileNetV2, were used in this study for comparison.

2.7 Model evaluation index

This study adopted *Top*_1 Accuracy to test the generalization ability of the model. In the prediction, the value with the highest probability in the last probability vector was adopted as the prediction result. *Top*_1 Accuracy is defined as the percentage obtained by dividing the total number of correctly predicted images by the total number of images participating in the prediction. The calculation formula is shown in Equation (2).

$$Top\_1=(Num_r/Sum)\times 100\% \quad (2)$$

where, Num_r refers to the total number of correctly predicted images, and *Sun* refers to the total number of predicted images.

3 Experimental results and analysis

3.1 Experimental environment and parameter settings

This study used Pytorch 1.2 deep learning framework with NVIDIA GeForce GTX 1650 graphics card with 4G memory, and the bottom layer used CUDA 10.1 as the underlying parallel computing framework. In terms of training strategy, the Batch Size was 6, a total of 200 iterations were trained on the training set, the initial learning rate was $1e^{-4}$, the learning decay rate was 0.92, and the duration of a training session was about 14 hours. VIT was selected as the deep learning network to fuse the five vegetation index images with RGB visible images separately to complete the multispectral fusion dataset. The multispectral fusion dataset with five different vegetation indices added was trained separately with the visible RGB dataset, and the characteristic vegetation indices were selected by *Top*_1 testing and comparison of the optimal model. Each experimental method was trained more than five times, and the optimal classification model of *Top*_1 test was retained.

3.2 Finding the optimal band/channel combinations

By fusing each of the five vegetation indices with the RGB visible images, the most suitable combination of feature bands for identifying multispectral litchi flowering rate images was found. As can be seen from Table 3, when RGB was combined with vegetation indices, the obtained *Top*_1 accuracy was slightly improved in all cases.

Table 3 Model accuracy when RGB is combined with individual vegetation indexes

Number	RGB +	GNDVI	LCI	NDRE	NDVI	OSAVI	*Top*_1
1	√						90.74
2	√	√					91.85
3	√		√				90.93
4	√			√			92.22
5	√				√		**93.15**
6	√					√	92.61

In Table 3, the model accuracy improvement is fewer when RGB was combined with GNDVI and LCI, which is not effective in promoting canopy flowering rate recognition. Therefore, in this study, the other three bands NDRE, NDVI, and OSAVI were tested in combination with RGB, the obtained *Top*_1 accuracy is shown in Table 4. Above the Table 3 and Table 4, the accuracy is highest when RGB was fused with OSAVI and NDVI bands. Therefore, the multispectral band combination of RGB+OSAVI+NDVI was selected as the optimal combination in this study.

Table 4 Model accuracy and control group accuracy when RGB was combined with NDRE, NDVI, and OSAVI

Number	RGB +	NDRE	NDVI	OSAVI	LCI	GNDVI	*Top*_1
1	√	√	√				91.48
2	√	√		√			94.26
3	√		√	√			**95.00**
4	√	√	√	√			93.89
5		√	√	√	√	√	90.56
6	√	√	√	√	√	√	93.52

3.3 Channel data Normalization

Since the spectral images have values between -1 and 1, their mean and standard deviation do not exceed 1, and the standard deviation is smaller than the mean, so the difference of the image data will be larger than the original one after calculation using Equation (1). The normalization will make the differences between canopies with different flowering rates more obvious, and the neural network model can learn the difference information better to improve the accuracy of the model. Before normalization, observing the output data, it can be seen that the loss value fluctuated greatly in the early training period and the training loss finally converged to 0.21. After normalization, the loss value fluctuated slightly and the training loss converged to 0.02. The accuracy of the model *Top_1* obtained from the *RGB + OSAVI + NDVI* dataset after several training sessions improved from 95.0% to 97.22%, showing that the normalization can significantly improve the generalization ability of the model, further extracting the vegetation index information of the feature bands and training a better model.

3.4 Network comparison experiments

Three neural networks, VGG16, MobileNetV2, and ResNet50, were used in this study for comparison. With the same dataset, the Batch size was set to the maximum value of memory according to the computer configuration. The learning rate was selected after several attempts to select the optimal learning rate of the corresponding network. The experimental results are shown in Table 5. A comparison of the training loss curves of the four neural networks is shown in Figure 10.

Table 5 Comparison of experimental results of four neural networks

Network	Learning Rate	Batch size	*Top_1*
ResNet50	1e-4	28	96.66%
VGG16	1e-5	12	87.96%
MobileNetV2	1e-3	36	94.81%
ViT	**1e-4**	**6**	**97.22%**

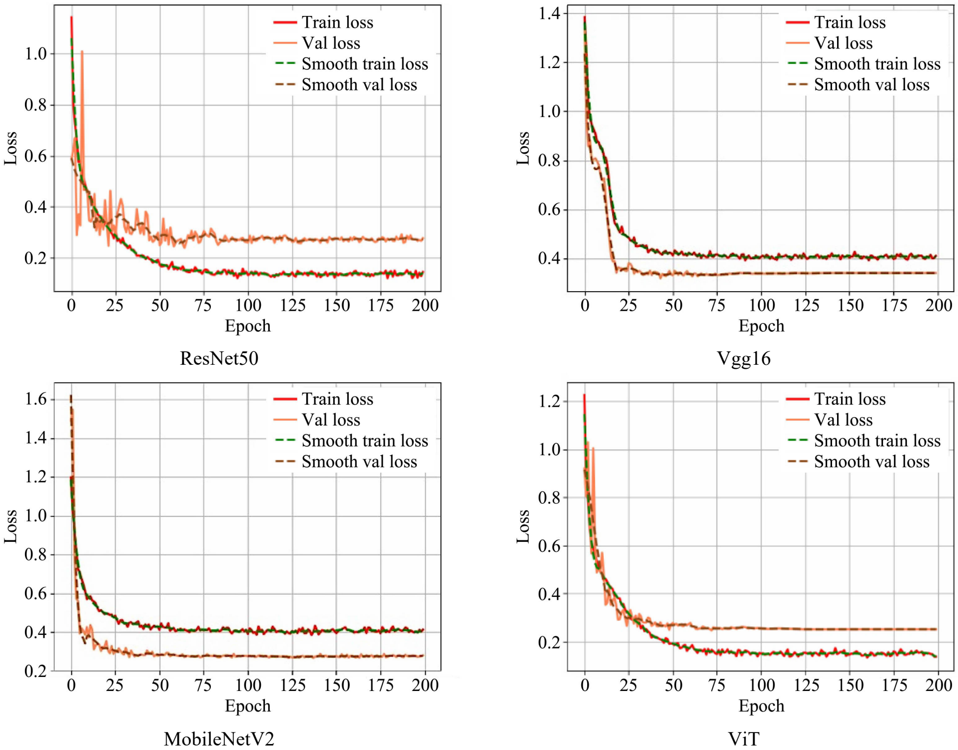
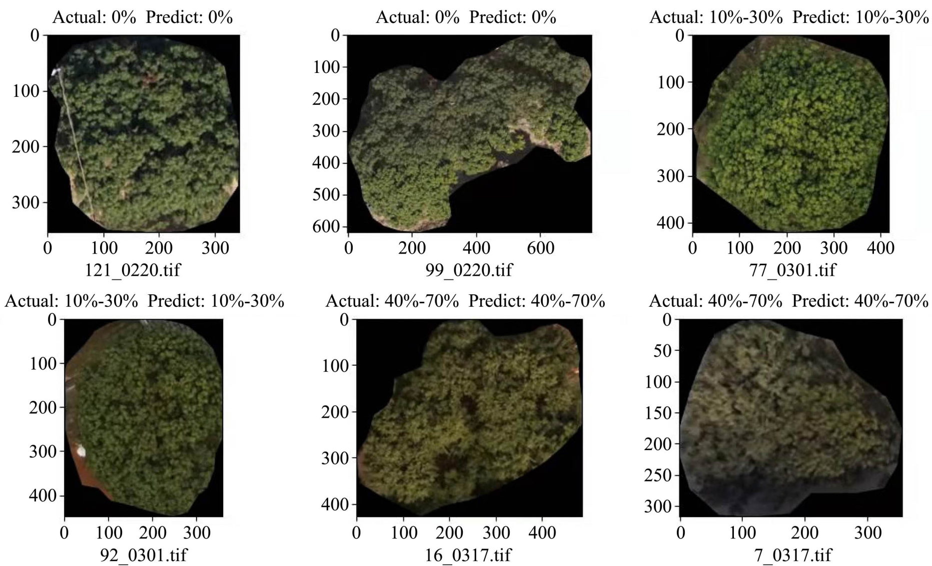


Figure 10 Comparison of loss curves of four neural networks

3.5 Visualization of flowering rate recognition

The visualization of litchi canopy flowering rate recognition is shown in Figure 11. Since the five-channel images cannot be observed normally, the first three channels (i.e., R, G, and B) of the five-channel images are selected for display. The actual label category as well as the model predicted category are displayed above each canopy image. The text indicated by red show the incorrect result.



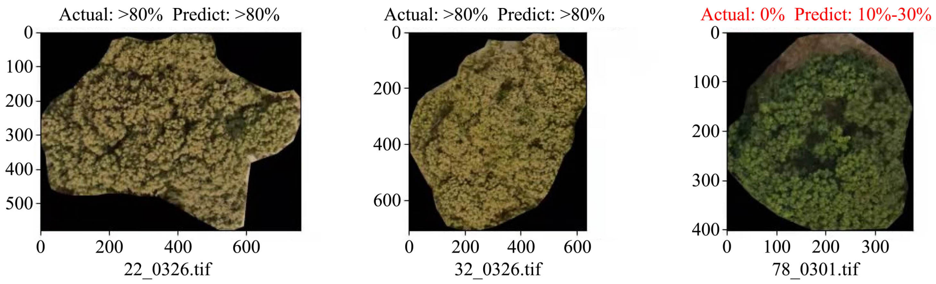


Figure 11 Results of flowering rate identification

4 Conclusion

In order to estimate the flowering rate of litchi using the multi spectral image of UAV, the following work was completed in this study. The best combination of RGB, OSAVI and NDVI, which are most helpful to distinguish the flowering rate of litchi canopy, was determined among the five vegetation index and RGB bands. It is also confirmed that only vegetation index is not conducive to litchi canopy classification. It is necessary to combine RGB and vegetation index to reduce the interference of non vegetation information on litchi crown under the influence of vegetation index, which is conducive to better extraction of litchi crown features by deep learning network. ViT deep learning method achieves best results in the recognition of the litchi flowering rate compared with other mainstream neural networks. Also, after normalization for the data of the selected optimal band combination, the classification accuracy was the highest, reaching 97.22%.

The work done in this study makes the realization of efficient and intelligent orchard management, greatly reduce the labor of gardeners and better monitor the agricultural information of the orchard, makes fast and accurate agricultural decisions for cultivating high-yielding litchi.

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