Portable Kiwi Variety Classification Equipment Based on Transfer Learning

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Abstract. China is one of the largest countries producing kiwifruit, and there are many kinds of kiwifruit in China. The identification of kiwifruit varieties has important application value in kiwifruit automatic picking robots and kiwifruit sorting factories. The paper studies the classification of kiwifruit varieties based on deep learning, and studies the deployment and application of kiwifruit classification model on the Jetson Nano artificial intelligence development board. A portable device used for classification of kiwifruit varieties was designed and developed. This paper studied the selection of various parts of the portable device of kiwifruit classification and designed the portable device shell. The portable device shell was obtained through the 3D printer, assembled the parts, and obtained the portable kiwi variety classification equipment. The construction of the kiwifruit dataset of “Cuixiang”, “Qinmei”, “Xuxiang” and “Hayward” kiwis was studied and using data augmentation to introduce variations into the data. According to the characteristics of the problem of 4 types of kiwifruit classification, the methods and advantages of transfer learning are discussed. Using transfer learning based on three pre-training models Xception, ResNet50, DenseNet121. Comparative analysis of the model size, training speed, convergence, and recognition accuracy of the transfer learning model based on Xception, ResNet50, and DenseNet121, and concluded that in Xception, ResNet50, and DenseNet121, the transfer learning model based on DenseNet121 pre-trained model has the best effect on the classification of four kiwifruit varieties, with fast convergence speed, smallest model, and high recognition accuracy of 97.79%. This paper studied the deployment and experiment of the deep learning model on the Jetson Nano development board. Using the PyTorch to perform transfer learning based on the DenseNet121 pre-training model. After using the TensorRT acceleration engine, it took an average of 0.035s to classify each image, and the real-time classification FPS reached an average of 30, the accuracy rate of the model on the validation set is 93.63%, achieving fast and accurate classification of kiwi varieties.

Keywords: transfer learning, image classification, kiwifruit, portable device, jetson nano
1. Introduction

In order to overcome the low automation of kiwifruit picking and sorting, one of the key problems to be solved is the identification and classification of kiwifruit varieties. Many scholars have studied the classification methods of kiwifruit varieties [1-3]. The recognition and classification of fruit image has been studied for a long time. It is a common method to extract fruit image features manually, and then classify fruit by BP neural network classifier, SVM classifier, k nearest neighbor classifier and other classifiers.

Lu Qiuxia used BP neural network classifier to classify apple, orange, pear and banana by extracting three main features of shape, color and texture of fruit image. The experimental results show that the recognition accuracy of test samples is more than 90%, the recognition time of single image is about 2.35s, and the recognition speed is slow [4]; Meng Dawei studied the extraction of color features and texture of fruit. The experimental results show that the average accuracy of fruit classification using the two features is 82.2% [5]. Traditional fruit recognition and classification methods need artificial design and extraction of fruit image features, such as fruit shape, color, surface texture, area and other features. The selection and extraction effect of fruit features has a very obvious impact on fruit recognition and classification. The artificial design and selection of features is subjective and depends on experience, and the process of artificial extraction of image features is relatively slow. Because of the complexity, the number of training set images that people often create is small, and the robustness of fruit image recognition and classification is poor. In recent years, thanks to the increase of various types of data, the enhancement of computer computing power and the maturity of learning algorithm, deep learning technology has developed rapidly, and has been applied to the research of fruit recognition and classification, and achieved good results. Zeng Pingping proposed a fruit image classification and recognition model based on convolution neural network by referring to the classical convolution neural network lenet-5 structure, and classified five kinds of fruits, including apple, pear, orange, orange and peach. The experimental results show that the recognition accuracy of the model for these five kinds of fruits is 96.88%, which proves the effectiveness of convolution neural network for multi classification and recognition of fruit image [6] Lian Xiaoqin and others used the perception-v3 model for transfer learning, and realized the classification of apple, banana, kiwifruit, mango, orange, pear and other six kinds of fruits. The results showed that the recognition accuracy of the method using the perception-v3 model transfer learning was greatly improved compared with the traditional fruit recognition methods (BP, SVM, PCA, sift + SVM) [7], and the recognition accuracy of BP was 83.9%, SVM was 81.1% PCA and sift + SVM are 78.4%, 90.2% and 97.7% respectively. The recognition and classification of two kinds of avocado are carried out by using deep convolution neural network [8]. The designed network structure consists of four convolution layers and four maximum pooling layers. The experimental results show that the recognition accuracy of the model for verification set image is 99.84%, and the recognition accuracy of Mohamed I El kahlout et al. Used deep convolution neural network to recognize and classify three kinds of peaches [9], and the experimental results showed that the recognition accuracy of three kinds of peaches was 100%; Mohammed O. al shawwa et al. Used convolution neural network to recognize and classify 13 kinds of apples [10], and the recognition accuracy of Apple images in test set was 100%. A large number of studies show that the deep convolution neural network method is feasible and efficient in fruit recognition and classification [11-14].

In view of the above problems, this paper proposes a method of kiwifruit variety classification based on transfer learning, and studies the portable device of kiwifruit variety classification. The research results are of great significance in providing support for automatic classification and picking of kiwi fruit by kiwi fruit picking robot and realizing quick and accurate sorting of kiwi fruit in the factory.
2. Design of portable equipment for Kiwifruit variety classification

2.1. Hardware selection

This paper introduces the main hardware selection and function of kiwifruit variety classification portable device, including the selection of development board, display, power supply and camera.

In this paper, the development board is the Jetson nano artificial intelligence development board of NVIDIA, as shown in Figure 1. Jetson nano is a lightweight, customized tool kit for robot developers released at the GTC (GPU Technology Conference) conference in Silicon Valley in March 2019. It is equipped with 4-core cortex-a57 processor. GPU is NVIDIA with 128 CUDA cores Maxwell architecture can provide 472 Gigabit floating-point computing power, and the power consumption is as low as 5W. It is the most cost-effective development board that provides edge computing function at present. Jetson nano supports a variety of deep learning frameworks, including tensorflow, pytorch, keras and caffe.

![Figure 1. Jetson Nano developer kit](image1.png)

In order to provide a convenient way of human-computer interaction for Kiwifruit variety classification portable device, we decided to equip it with a touch control display, which can not only save the work of using keyboard and mouse to control Jetson nano, but also display the working process and recognition results of Jetson nano through the display. After comprehensive consideration, we decided to use waveshare's 7-inch HDMI LCD (H) with high compatibility. The real object is shown in Figure 2. The product is a universal HDMI display with 1024 × 600 ultra clear resolution and a toughened glass capacitive touch panel. Support raspberry pie, Jetson nano and various mini PCs, and support Windows 10, raspbian, Ubuntu, Kali and other operating systems.

![Figure 2. 7inch HDMI LCD. a, Front; b, Back](image2.png)
Jetson nano has two power supply modes: one is powered by micro USB interface, supporting 5V / 2A input; the other is powered by DC power supply, supporting 5V / 4A DC input. These two power supply methods have their own advantages and disadvantages. DC power supply is more sufficient than micro USB interface power supply. It can start the high-power (10W) mode of Jetson nano, and support Jetson nano to access more USB devices. When micro USB interface power supply, Jetson nano can connect to more USB devices Nano can only enable normal power consumption (5W) mode, but micro USB interface power supply can use "power bank" as power supply, which is more convenient and can meet the application of Jetson nano in mobile. Considering the electricity quantity and matching, we choose the 20 000 MAH millet mobile power supply as the power supply equipment of kiwifruit variety classification portable equipment.

In terms of image and video acquisition, Jetson nano supports USB camera and CSI camera. For general USB cameras, you can plug and play on Jetson nano. For CSI cameras, Jetson nano only supports the imx219 core chip. NVIDIA officially recommends the second generation HD camera of raspberry pie, as shown in Figure 3. The camera is equipped with 8 megapixel Sony imx219 sensor expansion board, with a fixed focus lens, which can obtain 3280 * 2464 pixels of pictures. It also supports 1080p30720p60640 * 480p60 / 90 camera function, and is connected to other devices through CSI interface.

![Raspberry Pi Camera V2](image)

**Figure 3.** Raspberry Pi Camera V2

2.2. *Shell design and physical assembly*

In this paper, the main application scenarios of kiwi fruit classification portable equipment are kiwi fruit picking robot and kiwi fruit sorting automatic chemical plant. Therefore, the requirements of the kiwifruit variety classification equipment are compact structure, light weight and complete function. According to the design requirements of kiwifruit variety classification portable device, the SolidWorks 3D isometric drawing of its shell is designed, as shown in Figure 4.

![Isometric view of the shell](image)

**Figure 4.** Isometric view of the shell
The shell is composed of three layers, the bottom layer is used for Jetson nano development board, the middle layer is used for mobile power supply, and the top layer is used for display screen. The shell can protect Jetson nano and coordinate the relative position of parts in kiwi fruit sorting equipment.

The main components of the portable device include Jetson nano, mobile power supply, display screen, camera and device shell. SolidWorks is used to draw the three-dimensional part drawings of Jetson nano, mobile power supply, display screen, camera, equipment shell and camera shell. After the parts are assembled, the three-dimensional assembly drawing of SolidWorks is obtained, as shown in Figure 5.

![Figure 5. SolidWorks assembly drawing of portable equipment](image)

The kiwifruit variety classification portable equipment is shown in Figure 6 after the assembly.

![Figure 6. Kiwi variety classification portable device](image)

3. Kiwifruit image acquisition and expansion

Kiwifruit images were collected on September 30, 2019. In the kiwifruit orchard of Mei County, Baoji City, Shaanxi Province, images of four varieties of kiwifruit were collected, including Cuixiang, Qinmei, Xuxiang and Hayward, as shown in Figure 7.
Figure 7. 4 kinds of kiwi collected. a, Cuixiang; b, Qinmei; c, Xuxiang; d, Hayward

A total of 2088 images of four kinds of kiwifruit were collected initially. After eliminating the invalid images (such as excessive blur, no kiwifruit in the image, only a small part of Kiwifruit in the image, etc.) caused by human errors in the process of photographing, 2056 kiwifruit images were finally obtained. The training set and verification set were divided according to the ratio of about 4:1. The number of images of all kinds of kiwifruit is shown in Table 1.

Table 1. Number of 4 kinds of kiwi

| kinds of kiwi | Training set image / piece | Verification set image / piece | Total number / piece |
|--------------|---------------------------|-------------------------------|---------------------|
| Cuixiang     | 331                       | 79                            | 410                 |
| Qinmei       | 499                       | 124                           | 623                 |
| Xuxiang      | 407                       | 102                           | 509                 |
| Hayward      | 411                       | 103                           | 514                 |

When using kiwifruit image to train the deep convolution neural network, if there are too few images in the training set, it will often lead to the over fitting phenomenon of the trained model. Therefore, in order to increase the universality of the training data, improve the detection ability of the model for unknown images, and prevent the over fitting phenomenon, it is necessary to expand the training set image.

The image expansion method used in this paper is to use the built-in function imagedatagenerator() of keras, which can expand the image data by performing rotation, translation, cutting, flipping and scaling operations on the image. The parameter set is rotation_range = 40, width_shift_range = 0.2, height_shift_range = 0.2, shear_range = 0.2, zoom_range = 0.2, horizontal_flip = True. Specifically, rotation_range = 40 means that the image can be rotated between 0 and 40 degrees, width_shift_range = 0.2 means that the image can translate 0-20% of the original image in the horizontal direction, height_shift_range = 0.2 means that the image can translate 0-20% of the original image in the vertical direction, shear_range = 0.2 refers to the shear strength of the image is 0.2, the anti clockwise shear angle, in degrees, zoom_range = 0.2 means that the image can be reduced or enlarged, ranging from 0 to 20%, horizontal_flip = true means the image can be flipped horizontally. After setting these parameters, when training the convolutional neural network with the training set image, the training set image will change arbitrarily within the set parameter range, which realizes the expansion of the training set image.

The image of Qinmei kiwifruit in a training set is shown in Figure 8. There are many situations after the transformation of imagedatagenerator function. As shown in Figure 9, there are eight situations after the transformation of figure 8.
4. Classification model of kiwifruit varieties based on Transfer Learning

4.1. Transfer learning
Transfer learning is a method of machine learning, which means that one pre training model is reused in another task. In general, transfer learning is an optimization that can save time or get better performance. Fine tune of deep neural network is a migration method of deep neural network, which is an important concept in deep learning. Fine tuning is to make use of the deep neural network that has been trained by others to train and adjust according to their own tasks. Compared with training a neural network from scratch, this method can save a lot of computing resources and time, improve the computing efficiency, and even improve the accuracy.

The advantages of fine tuning include the following four points:

(1) Mature pre training models developed by researchers, such as VGG, googlenet, RESNET, can be used to reduce the difficulty and cost of development.

(2) The pre trained model is usually carried out on large data sets, and has the ability to extract shallow basic features and deep abstract features. At the same time, it virtually expands the training data, which makes the model more robust, better generalization ability, and reduces the risk of over fitting.

(3) There is no need to train the network from scratch for new tasks, which saves computing resources and time cost.

(4) The implementation of fine-tuning is less difficult.

This paper adopts tensorflow2.0 deep learning framework, with built-in keras as a high-level API. You can find the pre training model as shown in Table 2 by looking up the user documents of keras, and the top-5 precision refers to the performance of the model on the Imagenet verification set [15].
### Table 2. Pretrained models in Keras

| Model               | Size  | Top-5 accuracy | Parameter    |
|---------------------|-------|----------------|--------------|
| Xception            | 88 MB | 0.945          | 22,910,480   |
| VGG16               | 528 MB| 0.901          | 138,357,544  |
| VGG19               | 549 MB| 0.900          | 143,667,240  |
| ResNet50            | 98 MB | 0.921          | 25,636,712   |
| ResNet101           | 171 MB| 0.928          | 44,707,176   |
| ResNet152           | 232 MB| 0.931          | 60,419,944   |
| ResNet50V2          | 98 MB | 0.930          | 25,613,800   |
| ResNet101V2         | 171 MB| 0.938          | 44,675,560   |
| ResNet152V2         | 232 MB| 0.942          | 60,380,648   |
| InceptionV3         | 92 MB | 0.937          | 23,851,784   |
| InceptionResNetV2   | 215 MB| 0.953          | 55,873,736   |
| MobileNet           | 16 MB | 0.895          | 4,253,864    |
| MobileNetV2         | 14 MB | 0.901          | 3,538,984    |
| DenseNet121         | 33 MB | 0.923          | 8,062,504    |
| DenseNet169         | 57 MB | 0.932          | 14,307,880   |
| DenseNet201         | 80 MB | 0.936          | 20,242,984   |
| NASNetMobile        | 23 MB | 0.919          | 5,326,716    |
| NASNetLarge         | 343 MB| 0.960          | 88,949,818   |
| EfficientNetB0      | 29 MB | -              | 5,330,571    |

Considering the top-5 recognition accuracy and model size of the pre training model on Imagenet data set, xception, resnet50 and densenet121 models are selected as the pre training models of transfer learning. Four kinds of kiwifruit data sets are used for training fine-tuning model, and the recognition accuracy on Kiwifruit verification set is compared.

#### 4.2. Construction and training of kiwifruit variety classification model

Xception model was proposed by Fran à OIS Chollet [16] in 2017. It is an improvement of concept V3 proposed by Google team. It uses separable convolution to replace the convolution operation in the original concept v3. The top-5 accuracy of xception model on Imagenet dataset is 0.945, which is higher than 0.937 accuracy of inception v3. Meanwhile, the number of parameters decreases. The residual connection mechanism similar to RESNET is added to xception to accelerate the convergence process of xception and obtain higher accuracy. RESNET mainly solves the problem that the deep convolution neural network model is difficult to train and the gradient of deep convolution neural network disappears. Resnet50 is a 50 layer deep residual network [17], which contains several basic modules of RESNET. The core of RESNET is to establish a bypass connection between the front layer and the back layer. The basic idea of densenet model is basically the same as RESNET, but different from RESNET, it establishes a dense connection between the front layer and all the back layers, connecting all the layers, and each layer accepts all the front layers as its additional input. Another feature of densenet is feature reuse. The author of densenet proposed four kinds of densenet network structures [18], and densenet121 is one of them.

After determining the selected pre training model, we need to use the self built kiwifruit data set to train the pre training model, that is, fine-tuning. There are three methods of fine-tuning: (1) only modify the output category of the last layers or the last softmax layer of the pre training model; (2) freeze the initial layer of the pre training model, only train the remaining layers; (3) train the pre training model All layers of.

This paper aims to realize the classification and recognition of four kinds of kiwifruit. The data set of kiwifruit is similar to the Imagenet data set used to train the pre training model. For example, the Imagenet data set contains many fruits, such as apples, strawberries, cherries and so on. However, the classification and recognition of kiwifruit varieties is specific only for kiwifruit, so the data set of kiwifruit is similar to that of Imagenet data sets have some similarity, but the similarity is low. Therefore, this paper will change the structure of the last few layers of the pre training model, and train the model from scratch on the basis of Imagenet weight parameters.
Taking xception as an example, the last layer is removed from the network structure, and then a fully connected layer with 512 neurons is added after the average pooling layer, with the activation function of relu, and then a fully connected layer with 4 neurons (namely prediction layer) is added, with the activation function of softmax. The modified network output is the prediction probability value of four kiwifruit species. The network structure modification of the other two pre-training models is the same as that of xception.

The migration learning training process of the pre-model is carried out on the cloud server of Google colab, and the NVIDIA Tesla P100 GPU is used to accelerate the calculation. The program is programmed in tensorflow 2.0 framework, and the programming language is python. The python version and the version information of the library used in the program are as follows:

```
sys.version_info(major=3, minor=6, micro=6, releaselevel='final', serial=0)
mpllib 3.2.1
mlxtend 0.17.2
numpy 1.18.2
pandas 0.25.3
sklearn 0.22.2.post1
tensorflow 2.1.0
tensorflow_core.python.keras.api._v2.keras 2.2.4-tf
```

The model is trained from the beginning on the basis of ImageNet weight parameters. The loss function is cross entropy loss function, and the optimizer is SGD. The learning rate is 0.0001, momentum is 0.9, and the training cycle is 80 times.

4.3. Model training results and comparative analysis

![Figure 10](image-url)  
**Figure 10.** Accuracy and loss of three different transfer learning models. a, Training and validation accuracy of model based on Xception; b, Training and validation loss of model based on Xception; c, Training and validation accuracy of model based on ResNet50; d, Training and validation loss of model based on ResNet50; e, Training and validation accuracy of model based on DenseNet121; f, Training and validation loss of model based on DenseNet121
After the training, we get the transfer learning model based on three different pre training models. The change of accuracy and loss in the training process is shown in Figure 10.

It can be found from Figure 10 (a) (b) that the recognition accuracy of the transfer learning model based on the pre training model xception is basically the same on the training set and the verification set, and there is no obvious over fitting or under fitting. However, after 80 cycles of training, the accuracy still has an upward trend, and the loss value is not small enough, indicating that the model can continue to train to achieve higher recognition accuracy. From Figure 10 (c) (d), it can be found that the recognition accuracy of the transfer learning model based on the pre training model resnet50 in the training set and the verification set is very different in the first 10 training cycles, but it is basically the same after the 20th training cycle, and there is no obvious over fitting or under fitting; from Figure 10 (E) (f), it can be found that the recognition accuracy of the transfer learning model based on the pre training model DenseNet121 in the training set and the verification set is basically the same, and there is no obvious over fitting or under fitting. After 60 training cycles, the recognition accuracy and loss value tend to be stable and basically do not change.

The results of transfer learning model based on xception, resnet50 and densenet121 are compared as shown in Table 3.

### Table 3. Comparison of model training results

| Pre-training model | Pre-training model size | Training parameters needed | Training per cycle time consuming | 10 training cycles | 30 training cycles | 60 training cycles | 80 training cycles |
|-------------------|-------------------------|----------------------------|-----------------------------------|-------------------|-------------------|-------------------|-------------------|
| Xception          | 88MB                    | 21858092                   | 58s                               | 0.8064            | 0.9069            | 0.9436            | 0.9559            |
| ResNet50          | 98MB                    | 24585732                   | 30s                               | 0.2353            | 0.9706            | 0.9779            | 0.9779            |
| DenseNet121       | 33MB                    | 7480708                    | 41s                               | 0.9412            | 0.9706            | 0.9755            | 0.9779            |

It can be found from table 3 that the size of densenet121 pre training model is the smallest and the parameters need to be trained are the least; resnet50 training speed is the fastest, which takes about 30 seconds per week, twice as fast as xception training time per cycle; in terms of recognition accuracy of verification set image, after 80 training cycles, densenet121 and resnet50 are 97.79%, while xception recognition accuracy is slightly lower 59%.

The change curve of the recognition accuracy of the transfer learning model based on xception, resnet50 and densenet121 pre training models in the verification set of kiwifruit images after training is shown in Figure 11.

![Figure 11. Validation accuracy of 3 models](image)

It can be seen from Figure 11 that the transfer learning based on densenet121 pre training model has the best effect on Kiwifruit variety classification, with fast convergence speed and high recognition
accuracy; the transfer learning based on resnet50 pre training model has the second effect, with very low accuracy in the first 10 training cycles, but the model converges rapidly after the 10th training cycle, with high recognition accuracy. Xception pre training model has the worst transfer learning effect among the three models, slow convergence speed, and the recognition accuracy is slightly lower than the other two models in the first 80 cycles. However, the accuracy of xception pre training model still has an upward trend, and the accuracy of xception pre training model may be higher than the other two models in continuous training.

To sum up, in xception, resnet50, densenet121 three models, the transfer learning based on densenet121 pre training model has the best effect on the classification of four kiwifruit varieties, with the smallest model size, medium training time per week, the fastest model convergence and the highest recognition accuracy.

5. **Deployment and experiment of kiwifruit variety classification model**

The deep convolution neural network model trained by transfer learning needs to be deployed on the artificial intelligence development board Jetson nano to realize the development of portable device for Kiwifruit variety classification based on transfer learning. The deployment of the model on Jetson nano is mainly divided into three parts

(1) Setting of programming environment on Jetson nano. The setting of programming environment on Jetson nano is mainly to install python, tensorflow, numpy, Matplotlib, pandas and other required libraries and some necessary dependencies for Jetson nano.

(2) The preparation of kiwifruit recognition program. The preparation of kiwi fruit recognition program mainly includes loading the trained transfer learning model, calling CSI camera to take pictures of kiwi fruit, preprocessing the obtained kiwi fruit photos, using the transfer learning model to predict and displaying the prediction results.

(3) Visualization and optimization of kiwifruit recognition interface. The visualization and optimization of kiwi fruit recognition interface is a very important part. The friendly kiwi fruit recognition interface can make users use the kiwi fruit classification program efficiently and conveniently and observe the recognition results clearly.

Jupyter notebook is a web-based interactive programming environment. The kiwi fruit recognition interface is designed on the notebook, as shown in Figure 12. The left side of the interface is the real-time video obtained by the camera. Users can observe the image obtained by the camera on the left side. When the kiwi fruit enters the field of vision of the camera, click the "prediction" button on the lower left side to take photos of the kiwi fruit. The pictures of the kiwi fruit taken by the camera will be displayed on the right side of the interface, and at the same time on the top right side of the interface, the variety prediction result of the photo taken kiwifruit image will be displayed, as shown in the figure, the variety prediction result of the kiwifruit is "Hayward".

![Figure 12. Kiwifruit variety classification interface](image-url)
When using Jetson nano to identify kiwifruit varieties, after clicking the "prediction" button, about 80 seconds later, the upper right side of the interface displays the predicted results. The speed of identification is slow, and sometimes the program crashes due to insufficient memory, and the program runs unsteadily.

In order to solve the problem of slow recognition speed found in the experiment, pytorch is used for transfer learning based on densenet121 pre training model. The loss function used in training is cross entropy loss function, the optimizer used is SGD, the learning rate is initially set to 0.01, the learning rate is reduced by 10 times every 30 training weeks, the momentum is set to 0.9, the training cycle is 61 times, and the accuracy of verification set is 61 weeks 93.63% during the period. After training, the model is saved as pytorch model. The saved pytorch model is transformed into onnx model, and then the onnx model is generated into the acceleration engine “densenet121. Onnx. 1.1” by tensorrt GPU.FP16. Engine”. Finally, the stored tensorrt acceleration engine can be used to realize the rapid classification of kiwifruit varieties. The effect of fast classification of kiwifruit varieties by tensorrt acceleration engine is shown in Figure 13. The real-time image is obtained by camera and the kiwifruit recognition result is displayed on the top left of the screen. FPS is about 30.

The experimental results show that the transfer learning model based on pytorch deep learning framework uses tensorrt to accelerate the classification of single kiwifruit image on Jetson nano using GPU, which takes an average of 0.035 seconds, and the FPS for real-time detection and classification of kiwifruit reaches 30.

6. Conclusion

In this paper, four kinds of kiwifruit, Cuixiang, Qinmei, Xuxiang and Hayward, in Meixian kiwifruit orchard of Baoji City, Shaanxi Province, are taken as the research objectives. A method of kiwifruit variety classification based on transfer learning is proposed, and a portable device of kiwifruit variety classification based on transfer learning is developed. Specifically:

1) The selection of various parts of the portable device is carried out, the shell is designed, and the 3D drawing and physical assembly of the portable device are completed.

2) The images of "Cuixiang", "Qinmei", "Xuxiang" and "Hayward" were collected, and the kiwifruit data set was constructed.

3) The classification model of kiwifruit varieties was constructed by transfer learning method. The model size, training speed, convergence and recognition accuracy of transfer learning model based on xception, resnet50 and densenet121 were compared and analyzed. The results showed that the transfer learning based on densenet121 pre training model was more effective in xception, resnet50 and densenet121. The results showed that the classification of four kiwifruit varieties was the best, and the recognition accuracy was 97.79%.

4) The classification model of kiwifruit varieties was built in Jetson. In the deployment of nano development board, pytorch deep learning framework is used to carry out transfer learning based on
densenet121 pre training model. After 61 training cycles, the recognition accuracy of the model on the verification set reaches 93.63%. The average classification time of each kiwifruit image using tensorrt acceleration engine is 0.035 s, and the real-time detection and classification FPS reaches 30, which realizes the rapid classification of kiwifruit varieties. Accurate classification.

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