Method for the detection and classification of quinoa seeds via computer vision

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Abstract: To solve the problem that there are many human factors, great difficulty, and low efficiency in distinguishing quinoa seeds from weed seeds and distinguishing the quality of quinoa seeds by appearance, a method of quinoa seed detection and classification based on computer vision is proposed. In this study, convolutional neural network and Vision Transformer (ViT) were used to quickly and nondestructively classify different quinoa seeds and weed seeds. The dataset used in this experiment was 1440 sample images containing quinoa seeds and weed seeds, which were divided into training set, test set, and validation set at a ratio of 8:1:1. The training set was 1152 pieces, test set was 144, and the validation set was 144 pieces. The convolutional neural network model and ViT model based on deep learning were established. The results show that the average classification accuracies of MobileNet, VGG16, ResNet50, and ViT models used in the experiment are 93.75%, 90.97%, 93.75%, and 98.61% respectively. The accuracy of ViT classification is much higher than that of convolutional neural networks, establishing a benchmark for quinoa seed classification. This study provides a reproducible dataset construction method and a dual-imaging strategy, and demonstrates practical deployment value for automated seed grading and purity testing.

Keywords: quinoa seeds, convolutional neural network, VGG16, ResNet50, MobileNet, ViT
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1 Introduction

Quinoa (*Chenopodium quinoa*) is an annual dicotyledonous facultative halophytic herb belonging to the family Chenopodiaceae. Rich in amino acids, minerals, and various other nutrients, it is hailed as a “super grain” and the most suitable complete nutritional food[1]. As the only single plant that can meet the basic nutritional needs of the human body[2], quinoa is referred to by international nutritionists as “nutritional gold”, “super grain”, and “mother of grains”, among other titles. Meanwhile, the United Nations designated 2013 as the “International Year of Quinoa”[3]. Coupled with its tender, juicy, and palatable characteristics, quinoa has become a popular fashionable and healthy food among many people. The selection and cultivation of quinoa seeds are crucial to quinoa breeding and also an important link in ensuring high and stable yields of quinoa seeds. However, due to the small size of quinoa seeds, it is difficult and time-consuming to distinguish high-quality quinoa seeds from inferior ones by their appearance. Furthermore, black quinoa seeds are extremely similar to weed seeds, making manual sorting extremely labor-intensive and challenging. Sowing quinoa seeds mixed with weed seeds will significantly affect quinoa yields and reduce the income of enterprises or farmers. Effective classification of quinoa seeds through machine vision is conducive to selecting high-quality seeds during quinoa cultivation, reducing the industry’s reliance on manual labor, and enhancing the competitiveness of related industries. It also holds great significance for the upgrading of China’s quinoa industry.

Machine vision technology can non-destructively and rapidly acquire surface feature information of samples. With the continuous development of computer technology and information science, the level of machine vision at home and abroad has been constantly reaching new heights[4-7]. This technology has been widely applied in various fields including agriculture, where it can be used for path navigation, weed identification, and the detection and grading of various fruits and vegetables[8-13]. Classification methods based on computer vision also offer advantages such as high precision, high efficiency, and freedom from interference caused by human subjective factors. A typical example of such methods is the Convolutional Neural Network (CNN), which has been used in visual recognition and classification tasks since the late 1980s and is one of the most common deep learning methods[14,15]. In 2019, Chen et al.[16] proposed a fish recognition method based on the FTVGG16 convolutional neural network, with the model achieving an average accuracy of 97.66%. In 2021, Sun et al.[17] proposed an improved MobileNet-V2 for identifying crop diseases under complex backgrounds, and the improved model reached a recognition

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accuracy of 92.20%. In 2024, Maeda-Gutiérrez et al.[18] evaluated plant health using artificial intelligence, comparing ResNet-50 with Inception V3 and Vision Transformers; the ResNet-50 architecture achieved an accuracy of 99.83%. The Transformer model proposed by Google in 2017 caused a great sensation, and subsequent vision models based on Transformer have developed rapidly, becoming one of the mainstream approaches in the field of computer vision[19,20]. In 2022, Fu et al.[21] proposed a corn growth period classification method based on the Swin Transformer model, which achieved an overall accuracy of 98.7% on the original test set, providing technical support for the intelligent monitoring of corn growth stages. In this study, three convolutional neural networks (MobileNet, VGG16, and ResNet50) and the ViT (Vision Transformer) network structure were used to realize the classification of quinoa seeds. This work is positioned as a benchmark study for quinoa seed classification. The main contributions include a representative dataset covering white quinoa (high/low quality), black quinoa, and weed seeds; a tailored imaging strategy combining an industrial camera and a multispectral system; and a systematic comparison of four mainstream deep learning models under transfer learning, with an emphasis on practical deployment value for automated seed grading.

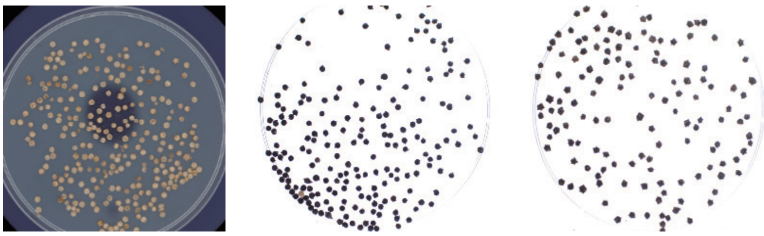
2 Experimental design and analysis

2.1 Experiment preparation

2.1.1 Testing instruments and equipment

According to the image acquisition requirements of quinoa seeds, a set of image acquisition devices was independently designed. The experimental setup consists of an industrial camera, a dark box, a light source, a computer, and other components. A MindVision MV-GE1600C industrial camera equipped with an MV-LD-8-3M-A lens (focal length: 8 mm; pixel size: 1.34×1.34 μm) was adopted. The camera was fixed at the top of the dark box, approximately 30 cm away from the measured objects. Two LED lamps were used as light sources, and an arbitrary number of black quinoa seeds and weed seeds were collected separately for imaging. Weed seeds are very similar to quinoa seeds in terms of size, shape, color, and other aspects. Since white quinoa seeds are relatively light in color, their quality (e.g., whether they are moldy, damaged, or infested by pests) is usually reflected by subtle differences in texture, color, or shape. These differences may have low contrast or blurred edges in images, making it difficult to distinguish them clearly using traditional imaging methods. Therefore, this study adopted a multispectral imaging system, namely the VideometerLab 4 (Videometer A/S, Hørsholm, Denmark), to acquire multispectral images. This system has a pixel resolution of 2920×2920 and can capture real-time data regarding surface color, texture, and chemical composition of seeds with an imaging area of 90 mm × 90 mm. Data were acquired at 19 excitation wavelengths (365, 405, 430, 450, 470, 490, 515, 540, 570, 590, 630, 645, 660, 690, 780, 850, 880, 940, 970 nm), encompassing visible, ultra-violet (UV), and near-infrared (NIR) light. The collected images of white quinoa seeds, black quinoa seeds, and weed seeds are shown in Figure 1.

In this study, the industrial camera (MindVision MV-GE1600C) was used to capture images of black quinoa seeds and weed seeds, while the VideometerLab 4 multispectral imaging system was used to capture images of white quinoa seeds. For white quinoa seeds, RGB images were extracted from the multispectral data. All RGB images (from both sources) were then subjected to the same preprocessing pipeline described in Section 2.2.1.



a. White quinoa seed b. Black quinoa seed c. Weed seed

Figure 1 Image of quinoa and weed samples

2.1.2 Test environment

In this study, the operating system was Windows 10, with TensorFlow 2 as the deep learning framework, Python 3.8 as the programming language, 16 GB of memory, and a 12th Gen Intel(R) Core(TM) i7-12700H processor running at 2.3 GHz.

2.1.3 Parameter settings

Epoch: An epoch refers to a process where all data completes one forward computation and backpropagation in the network. In this study, the number of epochs was set to 200 for the MobileNet, ResNet50, and ViT models, and 100 for the VGG16 model.

Batch_size: Batch size is a mandatory parameter for neural network training, referring to the number of samples used per training iteration. It determines training efficiency and accuracy. The batch size in this study was set to 32.

Learning rate: The learning rate is a crucial parameter in deep learning, which determines whether and when the objective function can converge to a local minimum. If the learning rate is too small, the convergence process will be slow; if it is too large, convergence may fail to occur. The minimum learning rate was set to 0.0001, and the maximum learning rate was set to 0.01.

2.2 Experimental procedure

2.2.1 Image preprocessing

First, the images were converted to grayscale images. Then, the Otsu algorithm was used to calculate the threshold for converting the grayscale images into binary images. Median filtering was adopted to remove noise. On this basis, the segmentation regions were precisely delineated to completely remove the background and achieve full segmentation of individual seeds. Figure 2 presents the flowchart of the complete image segmentation process for individual seeds. Finally, the original RGB images corresponding to the preprocessed single-seed images were input into the deep learning models for feature extraction and classification.

To clarify, the original RGB images came from two sources: direct RGB output from the industrial camera for black quinoa seeds and weed seeds, and RGB channel extraction from the multispectral data for white quinoa seeds. Regardless of the source, all RGB images were processed uniformly according to the pipeline in Figure 2, including grayscale conversion, Otsu algorithm, median filtering, segmentation region delineation, and background removal.

In the end, the original images of 1520 seeds were obtained in this study. The original images were manually screened to eliminate unqualified samples such as blurred, occluded, and abnormal exposure, and finally 1440 effective images of seeds were retained. Subsequently, each type of seed image after screening was accurately marked to clarify its category (white quinoa, black quinoa, weed seeds) and the quality grade of white quinoa seeds (such as high quality and low quality). The effective images of 1440 seeds were divided into training set, test set, and validation set according to the ratio of 8:1:1, in which the training set was 1152, the test set was 144, and the validation set was 144. It was ensured that each category was included in the training set, test set, and validation set.

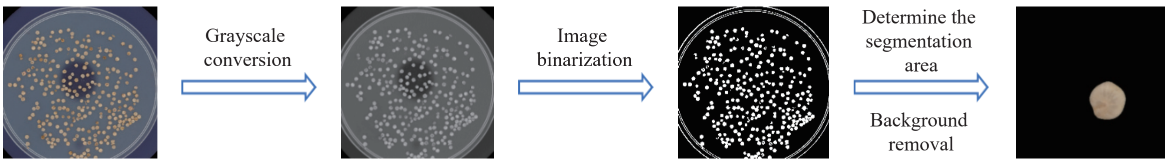


Figure 2 Flowchart of image segmentation

2.2.2 Data augmentation

The data augmentation methods used in this study include image flipping, image rotation, and noise addition.

1) Image flipping: As a commonly used data augmentation method, image flipping refers to a technique of generating new images by horizontally or vertically flipping the original images with a certain probability[22]. In this study, the flip operation on images was implemented by calling the Flip(·) function in OpenCV[23-25].

2) Image rotation: Image rotation involves rotating an image by a specific angle around a predetermined rotation center, where the rotation angle can be set manually. In this study, the WarpAffine(·) function in OpenCV was used to perform the image rotation operation.

3) Noise addition: Noise addition is also a widely used data augmentation method. It generates new images by randomly creating discrete pixel points on the original images, with common techniques including Gaussian noise and salt-and-pepper noise[26-27]. To achieve data augmentation, this study added Gaussian noise to the images by calling the Random_noise(·) function in the Util library.

The above image flipping, rotation, adding Gaussian noise and brightness adjustment and other data augmentation methods are used to process the training set, and finally a training set containing 2652 seed images is constructed to prevent overfitting.

2.2.3 Transfer learning

Transfer learning refers to a learning process that leverages the similarities between data, tasks, or models to apply a model trained in a prior domain to a new domain[28-30]. In this study, transfer learning was implemented on the MobileNet, VGG16, ResNet50, and ViT network models respectively. Regarding the ViT model, this study did not adopt a self-designed ViT architecture but instead used the standard ViT-Base/16 model released by the Google Research team. The specific configurations of this model are as follows: Patch size: 16×16; Hidden dimension: 768; Transformer layers: 12; Attention heads: 12; MLP size: 3072. After sufficient training on large datasets, a pre-trained model and its initial weights were obtained. The pre-trained weights of the ViT-Base/16 model used in this study were sourced from the official TensorFlow model repository. These weights were trained on the ImageNet-21K dataset and fine-tuned on ImageNet-1K. Using the initial weights of pre-trained models can effectively improve training efficiency and accuracy. Therefore, to achieve better training results, this study adopted transfer learning by introducing the initial weights of the pre-trained model, followed by fine-tuning the model—freezing the underlying parameters, adjusting the weights, and retraining the new network. Finally, the trained models were tested using the validation set to compare their classification performance.

3 Test results

The seeds were classified into four categories: A, B, C, and D, as shown in Figure 3.

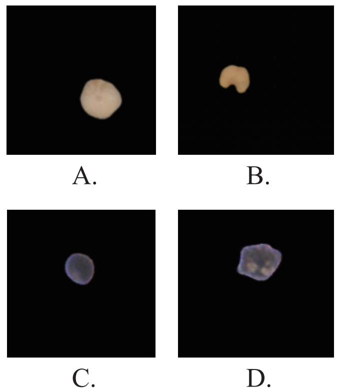


Figure 3 Seed category

Category A: High-quality white quinoa seeds. These seeds are tablet-shaped with a bright, glossy appearance and intact morphology.

Category B: Low-quality white quinoa seeds. These seeds are shriveled, blackish-yellow, and dull, with some being incomplete or fragmented.

Category C: Black quinoa seeds.

Category D: Weed seeds.

3.1 MobileNet network training results

The heatmap of the confusion matrix for the MobileNet network classification results is shown in Figure 4. A confusion matrix is a key tool for evaluating the performance of classification models, as it intuitively presents the error distribution of the model through a heatmap.

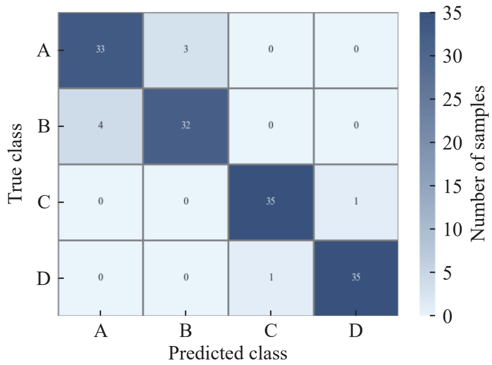


Figure 4 MobileNet network classification confusion matrix thermodynamic diagram

As can be seen from Figure 4, in the classification and prediction using the MobileNet network model: Among the 36 high-quality white quinoa seeds in the testset, 33 were correctly predicted, and 3 were incorrectly classified as low-quality white quinoa seeds. Among the 36 low-quality white quinoa seeds in the test set, 32 were correctly predicted, and 4 were incorrectly classified as high-quality white quinoa seeds. Among the 36 black quinoa seeds in the test set, 35 were correctly predicted, and 1 was incorrectly classified as a weed seed. Among the 36 weed seeds in the validation set, 35 were correctly predicted, and 1 was incorrectly classified as a black quinoa seed. Figure 5 shows the MobileNet classification result diagram.

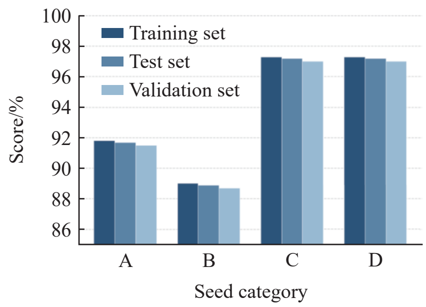


Figure 5 Classification results of MobileNet

As can be seen from Figure 5, under the MobileNet network classification on the test set, for high-quality white quinoa seeds, the precision of classification prediction was 89.19%, the recall rate was 91.67%, and the F1-score was 90.41%. (The F1-score, also known as the F1 measure, is a statistic used to evaluate the accuracy of binary classification models. It is the harmonic mean of precision and recall, providing a single metric for assessing model performance.) For low-quality white quinoa seeds, the precision was 91.43%, the recall rate was 88.89%, and the F1-score was 90.13%. For black quinoa seeds, the precision was 97.22%, the recall rate was 97.22%, and the F1-score was 97.22%. For weed seeds, the precision was 97.22%, the recall rate was 97.22%, and the F1-score was 97.22%. As indicated by the MobileNet loss function curve in Figure 6, the model gradually converged with the increase in the number of training iterations, demonstrating a good fitting effect.

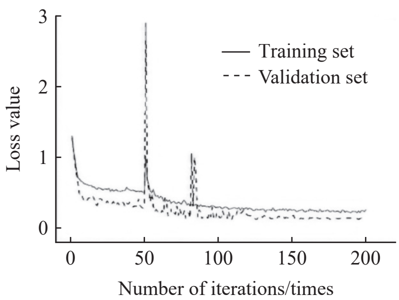


Figure 6 MobileNet loss function images

3.2 VGG16 network training results

The heatmap of the confusion matrix for the VGG16 network classification is shown in Figure 7.

As can be seen from Figure 7, in the classification and prediction using the VGG16 network model: Among the 36 high-quality white quinoa seeds in the test set, 32 were correctly predicted, and 4 were incorrectly classified as low-quality white quinoa seeds. Among the 36 low-quality white quinoa seeds in the test set, 31 were correctly predicted, and 5 were incorrectly classified as high-quality white quinoa seeds. Among the 36 black quinoa seeds in the test set, 34 were correctly predicted, 2 were incorrectly classified as high-quality white quinoa seeds, and 2 were incorrectly classified as weed seeds. Among the 36 weed seeds in the test set, 34 were correctly predicted, and 2 were incorrectly classified as black quinoa seeds. Figure 8 shows the VGG16 classification result diagram.

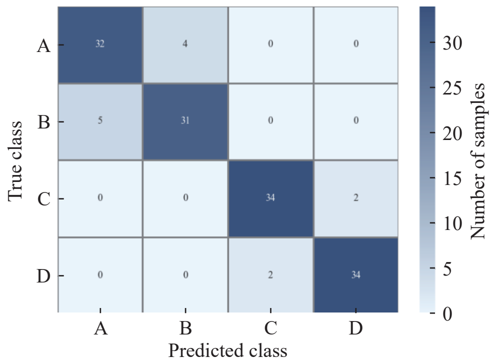


Figure 7 VGG16 network classification confusion matrix thermodynamic diagram

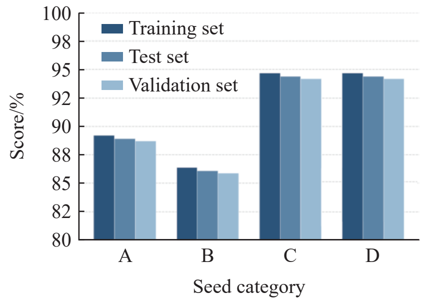


Figure 8 VGG16 classification results

As can be seen from Figure 8, under the VGG16 network classification of the test set: For high-quality white quinoa seeds, the precision of classification prediction was 86.49%, the recall rate was 88.89%, and the F1-score was 87.67%. For low-quality white quinoa seeds, the precision was 88.57%, the recall rate was 86.11%, and the F1-score was 87.32%. For black quinoa seeds, the precision was 94.44%, the recall rate was 94.44%, and the F1-score was 94.44%. For weed seeds, the precision was 94.44%, the recall rate was 94.44%, and the F1-score was 94.44%. As indicated in Figure 9, the model began to converge when the number of iterations reached approximately 60, showing a good fitting effect.

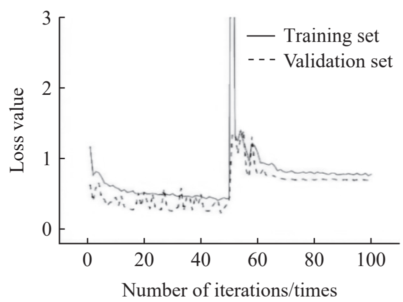


Figure 9 VGG16 loss function images

3.3 ResNet50 network training results

The heatmap of the confusion matrix for the ResNet50 network classification is shown in Figure 10.

As can be seen from Figure 10, in the classification and prediction using the ResNet50 network model: Among the 36 high-quality white quinoa seeds in the test set, 33 were correctly predicted, and 3 were incorrectly classified as low-quality white quinoa seeds. Among the 36 low-quality white quinoa seeds in the test set, 32 were correctly predicted, and 4 were incorrectly classified as high-quality white quinoa seeds. All 36 black quinoa seeds in the test set were correctly predicted, and all 36 weed seeds in the test set were correctly predicted. Figure 11 shows the ResNet50 classification result diagram.

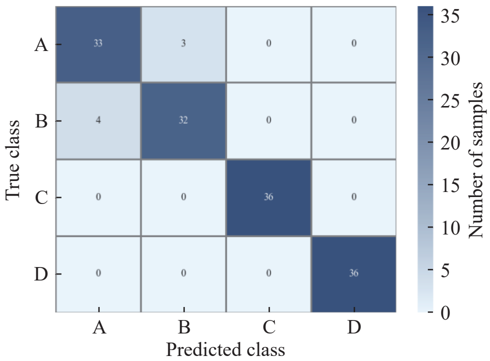


Figure 10 ResNet50 network classification confusion matrix thermodynamic diagram

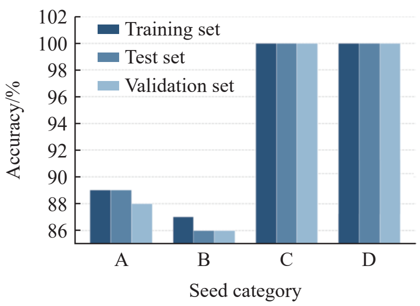


Figure 11 ResNet50 classification results

As can be seen from Figure 11, under the ResNet50 network classification of the test set, for high-quality white quinoa seeds, the precision of classification prediction was 86.49%, the recall rate was 88.89%, and the F1-score was 87.67%. For low-quality white quinoa seeds, the precision was 88.57%, the recall rate was 86.11%, and the F1-score was 87.32%. For black quinoa seeds, the precision was 100.00%, the recall rate was 100.00%, and the F1-score was 100.00%. For weed seeds, the precision, recall rate, and F1-score were all 100.00%. As indicated by the ResNet50 loss function curve in Figure 12, the model began to converge when the number of iterations reached approximately 80, demonstrating a good fitting performance.

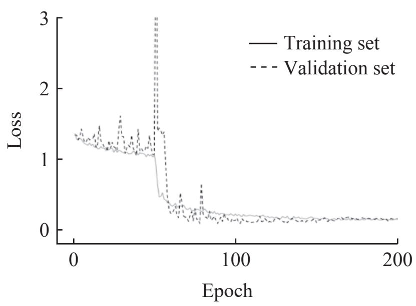


Figure 12 ResNet50 loss function image

3.4 ViT network training results

The heatmap of the confusion matrix for the ViT network model classification is shown in Figure 13.

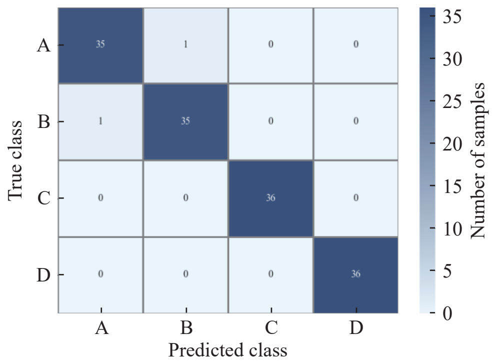


Figure 13 ViT network classification confusion matrix thermodynamic diagram

As can be seen from Figure 13, in the classification and prediction of the test set using the ViT network model: Among the 36 high-quality white quinoa seeds in the test set, 35 were correctly predicted, and 1 was incorrectly classified as a low-quality white quinoa seed. Among the 36 low-quality white quinoa seeds in the test set, 35 were correctly predicted, and 1 was incorrectly classified as a high-quality white quinoa seed. All 100 black quinoa seeds and 100 weed seeds in the test set were correctly predicted. Figure 14 shows the ViT classification result diagram.

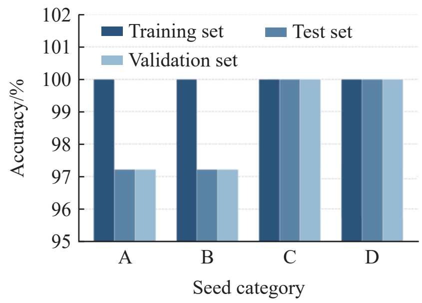


Figure 14 ViT classification results

As can be seen from Figure 14, under the ViT network classification: For high-quality white quinoa seeds, the precision, recall rate, and F1-score of classification prediction were all 97.22%. For low-quality white quinoa seeds, the precision, recall rate, and F1-score were all 97.22%. For black quinoa seeds, the precision, recall rate, and F1-score were all 100.00%. For weed seeds, the precision, recall rate, and F1-score were also all 100.00%. As indicated in Figure 15, the model gradually converged with the increase in the number of iterations, demonstrating a good fitting effect.

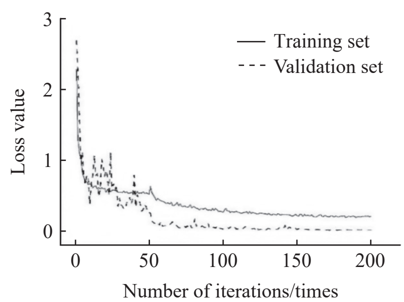


Figure 15 ViT loss function images

The classification results of the four models are shown in Table 1. The average classification results of the image dataset are presented in Table 2.

As can be seen from Tables 1 and 2, for the MobileNet network model, the average precision of classification was 93.77%, the average recall rate and accuracy were both 93.75%, and the average F1-score was 93.75%. For the VGG16 network model, the average precision was 90.99%, the average recall rate and accuracy were both 90.97%, and the average F1-score was 91.22%. For the ResNet50 network model, the average precision was 93.77%, and the average recall rate, accuracy, and F1-score were all 93.75%. For the ViT network model, the average precision, recall rate, accuracy, and F1-score were all 98.61%. In the detection of quinoa seeds, the classification performance of the four network models was ranked as follows: ViT > MobileNet = ResNet50 > VGG16.

Table 1 Image dataset classification results

Network model	Seed category	Class-wise accuracy/%	Recall rate/%	F1/%	Overall accuracy/%
MobileNet	*A*	89.19	91.67	90.41	93.75
	B	91.43	88.89	90.13	
	C	97.22	97.22	97.22	
	D	97.22	97.22	97.22	
VGG16	*A*	86.49	88.89	87.67	90.97
	B	88.57	86.11	87.32	
	C	94.44	94.44	94.44	
	D	94.44	94.44	94.44	
ResNet50	*A*	86.49	88.89	87.67	93.75
	B	88.57	86.11	87.32	
	C	100.00	100.00	100.00	
	D	100.00	100.00	100.00	
ViT	*A*	97.22	97.22	97.22	98.61
	B	97.22	97.22	97.22	
	C	100.00	100.00	100.00	
	D	100.00	100.00	100.00	

Note: Class-wise accuracy refers to the classification accuracy of a single category, calculated as the ratio of correctly predicted samples to the total samples in the corresponding category. Overall accuracy refers to the micro-average accuracy, calculated as the ratio of the total number of correctly predicted samples across all categories to the total number of test samples, which reflects the overall classification performance of the model.

Table 2 Average classification result of image dataset

Network model	Average precision rate/%	Average recall rate/%	Overall accuracy/%	Average F1/%
MobileNet	93.77	93.75	93.75	93.75
VGG16	90.99	90.97	90.97	91.22
ResNet50	93.77	93.75	93.75	93.75
ViT	98.61	98.61	98.61	98.61

Note: Average precision rate and Average recall rate are macro-average metrics, calculated as the arithmetic mean of the corresponding metrics across all categories. Taking MobileNet as an example, the average precision rate = (89.19%+91.43%+97.22%+97.22%)/4=93.77%. Overall accuracy is the micro-average accuracy, consistent with the definition in Table 1, which is used to reflect the overall performance of the model on the test set.

4 Discussion

The quinoa seed testing method proposed in this study enables rapid and precise identification of quinoa seed varieties (white quinoa/black quinoa) and quality grades (premium/substandard), accurately distinguishing quinoa seeds from weed seeds to achieve seed purity testing. For future research, state-of-the-art fine-grained classification models will be considered for integration to further optimize the model's deployment performance in practical scenarios such as field detection and portable devices. To identify quinoa seeds affected by pests and diseases, subsequent collection of seed samples from different pest and disease types is required. Combined with spectral and morphological characteristics, specialized research should be conducted to further expand the application scope of the method. Meanwhile, it can effectively cope with complex scenarios such as light variations and occlusions, enhancing the stability and reliability of detection. This method enables automated detection, reducing labor costs and the demand for professional detection equipment, thereby realizing the automated grading and classification of seeds. It not only improves the production efficiency of quinoa seeds but also provides technical support for the intelligent development of the quinoa seed industry and the selection of high-quality seeds in the quinoa industry.

5 Conclusions

Currently, the distinction between quinoa seeds and weed seeds, as well as the quality evaluation of quinoa seeds, relies solely on sensory identification. This method is plagued by numerous human factors, strong subjectivity, and low accuracy. To address these issues, this study adopted the idea of transfer learning and employed deep learning techniques to conduct recognition and classification research on quinoa seed images. The results have verified the feasibility of deep learning in quinoa seed classification.

This study compared the classification performance of quinoa seed detection under four networks: the MobileNet, VGG16, ResNet50, and the ViT network. Among them, the ViT network model achieved the highest precision and overall accuracy, demonstrating high recognition accuracy and robustness. It can effectively classify quinoa seeds, possessing certain application value and providing a reference for subsequent research.

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