DAMAGE CLASSIFICATION OF CASTOR SEEDS BASED ON MODIFIED AlexNet / 基于卷积神经网络的蓖麻种子损伤分类

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DOI: https://doi.org/10.35633/inmateh-76-03

***Keywords:** castor seeds, classification of damage, modified AlexNet, damage identification device*

ABSTRACT
The germination of castor seeds was affected by different damage forms after shelling. Traditional methods could not express the change of mechanical damage characteristics on the surface of castor seeds. In the study, an improved migration learning algorithm for castor seed damage classification was adopted. The convolution kernel size of the first convolutional layer of the AlexNet model was modified, part of the convolutional layer was divided into two layers to increase the depth of the convolution model. Then a multi-scale convolution kernel was added to extract the damage characteristics of castor seeds. The results showed that combined with the hyperparameter optimization of convolutional layer stratification and the AlexNet model, the classification effect was improved. The average test accuracy was 98.10%. After the addition of multi-scale convolution, the average test accuracy was improved by 0.57%. The results show that the classification accuracy of cracked castor seeds is 71%, and the classification accuracy of castor seeds with missing shells is 63%. The classification accuracy of whole castor seeds is 67%. The verification of damage identification device for castor seeds was developed to verify the correctness of the algorithm. This study provided a theoretical and convolutional network model supported for the development of an online real-time damage classification detection system for castor seeds.

摘要
蓖麻种子发芽率主要是脱壳后不同形式的损伤引起。传统方法无法表达蓖麻籽表面机械损伤特征的变化。 本研究采用了一种改进的蓖麻种子损伤分类迁移学习算法，修改了 AlexNet 模型第一个卷积层的卷积内核大小。卷积层被分成两层，以增加卷积模型的深度。添加一个多尺度卷积核，以提取蓖麻种子的损伤特征。 结果表明，结合卷积层分层的超参数优化和 AlexNet 模型，分类效果得到了改善。 添加多尺度卷积后，平均测试精度提高了 0.57%。 实验结果显示，开裂蓖麻种子的分类准确率为 71%，缺失壳蓖麻种子的分类准确率为 63%。 整个蓖麻种子的分类准确率为 67%。 本研究为开发蓖麻种子的在线实时损害分类检测系统提供了理论支持。

INTRODUCTION
Castor plant is one of the world's top ten oil crops. Its seeds are rich in oil (35%-55% oil content depending on the species) and are also widely used as raw materials for detergent, cosmetics, medicines and biodiesel *(Acosta-Navarrete et al., 2017; Santos, 2019*). Because of its high viscosity, high ignition point, low freezing point, it is also made into lubricant and widely used in aviation, high-speed lathe and other industrial fields (*Li et al., 2018; Mosquera-Artamonov et al., 2018*). The damage of castor seeds in the process of shelling will directly affect germination and plant growth, and will also affect the yield of castor oil used for oil extraction. Therefore, it is very important to classify and detect damaged castor seeds, which needs to extract the defect features that affect the surface marks of castor seeds. The traditional conventional classification algorithms cannot meet the requirements of damage classification of castor seeds.

At present, convolutional neural network, transfer learning and other deep learning methods are attracting more and more attention. These learning methods have been widely used in image processing (*Kamilaris and Prenafeta-Boldú, 2018*), medical aviation, agriculture and other fields. In the field of agriculture, migration learning is often applied in the identification and classification of plant leaf diseases (*Huang et al., 2019; Rangarajan et al., 2018)*, the identification and location of crop pests (*DeChant et al., 2017; Thenmozhi and Srinivasulu Reddy, 2019)*, the identification and classification of crop fruits (*Liu et al., 2020)*, the location of plant organs and the prediction of growth potential (*Fengle and Zengwei, 2020; Liang et al., 2019; Yang, 2018)*, and so on. Relevant studies show that the pre-training model of migration learning has obvious advantages compared with traditional machine vision technology.

Through the classification of the integrity of different agricultural materials, it can be found that the classification method based on the depth model is more accurate and efficient than the traditional classification algorithms such as support vector machine, linear discriminant model, and artificial neural network (*Xie et al., 2020; Zhiheng et al., 2018; Zhu et al., 2020*). Through the improvement of AlexNet model, relevant studies have improved the accuracy and efficiency of classification, making the improved model more suitable for the objects needing classification (*Lv et al., 2020; Xiaoqing et al., 2019*). The surface stripes of castor seeds affected feature extraction and different damage features extraction required different algorithms, while traditional algorithms could not meet the classification of damage on castor seeds surface.

In this study, the AlexNet model was transferred to the classification of castor seed damage. The AlexNet network model was optimized by modifying the convolution kernel size of the first convolutional layer, layering partial convolution layers, and adding multi-scale convolution. It was optimized from batch size, learning rate to improve the test accuracy of the model. Finally, the modified AlexNet was verified by the damage identification device of castor seeds.

MATERIALS AND METHODS

Dataset construction

The typical variety of ZheBi No.4, widely planted in Tongliao Academy of Agricultural Sciences, Inner Mongolia, was selected as the test sample. The germination experiment showed that the two damaged types of seed shell missing and crack had the most significant effect on the germination of castor seeds. Therefore, castor seeds with these two damage types and whole (no damage) were classified.

In this study, an LT-USB 1080 CMOS industrial camera was used to shoot samples of castor seeds placed on white A4 paper under the indoor environment. The shooting distance was 5~10 cm, then 525 images were obtained. The resolution of the images was 1,920×1,080 pixels, and the images were cropped to 227×227 pixels of samples containing castor seeds. The image of castor seeds with seed shell missing castor seed, crackled castor seed and whole castor seed were flipped to expand the castor seed image data set. The seed shell missing castor seed, cracked castor seed, and the whole castor seed was named with 0_1.jpg, 1_1.jpg, and 2_1.jpg forms, respectively. In the training set, some castor seeds were shown in Fig. 1.

a. Seed shell missing castor seeds; b. Cracked castor seeds; c. Whole castor seeds (no damage)

Fig. 1 – Images of castor seeds of different types

AlexNet Model construction

The AlexNet model consists of five convolution layers, three maximum pooling layers, and three full connection layers, a total of eleven layers. The size of the input image is required to be 227×227×3 (227 pixels high, 227 pixels wide, 3 color channels). After convolution, the output image size is shown in equation (1) while after pooling, the output image size is shown in equation (2).

$$N_{out} = \frac{N_{in} - F + 2P}{S} + 1 \tag{1}$$

$$N_{out} = \frac{N_{in} - F}{S} + 1 \tag{2}$$

where, N_{out} is the image output size; N_{in} is the image input size; F is the size of the convolution kernel; P is the padding; S is the step size.

The image was input into the AlexNet model. Through the convolutional layer, local response normalization layer, and maximum pooling layer, the output image size is 27×27×96. In the second part, the data flow follows the convolutional layer, the maximum pooling layer, and the local response normalization layer successively, and the output image size is 13×13×256. The third part and the fourth part respectively contain a convolutional layer. After the convolution operation of two layers, the output image size is 13×13×384. The fifth part is the convolutional layer and the maximum pooling layer, then the output image size is 6×6×256. The sixth part and the seventh part are the full connection layer, each layer has 4096 neural units. To reduce overfitting, Dropout is added after the full connection layer. The eighth part is the output layer. The structural model is shown in Figure 2.

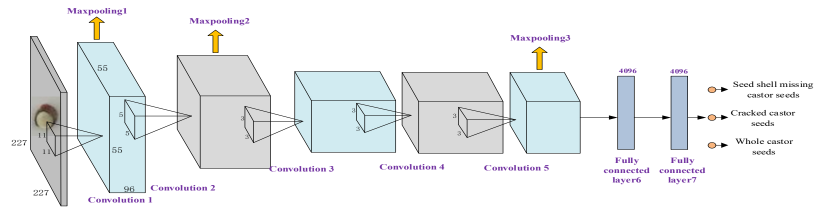


Fig. 2 - AlexNet network model diagram

The convolutional layer extracts the local features of the image through the convolution operation. After the feature map of the upper layer is processed by the convolution kernel, the feature map of the new layer can be obtained by the excitation function. The working process of the convolutional layer is as follows:

$$x_n^l = \sum_{i \in M_n} x_i^{l-1} * k_{in}^l + b_n^l \tag{3}$$

where, x^l_n is the n^{th} feature map of layer l; M_n is a set of feature mappings selected from the input feature mappings; k^l_{in} is the i^{th} element in the n^{th} convolution kernel of the layer l; b^l_n is the n^{th} offset of layer l; '*' is the convolution process.

The pooling layer is also called a downward sampling layer, which produces the sampling results of input feature maps and changes the size of features without changing the number of feature maps. The working process of the pooling layer is shown in equation (4):

$$x_n^l = f_{\text{down}}\left(x_n^{l-1}\right) + b_n^l \tag{4}$$

where, $f_{down}(\cdot)$ is the lower sampling function.

Evaluation Index

The accuracy of the classification algorithm is evaluated by the accuracy index, which is defined as equation (5):

$$a = \frac{N_C}{N_T} \times 100\% \tag{5}$$

where, a is the accuracy rate, %; N_C is the number of correctly classified samples; N_T is the total sample of training.

Operation platform

All the training and testing in this study are carried out on the same computer with the processor is Inter(R) Xeon(R) CPU E5-2643 v3 3.4 GHz, 32 G memory, AMD FirePro W7100 Graphics Adapter, and 8 GB of running memory, running under Windows 10 operation system.

Improvement of the AlexNet model method

Selection of the convolution kernel size

Convolution kernels are referred to as the local receptive field (LRF), which is a kind of filter. In this study, the convolution kernel size of the first convolutional layer in the AlexNet model is selected to learn the key features, to obtain better model performance. In this study, according to the literature(*DeChant et al., 2017; Liu, 2020*) and experimental experience, convolution kernel sizes of 5×5, 7×7, 9×9, 11×11, 13×13, and 15×15 were selected for training.

Convolution layer stratification

In this study, the convolutional layer 2 is divided into two layers, and the LRF size is modified to 3×3. The convolutional layer 3 is divided into two layers, and the LRF size is modified to 2×2. The convolutional layer 5 is divided into 2 layers, and the LRF size is modified to 2×2.

The parameters of each layer are shown in Table 1.

Table 1

Parameters of the convolutional network

CNN layers	Split layers	Output size	LRF size	Strides
Conv 1	Conv 1	55×55×96	11×11	4
Pooling 1	Pooling 1	27×27×96	3×3	2
Conv 2	Conv 2_1	29×29×256	3×3	1

CNN layers	Split layers	Output size	LRF size	Strides
	Conv 2_2	27×27×256	3×3	1
Pooling 2	Pooling 2	13×13×256	3×3	2
Conv 3	Conv 3_1	14×14×384	2×2	1
	Conv 3_2	13×13×384	2×2	1
Conv 4	Conv 4	13×13×256	3×3	1
Conv 5	Conv 5_1	14×14×256	2×2	1
	Conv 5_2	13×13×256	2×2	1
Pooling 3	Pooling 3	6×6×256	3×3	2
FC 6	FC 6	4096×1	\	\
FC 7	FC 7	4096×1	\	\
FC 8 (sorting)	FC 8 (sorting)	3×1	\	\

Adding multi-scale convolution

The structure of multiscale convolution is shown in Fig. 3.

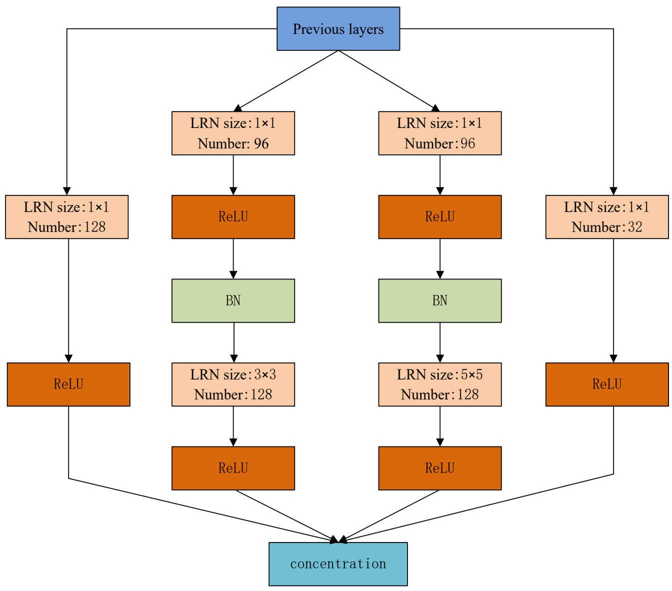


Fig. 3 – Structure of multi-convolution module

Multi-scale convolution has been widely used in VGG-Net, Inception series, GoogLeNet, and ResNet series. These networks have fully verified the superiority of multi-scale convolution in image recognition and target positioning. To learn better damage characteristics of castor seeds, a multi-scale convolution was added between convolutional layer 1 and convolutional layer 2. Three convolution kernels of different scales (1×1), (3×3), and (5×5), with the number of 32, 96, and 128 convolution kernels, were adopted to extract the sample image features in parallel. Then they merged into the same tensor and continue to pass them down.

RESULTS AND DISCUSSION

Influence of parameters on model performance

The influence of convolution layer 1 on the accuracy of model verification

In this study, the convolution kernel size of the first convolution layer of the AlexNet model was changed to learn the key features and obtain better model performance. The influence of the convolution kernel size on the recognition accuracy of the convolutional neural network is shown in Fig. 4.

When the convolution kernel size is 11×11, the average test accuracy is the highest. The results showed that there are significant differences in the shape characteristics among the data sets. So, the model network only needed to learn the shape features of the damage to ensure the fitting ability of the data. Therefore, the convolution kernel of convolutional layer 1 in this paper is selected 11×11.

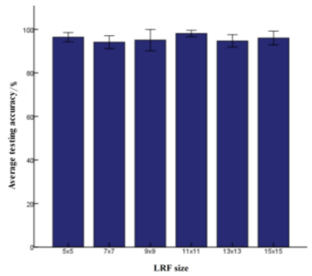


Fig. 4 – Average test accuracy under different convolution kernel sizes

Influence of learning rate on model performance

As an important super parameter in supervised learning and deep learning, learning rate determines whether the objective function converges to the local minimum and when it converges to the minimum. An appropriate learning rate can make the objective function converge to the local minimum in an appropriate time. Fig. 5 shows the curves of training accuracy and loss value. It can be seen that when the learning rate is 0.1, the training accuracy oscillates back and forth around the minimum value, and the loss value fluctuates within a wide range. After convergence, the loss value is relatively large, resulting in the over-fitting phenomenon.

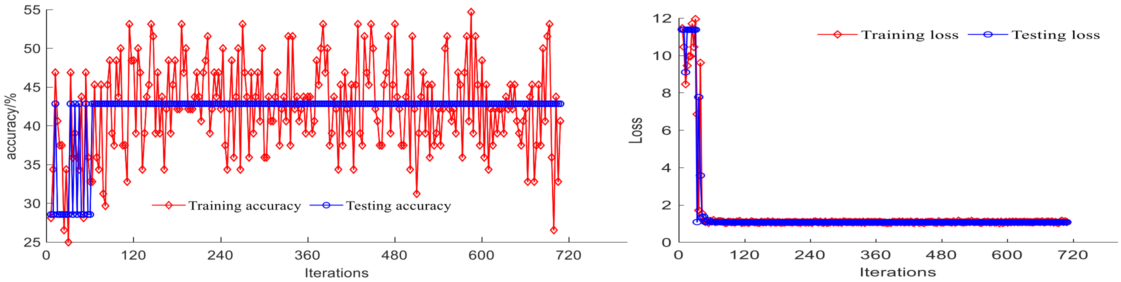
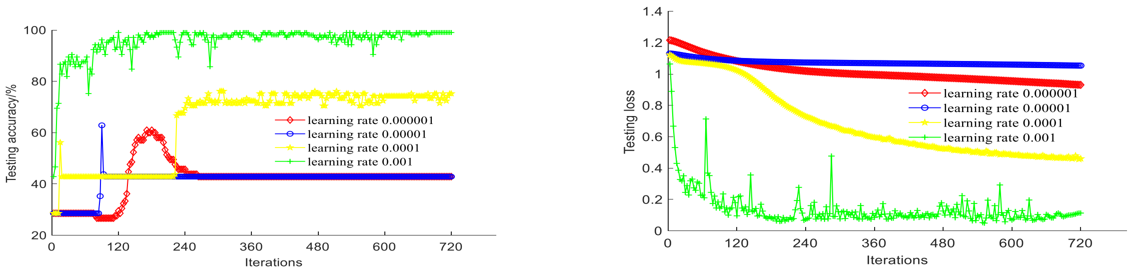


Fig. 5 – The curve of training, testing accuracy, and loss value with excessive learning rate

Fig. 6 is the graph of test accuracy and loss under different learning rates. When the learning rate is 0.00001 and 0.000001, the parameter to be optimized converges very slowly. After 700 iterations, the loss value converges slowly at close to 1. When the learning rate is 0.001, the model test accuracy is better, and the loss value converges near to 0. Therefore, this study chose a learning rate of 0.001 for training.



a) Test accuracy curve under different learning rates b) Test loss curve at different learning rates

Fig. 6 – Test accuracy and loss curves under different learning conditions

Influence of regularization on model accuracy

Regularization is an important means to control model complexity, combat over-fitting, and pursue a better prediction effect. In this study, L2 regularization is adopted to reduce the over-fitting phenomenon by adding a weight loss function. The regularization formula of L2 is shown as equation (6).

$$\Omega(\omega)=\frac{1}{2}\omega^T\omega \tag{6}$$

where, ω is the weight vector.

Influence of stratification of the convolutional layer on the model

The convolutional layer is divided into two layers, which can increase the depth of the network and detect the characteristics of the object to be detected more deeply, then improve the accuracy of the test. After repeated calculations, the average test accuracy of the convolutional layer stratified model is 98.10%, which is 0.48 percentage points higher than the original AlexNet model of 97.62%.

Influence of multi-scale convolution on the model

After adding multi-scale convolution based on the AlexNet model, the average accuracy on the test set is improved by 0.57%, which indicates that the features extracted by the model after introducing multi-scale convolution can more accurately express the features of different damage types.

Comparison of different models

To further verify the recognition effect of the model, the recognition effect of common deep convolutive neural network models such as VggNet-16, GoogLeNet, ResNet-50, and ResNet-101 on damage types of castor seeds is compared in the same experimental conditions.

VggNet-16 model

In the VGG (Visual Geometry Group) network, by using a smaller convolution filter, increasing the depth of the model structure to 16 layers and reducing the number of parameters, which is also known as VggNet-16. The structure model is shown in Fig. 7. The VggNet-16 model is composed of a continuous convolution layer with a convolution kernel of 3×3 and a maximum pooling layer with a convolution kernel of 2×2. Then two full connection layers are added, and the last layer serves as Softmax output. In this study, VggNet-16 was used to classify the damage of castor seeds and compared them with the improved AlexNet model.

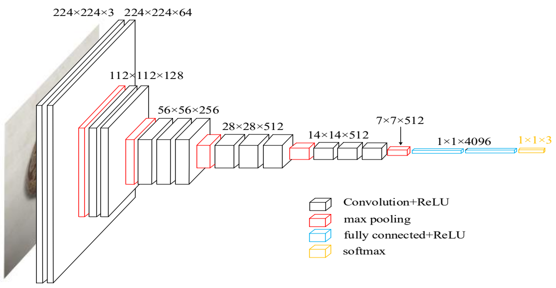


Fig. 7 – VggNet-16 network model diagram

GoogLeNet model

GoogLeNet is a deep convolution network model, which has achieved a good classification effect and improved computational efficiency in many applications. GoogLeNet is also known as the Inception Model. Its architecture consists of twenty-two layers, including 2 convolutional layers, 4 maximum pooling layers, 9 linear stacked Inception modules, and average pooling. Average pooling is applied at the end of the last inception module. Its structural model is shown in Fig. 8. In each initial module, multi-scale convolution such as 1×1, 3×3, and 5×5 are applied for dimension reduction. In this study, GoogLeNet was used to complete the task of castor seed damage classification and was compared with the improved AlexNet model.

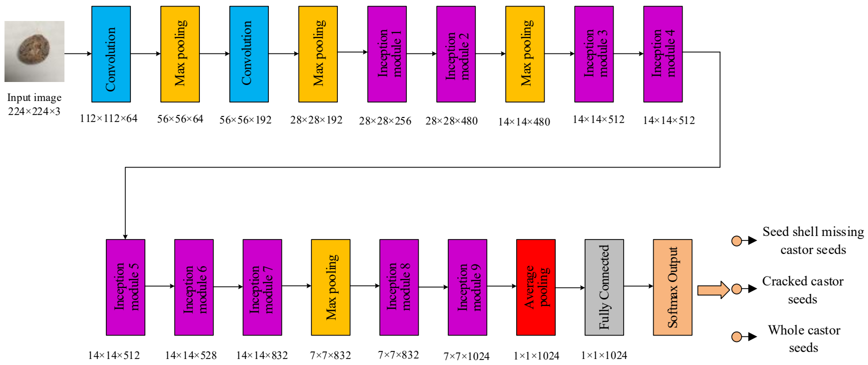


Fig. 8 – GoogLeNet The castor seed has two characteristic arcs, and the mechanical damage characteristics appear randomly on one of the network model diagram

ResNet-50 and ResNet-101 models

ResNet (Deep Residual network) has a good performance, its backpropagation will not encounter the problem of gradient disappearance. In this study, ResNet-50 and ResNet-101 were applied to complete the task of castor seed damage classification and were compared with the improved AlexNet model.

The output results of each model are shown in Table 2. It can be seen that the average test accuracy of the improved AlexNet model is 1.05% higher than that of the AlexNet model. The average test accuracy of the deep learning model based on VggNet-16 and GoogLeNet was slightly higher than the modified AlexNet model in this study. But the training efficiency was much lower than that of the model. VggNet-16 efficiency is 86.26% lower than modified AlexNet, and GoogLeNet efficiency is 56.72% lower than modified AlexNet.

The average test accuracy and training efficiency of ResNet-50 and ResNet-101 pre-training models are lower than modified AlexNet. Therefore, the model used in this study is more suitable for the classification of castor seeds damage types.

Table 2

Test accuracy under different depth models

DCNNS types	Test accuracy/%	Time/h
Modified AlexNet	98.67	1.16
AlexNet	97.62	0.63
VggNet-16	99.10	8.44
GoogLeNet	99.05	2.68
ResNet-50	96.83	4.80
ResNet-101	97.46	8.65

Design and verification of damage identification device for castor seeds

General composition of a damage identification device for castor seeds

The castor seed has two characteristic arcs, and the mechanical damage characteristics appear randomly on one of them. When castor seeds are placed naturally, only one of the character arcs can be picked up by the visual system. Therefore, it is necessary to carry out double-sided identification of castor oil seeds to ensure no damage to castor oil seeds missed detection. According to this requirement, when designing the damage identification device for castor seeds, the turning mechanism of castor seeds must be designed so that the two characteristic surfaces of castor seeds can be collected and recognized. At the same time, the system should include a castor seed conveying and identification mechanism for double characteristic surface detection of castor seeds. The three-dimensional structure diagram of the castor damage identification device is shown in Fig. 9.

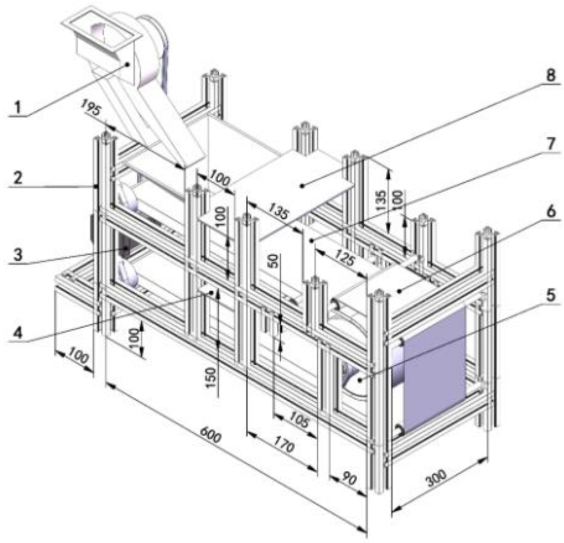


Fig. 9 – Stereo structure diagram of castor damage identification system

1.Castor seed planter; 2. Rack; 3. Electromotor; 4. Camera board Ⅱ; 5. Flipping roller; 6. Conveyor belt Ⅱ; 7. Conveyor belt Ⅰ; 8. Camera board Ⅰ

Experimental verification

In this study, the number of damage identified and classified was applied as the index to verify the rationality of the damage identification device for castor seeds. By comparing the accuracy of device identification with the actual damage accuracy, the superiority of the network model based on improved AlexNet is verified. The damage identification test device of castor seeds was developed. It can change the speed through the frequency modulator to obtain the appropriate speed.

It can verify the feasibility of the combination of the castor seed identification test device and the improved AlexNet model of castor seed damage classification method, it can also measure the stability of the identification performance of the castor seed identification device and verify the robustness of the interface algorithm.

The test equipment in this study is a self-developed damage identification test device for castor seeds. Fig.10 shows the experimental device for damage identification of castor seeds.

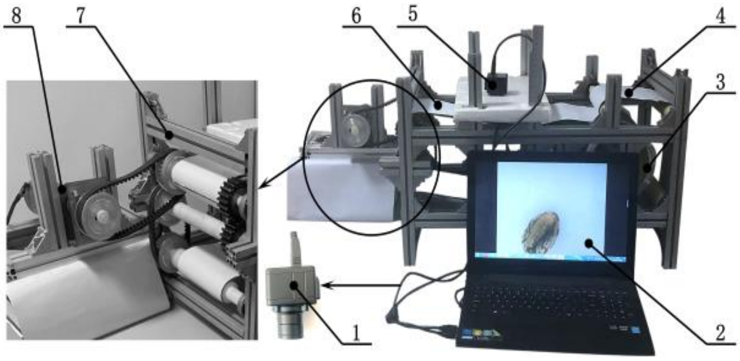


Fig. 10 – Experimental apparatus for damage identification of castor seeds

1. Camera Ⅱ; 2. Computer; 3. Flipping roller; 4. Conveyor belt Ⅱ; 5. Camera Ⅰ;
6. Conveyor belt Ⅰ; 7. Rack; 8. Electromotor

During the test process, castor seeds were placed on the conveyor belt of the castor seed damage device one by one in order through an artificially simulated seed planter. The photos of different types of castor seeds were taken by the camera and saved to the folder of the designated route. The type of castor seeds was verified through the interface of damage classification of castor seeds.

Since the first visual identification system can only verify one characteristic cambered surface of castor seed, three conditions should be taken into account on the process of validating the whole castor seed. When the castor seed is identified as a whole in the first visual system and cracked in the second visual system, the castor seed belongs to cracked castor seed. When the castor seed is identified as a whole in the first visual system and seed shell missing castor seed in the second visual system, it is identified as a seed shell missing castor seed. When the castor seed is identified as the whole in the first visual system and as whole in the second visual recognition system, it is identified as a whole castor seed. The verification results are shown in Fig.11.

a. Whole-Crack verification diagram b. Whole-Seed shell missing verification diagram

Fig. 11 – Verification of non-damaged (whole) castor seeds

Table 3

Repeat tests for each damage type device

Damage category	Predicted damage category			Classification performance			
	Crack	Seed shell missing	Whole	Accuracy / %	Actual damage rate / %	Theoretical damage rate / %	Damage rate difference / %
Crack	71	6	23	71.0	23.7	33.3	9.6
Seed shell missing	9	63	28	63.0	21.0	33.3	12.3
Whole	21	12	67	67.0	0.0	0.0	0.0

In this study, 100 castor seeds with cracks, 100 castor seeds with seed shells missing, and 100 castor seeds without damage (whole) were selected for verification. The verification results are shown in Table 3.

It can be drawn that the device can better identify and classify the three castor seeds. The accuracy of identification of cracked castor seeds was 71%, that of castor seeds with missing seed shell was 63%, and that of castor seeds with the whole shell was 67%. The damage rate of castor seeds was identified by damage. The actual crack damage rate was 23.7% in the process of identification, and the difference in damage rate was 9.6%. The damage rate of seed shell loss was 21.0%, and the difference in damage rate was 12.3%. It can be verified that the identification device and verification algorithm of castor seeds can meet the practical application.

CONCLUSIONS

To eliminate damage of castor seeds, an improved AlexNet model was proposed to classify castor seed damage types. The model was optimized by batch size, learning rate and regularization coefficient. The model was compared with other models and the damage identification device of castor seeds was used to test. The conclusions are as follows:

(1) Compared with other models, the improved AlexNet model has an average test accuracy of 1.05% higher than that of the original model under the same experimental conditions.

(2) The results of experiment show that the identification and classification accuracy of cracked castor oil seeds is 71%, and the identification and classification accuracy of castor seeds with missing shells is 63%. The classification accuracy of complete castor oil seeds is 67%.

(3) The damage rate of castor seeds was identified. The actual crack damage rate is 23.7% in the process of identification, and the difference in damage rate is 9.6%. The loss damage rate of seed shell is 21.0%, and the difference of damage rate is 12.3%, which verified that the identification device and verification algorithm of castor seeds could meet the practical application.

ACKNOWLEDGEMENT

This research was supported by the National Natural Science Foundation of China, China (51457312), the authors thank relevant scholars for their assistance in the literature.

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