Research on Wheat Impurity Image Recognition Based on Convolutional Neural Network

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Abstract. The doping rate is one of the important indexes to evaluate the quality grade and price of wheat. In order to accurately and quickly recognize impurities (wheat husk) in wheat grains, images of doped wheat were collected and Convolutional Neural Network (CNN) was used to realize the classification and recognition of grains and impurities in wheat grains. In this study, image segmentation and image enhancement were used to preprocess the acquired images to establish the image database of wheat grains and impurities. According to the characteristics of image data, the classic CNN, VGGNet and ResNet network models for wheat impurity images recognition were established. Simulation analysis shows that, compared with the classical CNN and VGGNet network models, the ResNet network model has the best recognition performance. The recognition accuracy of the test set is 96.94%, the recognition time is 5.60 ms.

Keywords: Convolutional neural network · Wheat grains · Impurities

1 Introduction

Wheat is one of the main food crops in China and also an important export product. According to China's wheat national standard [1], doping rate is one of the important indicators for evaluating wheat quality grade and price during wheat purchase and market circulation. At present, wheat impurity detection methods mainly include electric screening method, hand screening method [2], sensory detection method [3], and image detection method [4]. Electric screen method and hand screen method can not meet the requirements of rapid field detection because of the long detection time. Artificial sensory detection is easily mixed with subjective factors, which brings great uncertainty to wheat quality grading. In the aspect of image detection, researchers have studied wheat impurity recognition by using linear discriminant analysis model [5, 6], artificial neural network [7, 8] and other technologies, and achieved good recognition effect. However, the calculation process of this kind of method is relatively

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complicated, and the algorithm performance depends on the extracted input data features, which cannot meet the needs of actual image detection.

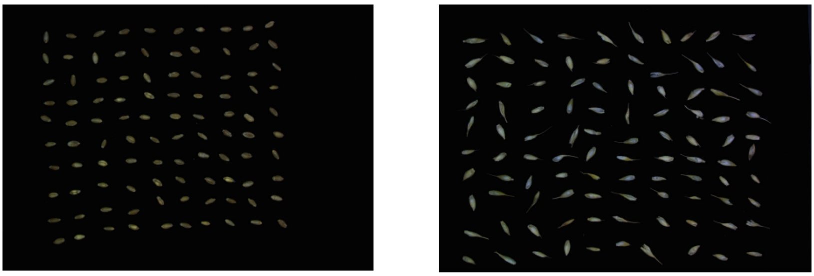
In recent years, deep learning has become a research hotspot in the field of image recognition. Deep learning technology represented by convolutional neural network has been applied to many aspects of the agricultural field [9–15]. Convolutional neural network can directly recognize the original image, avoiding the complex process of artificial feature design, selection, optimization and so on, and can well meet the needs of real-time detection. Therefore, in this paper, three convolutional neural network models, including classic CNN, VGGNet and ResNet, are adopted to realize the recognition of impurities in adulterated wheat. Through the establishment of wheat grains and impurities image database, model optimization design and recognition effect evaluation, the convolutional neural network with the best detection effect in the recognition of wheat impurity image is discussed.

2 Image Acquisition and Preprocessing

2.1 Image Acquisition

In this paper, the impurities in wheat grains was taken as the detection target, and the materials used in the experiment were from Xinglong National Grain Reserve Bank in Zhengzhou, Henan Province. Because the size and shape of wheat husk are different greatly, so the wheat husk with similar wheat grains size and shape is selected as the experimental material manually.

The background of image acquisition is black light-absorbing flocking background cloth, and the acquisition equipment is Sony camera (ILCE-7RM2 model, 42.4 million effective pixels). Wheat grains and impurities were randomly placed in a distribution of 10×10, as shown in Fig. 1. Among them, wheat grains and impurities were collected 3000 grains respectively.



(a) wheat grain (b) impurity

Fig. 1. Image acquisition sample.

2.2 Image Preprocessing

Image preprocessing is divided into three parts: multi-grain segmentation, size unification and data expansion, as shown in Fig. 2. First, the collected images are converted into grayscale images. Then, Graythresh function is used to find the optimal threshold to transform the grayscale image into a binary image. Finally, multi-grain images were segmented into single grain images by using the minimum outer rectangle method. The size of single grain image obtained by the minimum outer rectangle method is different, so it is necessary to unify the size of single grain image. In this study, the image size was unified as 32×32. Due to the small amount of image data collected, the images with the same size were left rotated 90° and 180° respectively. After image preprocessing, 18000 image sample sets were obtained, including 9000 wheat grain images and 9000 impurity images respectively.

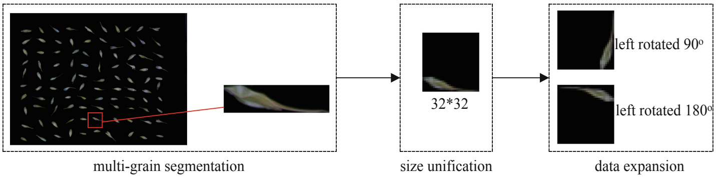


Fig. 2. Image preprocessing.

3 The System Model

3.1 Convolutional Neural Network Structure

In order to meet the requirements of real-time detection of adulterated wheat and considering the size of the sample in the image database established in this paper, a modified convolutional neural network structure suitable for this experiment was adopted.

Classic CNN Network. The classic CNN network is shown in Fig. 3. This network introduced the activation function layer ReLU on the basis of LeNet-5 network.

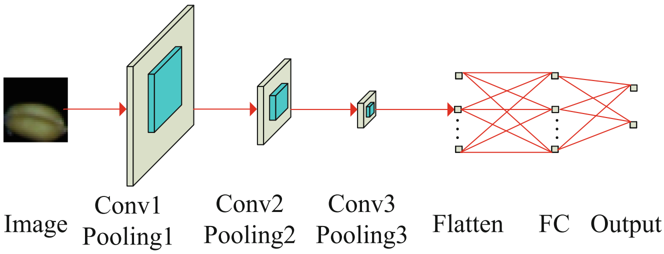


Fig. 3. Classic CNN network.

In Fig. 3, the classic CNN network structure has a total of 9 layers, including 3 convolution layers, 3 pooling layers, 1 Flatten layer, 1 full connection layer, and 1 output layer. After each convolution layer, there is a ReLU activation layer. The role of convolution layer is mainly to extract the features from the input image. The convolution kernel size of convolutional layer Conv1 is $5 * 5$, and the step size is 1. The size of the feature graph of the image after the convolution operation of Conv1 is 32×32. The convolution kernel size and step size of convolutional layer Conv2 and Conv3 are the same as those of convolutional layer Conv1. The pooling layer adopts the maximum pooling to perform the down-sampling operation on the feature map. The size of Pooling1 is $2 * 2$, and the step size is 2. The size of the feature graph obtained by sampling under Pooling1 of the pooling layer is 16×16. Pooling2 and Pooling3 have the same size of pooling region and step size as Pooling1. Flatten is often used in the transition from the convolutional layer to the fully connection layer, which acts as a one-dimensional input. The function of the full connection layer is to make full connections between each neuron in the layer and all neurons in the upper layer. The output dimension sizes of the network convolution layer, Flatten layer and full connection layer are 32, 64, 128, 2048 and 2 respectively.

VGGNet Network. The VGGNet network suitable for this test is shown in Fig. 4. Compared with the classic CNN network, VGGNet network is composed of two convolution layers and one pooling layer repeatedly superimposed.

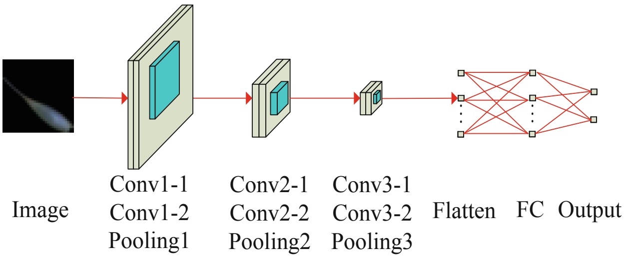


Fig. 4. VGGNet network.

In Fig. 4, the VGGNet network structure has a total of 12 layers, including 6 convolution layers, 3 maximum pooling layers, 1 Flatten layer, 1 full connection layer, and 1 output layer. The size of the convolutional kernel of the convolutional layer is all $5 * 5$, and the step size is all 1. The size of the pooling area of the pooling layer is $2 * 2$, and the step size is 2. The output dimension sizes of the network convolution layer, Flatten layer and full connection layer are 32, 32, 64, 64, 128, 128, 2048 and 2 respectively.

ResNet Network. The ResNet network of this test is shown in Fig. 5. Compared with the above model, the residual block structure is introduced to improve the system performance through residual learning.

Figure 5 shows that the ResNet network structure consists of 1 convolution layer, 3 residual layers, 2 average pooling layers, 1 Global Average Pooling layer, 1 full

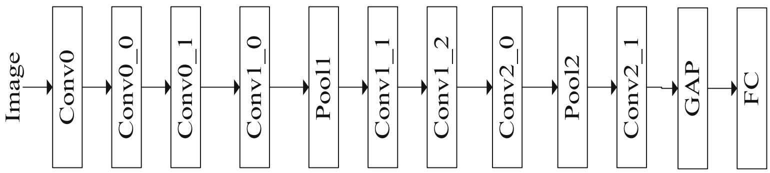


Fig. 5. ResNet network.

connection layer. The convolution kernel size of convolutional layer Conv0 is $5 * 5$. Due to the small image of the data set, the step size of the convolutional layer before input to the residual structure is set as 1, and the maximum pooled layer of is not passed. The three residual layers Conv0_x, Conv1_x and Conv2_x all adopt conventional residual block structure, and the number of residual blocks is 2, 3 and 2, respectively. The residual layer adopts the conventional residual block structure, as shown in Fig. 6. X is the input of the residual block, and F(X) is the residual learning. Learning makes F(X) go to 0, ignoring the depth.

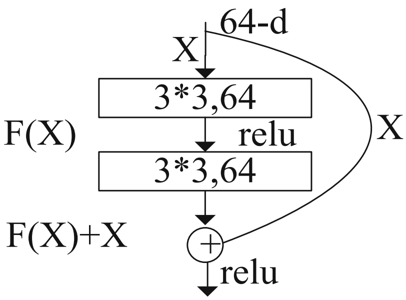


Fig. 6. Conventional residual block structure.

Among the 3 convolutional neural networks mentioned above, for the classic CNN network and VGGNet network, the Dropout layer is added after the full connection layer to reduce the parameters of network training and the complexity of the model.

The above three networks are classified by calculating the category probability of softmax function, which can be expressed as

$$y_{im} = \frac{e^{z_{im}}}{\sum_{k=1}^{K} e^{z_{ik}}} \tag{1}$$

Where, y_{im} is the prediction probability that the *ith* sample belongs to the m category; z_{im} is the product of the output vector of the *ith* sample and the parameter vector of class m; K is the number of categories; z_{ik} is the product of the output vector of the ith sample and the parameter vector of class k.

The classification cross entropy is taken as the loss function, and the calculation formula is

$$L = -\sum_{i=1}^{N} \hat{y}_{im} lg y_{im} \tag{2}$$

Where, L is the loss function; N is batch size; $\hat{y}_{im}$ is the expected value of the predicted probability of the *ith* sample belonging to class m.

3.2 Model Parameter Selection

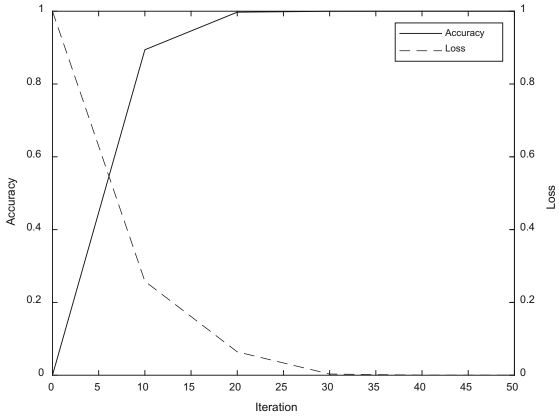
The experiment used TensorFlow framework and Python 3.6 programming language to build wheat grain and impurity recognition model on PyCharm platform. The batch size for network training was set to 144 and the number of iterations (epoch) was set to 100. Set the Dropout value to 0.5 for the classic CNN network and VGGNet network. The model parameters were optimized by the adaptive gradient descent method, where the learning rate was set at 0.001 and the momentum factor was set at 0.9.

4 Test Results and Analysis

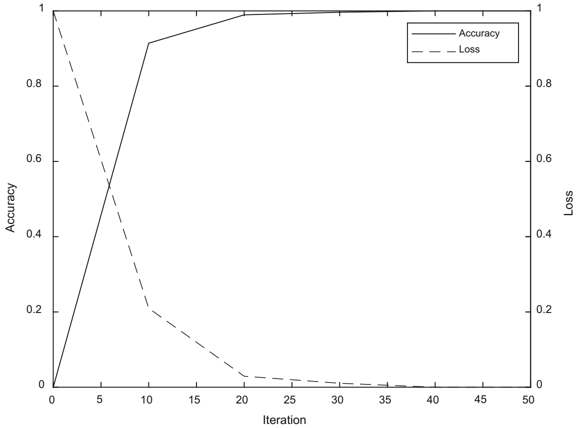
Using the wheat grains and impurities image database established in this paper, 7200 (80%) images of wheat grain and impurity images were selected as the training set, and 1800 (20%) images of wheat grain and impurity images were selected as the test set. Classic CNN, VGGNet and ResNet models were used to train the training set, and the change curves of training accuracy and loss were shown in Fig. 7(a), Fig. 7(b) and Fig. 7(c), respectively. It can be seen from the figure that the training accuracy of the classic CNN network tends to 1 and the loss tends to 0 when the number of iterations reaches about 20. Compared with the classic CNN network, VGGNet network has a complex structure. When the number of iterations reaches about 30, the training accuracy and loss tend to be stable. The number of iterations of the ResNet network tends to be stable is about 35.

The classical CNN, VGGNet and ResNet models after training were tested on the test set. The performance comparison of the three models is shown in Table 1.

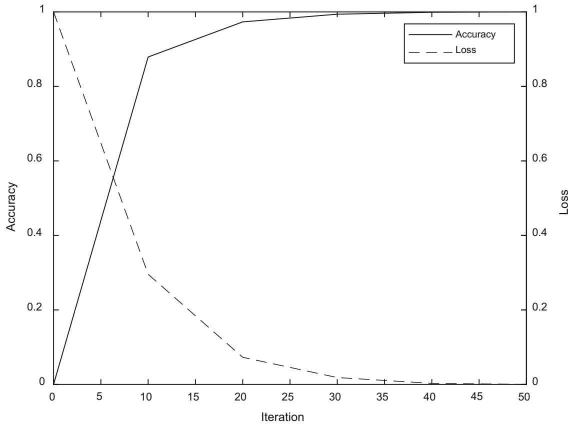
In Table 1, compared with the classic CNN network model and VGGNet network model, the ResNet network model has the highest accuracy in wheat impurity images recognition. At the same time, it can be found that the classical CNN network model has the shortest recognition time for each wheat grain (or impurity) image. Although the ResNet network model is more time-consuming than the classic CNN network model in wheat impurity image recognition, it can still meet the practical application of wheat impurity detection.Therefore, the performance of the ResNet network model constructed in this experiment is better than that of the classic CNN and VGGNet network models.



(a) Classic CNN network



(b) VGGNet network



(c) ResNet network

Fig. 7. Variation of network training accuracy and loss.

Table 1. Performance comparison of different network models.

Network model	Recognition accuracy (%)	Recognition time (ms)
Classic CNN	93.33	1.04
VGGNet	95.72	5.30
ResNet	96.94	5.60

5 Conclusion

This paper mainly discusses the application of convolutional neural network in wheat impurity recognition. Through the self-built wheat grain and impurity image database, the classical CNN, VGGNet and ResNet network models established in this paper were compared and analyzed. The results show that the recognition accuracy of the three convolutional neural network models is above 90%. In conclusion, the ResNet network model is more suitable for wheat impurity recognition.

Author Contributions. Chunhua Zhu and Tiantian Miao proposed the original idea and Tiantian Miao carried out the experiment. Chunhua Zhu and Tiantian Miao wrote the paper. Tiantian Miao supervised and reviewed the manuscript. All authors read and approved the final manuscript.

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Conflicts of Interest. The authors declare no conflict of interest.

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