VOLUME - 9, ISSUE - 8, August - 2020 • PRINT ISSN No. 2277 - 8160 • DOI : 10.36106/gjra

Original Research Paper

Computer Science

USING CONVOLUTIONAL NEURAL NETWORK AND RANDOM FOREST TO REALIZE POTATO SKIN DEFECT DETECTION

Jialong Su* Tiangong University, School of Computer Science and Technology, Tianjin 300387, China *Corresponding Author

Zhenkai Wan Tiangong University , Center for Engineering Internship and Training,Tianjin 300387,China

ABSTRACT Aiming at the problem that the potato skin defect detection algorithm does not fully extract the high-level features of the image and the detection accuracy is not high, a potato skin defect detection algorithm (CNN-RF) based on the combination of Convolution Neural Networks (CNN) and Random Forest (RF) models is proposed. In this paper, the final data set obtained by mirroring and random cropping methods from the images obtained by the laboratory machine vision platform was input into the convolutional neural network, and four types of defects, green skin, cracked groove, dry rot and budding data were used as the detection objects. Extract the high-level features of the images in the data set, then replace the Softmax layer of the convolutional neural network with a random forest, and use the trained output features as the input of the random forest model. In addition, use Gini impurity as the criterion for feature selection in the decision tree to verify the accuracy of the model's recognition and detection of potato skin defects. The results show that the accuracy rate of the proposed CNN-RF is 97.4%, and its performance is better than the detection effect of the Particle Swarm Optimization- support vector machines(PSO-SVM), AdaBoost, hyperspectral data dimensionality reduction method, Back Propagation Neural Network (BPNN) and conventional CNN model.

KEYWORDS : feature detection,convolution neural networks,random forest,defect detection

INTRODUCTION

The method of potato skin defect detection has always had the problems of high detection cost, low efficiency and high intensity [1], so it is the most important to propose a fast and efficient detection algorithm. Intelligent and efficient defect detection methods will inevitably replace the traditional industrial inspection process. This is the inevitable development trend of computer vision in the field of industrial intelligence. In recent years, the performance of deep learning in the field of computer vision [2-5] is hot, and the reason is that convolutional neural networks play an important role in the process. Compared with other algorithms, the detection efficiency of the CNN-RF algorithm proposed in this paper is higher. The particularity of sharing local weights can effectively avoid the complexity of data reconstruction when dealing with the image problem of multi-dimensional input vectors. Good processing of deformed and stretched image data. The use of this algorithm saves costs for the high-level feature extraction process of potato industrial inspection, and provides a more effective method for computer detection of image defects. The detection of potato skin defects has very important research value.

Although there has been a long research time for potato skin defect detection and classification problems, the results of image processing have always been difficult to achieve the desired effect. The potato external quality inspection system established by Hao Min and others can achieve potato defect detection with three indicators of external defects, weight and signature [5]. Li Jinwei and others used fast gray-scale interception and segmentation to separate potato epidermal defects, and used threshold method to identify and detect the separated defect areas, and respectively studied and analyzed the budding recognition rate and epidermal defect detection accuracy rate [6] Raz et al. used the image segmentation algorithm to extract the color features of the potato surface defect area, and used the extracted features to train the SVM classifier, the classification effect was more significant [7]. Cui Shengchun and others studied the method of using particle swarm optimization to optimize the relevant parameters of support vector machines, and proposed a brightness interception method based on the HIS color model, and used the RGB color model to detect potato spots [8].

Analysis and statistics of the above-mentioned defect detection algorithms show that the previous detection algorithms cannot efficiently extract the high-level data features of the image, and can only identify images with obvious defects. Especially the recognition rate of images with complex data features is not high. Moreover, it is not possible to detect and recognize the color and the texture characteristics of the potato defect at the same time. When the data set is large enough, the model detection accuracy is not high. Therefore, this paper proposes a CNN-RF method for potato epidermal defect detection based on this phenomenon. The potato epidermal defect image data set D collected and produced by laboratory equipment is used to construct and train a reasonable neural network model to improve the accuracy of potato epidermal defect detection. With the popularity of artificial intelligence and deep learning, deep learning has been widely used in the fields of speech and computer vision [9-10], and it has also been gradually applied to industrial defect detection modules. Huang Haojie[3] and others studied the neural network model of fruit type detection using deep learning. Liu Mengke [11] and others proposed the detection of track surface defects based on convolutional neural networks, and the test showed that the detection accuracy of track defects is significant.

CNN-RF MODEL DESIGN

The main work of this paper is as follows: First, First, the potato pictures are processed by mirroring and random cropping through the image acquisition equipment to form the final data image set required for the experiment, and some images that will be deformed and stretched can be better trained the CNN-RF model and improved the generalization ability of the model. The second is to design and improve the LeNet5 model [12] and train a convolutional neural network suitable for epidermal defect detection to further extract high-level features of the potato image data set. The third is to replace the Softmax layer with a random forest classifier, and use the extracted high-level features to train the random forest classifier to realize potato skin defect detection. The entire model can be divided into 3 modules.

The first module uses image acquisition equipment to obtain a large number of potato images, and preprocesses the original images through data augmentation methods. The specific operations include mirroring and random cropping. The processed image sets are combined into the required test data set.

The second module uses an improved LeNet5 neural network to extract features from the data set. The LeNet5 has 14 layers, including convolutional layer, downsampling layer, fully connected layer, Dropout layer, Batch Normalization layer, Flatten layer, Softmax layer, etc.

The third module is used to train the random forest classifier, replace the Softmax layer of the trained improved convolutional neural network with a random forest, and then use the output features obtained as an input to the random forest model, and finally the entire detection result Output. The flow of the CNN-RF model is shown in Figure 1

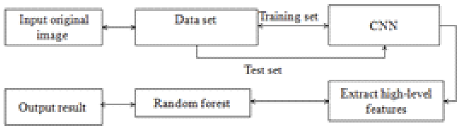

Figure 1: model flow chart of the CNN-RF

Convolutional neural network is a feed-forward neural network [13], which has been widely and efficiently applied in the fields of image processing and computer vision. It contains the characteristics of multiple hidden layer network structure, which can efficiently obtain some high-level features that cannot be extracted manually in the data set. However, the generalization ability of a single classifier is very poor when dealing with some data with more complex characteristics, and it is easy to produce over-fitting experiments. The integrated learning method can overcome this problem well [14]. Therefore, this paper adopts a method based on the combination of convolutional neural network and random forest, called CNN-RF model. In the convolutional layer of the convolutional neural network, the pixels are weighted and summed through the convolution kernel to obtain the feature map of the original image to achieve feature extraction Each neuron in the neural network shares the weight with the convolution kernel function, so that the number of various parameters is drastically reduced, and at the same time, the overfitting phenomenon of the entire model will be reduced [15]. The convolutional layer function expression is as follows:

$$x_j^l = f\left(\sum_{i \le M_j} x_j^{l-1} k_{ij}^l + b_j^l\right) \quad (1)$$

Among them, M_j is the feature map of the middle layer,l,k,and b represent the number of layers, convolution kernel and offset value, f represents the activation function, and often take sigmoid, tanh, ReLU and other functions. After the convolutional layer extracts some features of the data set image, the output features will be down-sampled, which can reduce the size of the feature map, which can reduce the dimensionality of the output features and can be very good. To avoid overfitting. The form of the sub-sampling function is as follows:

$$x_j^l = f(\beta_j^l down(x_j^{l-1}) + b_j^l) \quad (2)$$

Where down()represents the downsampling function.

LeNet5 is one of the typical convolutional neural networks. The network structure has 7 layers, including input layer, convolutional layer, sub-sampling layer, fully connected layer, etc. Judging from the results of various previous experiments, such as a typical handwritten character recognition experiment, it can make good use of the structural features of the image, which can more effectively extract the high-level features of the potato image, so the combination of the required test the skin defect detection target is a reasonable improvement to the LeNet5 model.

Improve CNN model

This paper chooses the improved LeNet5 convolutional neural network model to extract the high-level features of potato images. The improved CNN model structure has a total of 14 network structures, including Conv layer, Max_pooling layer, fully connected layer, Dropout layer, Dense layer, Batch Normalization layer, etc. The specific network structure is shown in Figure 2:

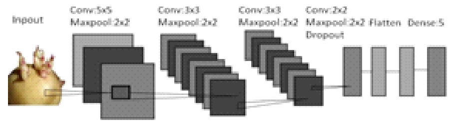

Figure 2:Improved LeNet5 network structure diagram

The specific layers of some CNN models are described in Table 1 below:

TABLE–1 PARTIAL LAYERS OF CNN MODELS

Layer (type)	Nuclear size	Output size	other
Conv1			
Max_pooling1	(2,2)	(122,122)	
Conv2	(3,3)	(60,60)	
Max_pooling2	(2,2)	(30,30)	
Conv3			Strides=2
Max_pooling3	(2,2)	(7,7)	
Conv4	(2,2)	(6,6)	Strides=1
Max_pooling4	(2,2)	(3,3)	
Dropout			Dropout=0.5
Flatten			
Dense_1			Neuron=128
Batch_Normalization_1			
Dense_2			Classify=5
softmax			

Random forest classifier

The Potato skin defect detection uses random forest [16] as the final classifier, and uses Gini impurity as the criterion for feature selection in decision trees.In the multi-classification problem, assuming that there are K classes, and the probability that the sample point belongs to the k-th class is p_k, sthen the Gini impurity of the probability distribution is:

$$Gini(p) = \sum_{k=1}^{k} p_k(1-p_k) = 1-\sum_{k=1}^{k} p_k^2 \quad (3)$$

$$Gini(D) = 1-\sum_{k=1}^{k} \left(\frac{|C_k|}{|D|}\right)^2 \quad (4)$$

Among them, C_k is the sample subset belonging to the kth class in D and K is the number of classes. The sample set D is divided into two parts according to whether the feature A takes a certain possible value, namelys

$$D_2 = D - D_1 ; D_1 = \{(x,y) \in D \mid A(x) = a\} \quad (5)$$

Then under the condition of feature A, the Gini impurity of set D is

$$Gini(D,A) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2) \quad (6)$$

Select the feature with the maximum value of the above formula as the feature of the decision tree to divide the left and right subtrees, and select the optimal parameter combination from it. The specific parameter value range can be screened and determined according to the test results to achieve more efficient defect detection Effect [17]. For the random forest model used in this experiment, specific parameters include n_estimators, min_samples_split, and min_samples_leaf, which represent the number of trees in the random forest, the minimum number of samples required for internal nodes to be split, and the minimum number of samples required for leaf nodes.

TEST RESULTS AND ANALYSIS

The computer hardware environment for all operations in this experiment is Nvidia 1080Ti, the operating system is Linux, and the language development tool is Python.

The experimental data set consists of images taken by the machine vision platform and data augmentation [18]. Select 50 images each with 5 characteristic points of green peel, budding, dry rot, crack and normal. Each category is mirrored and randomly cropped by data augmentation to obtain 5400 images, and 5400 potato color images are selected as the experiment Data set D is divided into training set of 4320 images and test set of 1080 images according to the ratio of 8:2, and the size of each image is adjusted to 248x248, and finally training set T (4320,248,248), test set V (1080,248,248)), as the input sample in the CNN-RF model data set.In the whole process, for the convenience of the experimental data, please pay attention to save the image in a unified format as JPG and name it with a unified naming method, such as the folders lvpi.JPG, chuya.JPG, ganfu.JPG, liegou.JPG, zhengchang. JPG. Part of the potato test data set is shown in Figure 3 below:

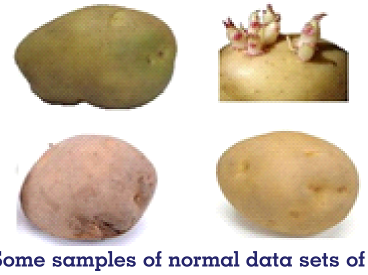

Figure 3:Some samples of normal data sets of green bark, sprouting and fissure

Selection of hyperparameters of CNN-RF model

In the experiment, the learning rate of the convolutional neural network and the parameter combination in the random forest [19] were screened according to the experimental effect. Analysis of the trend of defect detection effects shows that the data obtained for different learning rates are different, and the test results obtained by different parameter combinations are different.

During the experiment, it was found that the learning rate and the defect detection accuracy of the CNN-RF model had a curvilinear relationship during the training, so a quantitative research method is adopted. The number of training times is determined as the number of times when the data set has the best detection performance, and times is determined to be 210. According to experiments, the learning rate of 0.001 and 0.0001 is a separation point, and the accuracy rates are 74.8% and 82.3%, respectively. Of course, through in-depth study of neural network model training, we can know an experimental phenomenon that is as the learning rate of the entire neural network becomes lower, the corresponding training time will also become longer. Therefore, according to the actual training needs of the model, the learning rate of this experiment is determined to be 0.0001.

After the improved convolutional neural network training is completed, extract high-level features from the data set to obtain a new training set T'(4320, 5) and test set V'(1080, 5) , then Start training the random forest classifier with data sets T'and V'.For random forests, Choose different parameter combinations according to the changing trend of the test effect,and finally determined by screening as n_estimators=100,min_samples_split=3,min_samples_leaf =1.

Test results

After the test set and training set are fully trained to obtain the features of the CNN model, the test set V'(1080,5) is input to the random forest classifier for testing. The results of the test are counted, and the index evaluation is mainly from the two aspects of recall rate and accuracy rate. The specific results are shown in Table 2:

TABLE–2 DATA SET TEST RESULTS

Category	Accuracy	Rate	Recall	Rate
0	0.976	0.983	0.979	226
1	0.992	0.985	0.988	210
2	0.938	0.952	0.944	195
3	0.975	0.961	0.968	203
4	0.986	0.976	0.978	246
Avg/total	0.974	0.971	0.972	1080

According to the test results, the average accuracy rate is 97.4%, the highest accuracy rate for category 1 is 99.2%, and the lowest accuracy rate for category 2 is 93.8%, of which category 0 represents green skin defects and category 1 represents sprouting defects, category 2 Represents dry rot defects, category 3 represents fissure defects, category 4 represents normal.

For the same potato skin defect detection task, five parameter values are selected: green skin, sprouting, dry rot, cracking and normal. Comparing this article with the test detection accuracy of five common detection algorithms currently used in Data Set D, the results show that the accuracy of skin defect detection has been greatly improved. The PSO-SVM [7], which uses particle swarm algorithm to optimize SVM parameters, has an accuracy of 95% as the detection algorithm of the classifier. The accuracy of detection using BP neural network [20] is 93%, the accuracy of detection using AdaBoost [21] is 89.6%, the accuracy of detection using SVM[6] is 95%, and the accuracy of conventional CNN model detection is 96.1%. The specific comparison results are shown in Table 3 below.

TABLE– 3 CNN-RF ALGORITHM COMPARED WITH OTHER ALGORITHMS

Method	Detection accuracy (%)
PSO-SVM	95
BP neural network	93
AdaBoost	89.6
SVM classification	95
Regular CNN	96.1
CNN-RF	97.4

CONCLUSIONS

This paper proposes the CNN-RF algorithm in response to the low efficiency of the previous methods in the feature extraction of potato images with complex data dimensions. Replace the Softmax classifier in the neural network with a random forest, and then select a reasonable combination of parameters based on the test results of the data set. The CNN-RF model realizes the use of convolutional neural networks to extract high-level features from the data set, and the powerful random forest Integrate learning features to detect skin defects. The test results show that the detection accuracy of skin defects reaches 97.4%. From the experimental results, the CNN-RF method can better obtain the features of the data set required for the experiment, improve the detection accuracy, and build a more reasonable neural network model for the detection item through the deep learning method.

In the following research, the parameters of the convolutional neural network and random forest can be further improved and optimized to improve the efficiency of acquiring high-level features of the image. The number of samples in the data set can be expanded to try a deeper neural network. Expand the number of samples in the data set and try a deeper neural network structure to obtain more accurate detection results and reduce detection costs.

REFERENCES:

[1] Liu Wei. The Study of Algorithm of Potato Surface Defect Detection Based on Machine Vision [D].Daqing: Heilongjiang Bayi Agricultural University,2013.
[2] Singh J P . Designing an FPGA Synthesizable Computer Vision Algorithm to Detect the Greening of Potatoes[J]. international journal of engineering trends & technology, 2014, 8(8).
[3] Huang Haojie,Duan Xianhua,Huang Xinchen. Research and improvement of fruits detection based on deep learning [J].Computer Engineering and Applications, 2020, 56（3）:127-133.
[4] Al-Mallahi, A., et al. Detection of potato tub-ers using an ultraviolet imaging-based machinevision system. Biosystems Engineering 105.2(2010): 257-265.
[5] Hao Ming.Study on Potato External Quality Detection Technology Based on Machine Vision[D].Inner Mongolia Agricultural University,2009.
[6] Li Jinwei,Liao Guiping,Jin Jing,et al. Potato surface defect detection method based on gray cut-off segmentation and ten-color model[J]. Transactions of the Chinese Society of Agricultural Engineering,2010,26(10):236-242.
[7] RAZMN，MOUSAVI B S，SOLEYMANI F. A real-time mathe-matical computer method for potato inspection using machine vision［J］. Computers & Mathematics with applications，2012，63(1):268-279.
[8] Cui Shengchun.Research on Potato Shape and External Defects Based on Machine Vision [D]. China University of Mining and Technology,2017.
[9] ZEILERM D,FERGUS R.Visualizing and understanding convolutional networks: European conference on computer vision［C］. Amsterdam: IEEE ,2014: 818-833.
[10] SIMONYAN K,ZISSERMAN A.Very deep convolutional networks for large-scale image recognition: International conference onlearning representations［C］.San Diego: IEEE，2015.
[11] Liu Mengke,Wu Yang,Wang Xun. Implementation of Track Surface Defect Inspection Based on Convolutional Neural Network[J].Modern Computer, 2017(29):65-69.
[12] Fu Wei,Yang Yang. Audio classification methodbased onconvolutional neural network and random forest[J]. Journal of Computer Appli-cations, 2018,38(S2):58-62.
[13] CHEN Y,JIANG H,LI C,et al.Deep feature e-xtraction and classification of hyperspectral images basedon convolutional neuralnetworks[J].IEEE Transactions on Geoscience & Re-mote Sensing,2016,54(10):115-117.
[14] Zhu Huming,Li Peijiao,Li Cheng,et al. Summary of Research on Parallelization of Degree Neural Networks[J].Chinese Journal of Computers, 2018,41(8).
[15] KRIZHEVSKY A,SUTSKEVER I,HINTON E.ImageNet classification with deep convolutional neural networks;International conferenceon neural information processing systems[C].Lake Tahoe:NIPS foundation,2012:1907-1105.
[16] Zhou Zhihua.Machine Learning[M].Beijing:Tsinghua University press,2016.
[17] Fang Kuangnan,Wu Jianbin,Zhu Jianping,et al. A review of Technologies onrandom forests［J］. Statistics & Information Forum,2011,26(3) : 33-38.
[18] FERREIRA A,GIRALDI G.Convolutional neural network approachesto granite tiles classification［J］.Expert systems with applications,2017,84(30): 1-11.
[19] Qiu Yihui,MI Hong.Feature Extraction Method Based on Random Forest and Transduction[J].Journal of Xiamen University, 2010,49(03):333-338.
[20] Zhao Jing,He Dongjian.Research on computer recognition method of fruit shape[J].Transactions of The Chinese Society of Agricultural Engineering, 2001,17(2):165-167.
[21] BARNES M,DUCKETT T,CIELNIAK G,et al.Visual detectionof blemishes in potatoes using minimalist boosted classifiers［J］.Journal of food engineering,2010,98(3):339-346.