Original Article
Food Science and Technology

ISSN 0101-2061 (Print)
ISSN 1678-457X (Online)

DOI: https://doi.org/10.1590/fst.54322

CC BY

Quantitative damage detection of direct maize kernel harvest based on image processing and BP neural network

Yongle ZHU[1], Zheng MA[1*], Min HAN[1], Yaoming LI[1], Licheng XING[2], En LU[1], Hongyan GAO[1]

Abstract

Kernel direct harvesting is the mainstream technology of maize harvesting in the world today, it has significant impact on the maize kernel subsequent food processing. Direct harvest technology in china is not well developed due to the influence of growth environment, agronomy, etc., which leads kernel damage. The kernel damage is necessary studied in maize direct harvesting technology. Therefore, "Zheng Dan 958" was selected, the entrance clearance, export clearance, and cylinder speed as variables to carry out the kernel damage experiment. Processed the image of threshed maize kernel, extracted the crack and boundary characteristics of kernel damage, and established the BP neural network model to study the direct harvesting damage and optimize parameters. The results indicated that kernel damage increased with decreasing threshing clearance and increasing threshing intensity. In a certain threshing clearance, cylinder speed was the key factor affecting kernel damage. The R of model was above 0.95, the accuracy of damage quantitative identification was above 85%. When inlet clearance was 35 mm, outlet clearance was 15 mm, and cylinder speed was 300 rpm, kernel damage was small. Our findings will provide reference for kernel direct harvesting technology and improve harvest quality to meet food processing industry demands.

Keywords: maize harvesting; kernel damage; image processing; BP neural network.

Practical Application: Image feature extraction method used to examine maize kernel damage quantitatively. A BP neural network model for quantifying maize kernel damage was established. The effects of concave clearance and rotating speed on different damage types of kernel were studied. The combination of operation parameters with less damage of direct maize kernel harvest was optimized.

1 Introduction

Maize is the third largest grain crop globally, and in China, is one of the three major grain crops with the highest yield and area. Maize food processing products are indispensable in daily life. From 2008-2018, total maize production increased from 166 million tons to 257 million tons, representing a net increase in 91 million tons, maize planting area increased from 29.93 million ha to 42.13 million ha, representing a net increase in 12.2 million ha. It is expected that future maize production and planting area will continue to increase. Maize is also an important feed and industrial raw material. High production levels are crucial to maintaining grain production, animal husbandry and food security in China and globally. It is expected that the contribution of maize to national grain production will reach 90% by 2020 (National Bureau of Statistics, 2018). Therefore, developing methods for the mechanization of maize harvesting is required to improve kernel harvest quality for meet industrial and food processing demands.

Maize harvesting in developed countries has been mechanized since the end of the 20th century. Because the maize is operated on a large scale and the row spacing is consistent in developed countries, the whole row harvest is adopted. In addition, the moisture content of maize kernels is low during harvesting owing to the use of the one-ripening per year planting system, which has little damage to the directly harvested maize. During harvest, threshing after picking has been adopted, which involves harvesting the maize kernels directly by replacing the maize header of the combine harvester, adjusting the rotation speed of the cylinder and the threshing clearance (Chen et al., 2012). For example, The United States adopts advanced seeding equipment with electronic monitoring, automatic adjustment, and laser positioning to improve the positioning ability of the seeds, so that the seeding strips are more standardized and the control depth is more accurate and consistent. Airplanes are used to fertilize and spray pesticides at some of the larger farms. Generally, the direct harvest of maize kernel begins 2-4 weeks after the black layer or milk line disappears at the top of maize kernel. Field dehydration can reduce the kernel water content to 15-18% and reduce the drying cost (Hiregoudar et al., 2011; Mathanker & Hansen, 2014; Pastukhov et al., 2021).

At present, the main maize kernel harvesting methods in China involve harvesting ears, peeling, drying, threshing, and re-drying, which has high time and labor costs. However, maize picking, peeling, threshing, gathering and straw crushing can be completed at the same time by directly harvesting the maize kernels and greatly decreasing labor intensity while increasing production efficiency. Due to China's national conditions are

Received 29 Apr., 2022
Accepted 22 Jun., 2022
[1]*Key Laboratory of Modern Agricultural Equipment and Technology, Ministry of Education & Jiangsu Province, Jiangsu University, Zhenjiang, Jiangsu, China*
[2]*Jiangsu World Agricultural Machinery Co., Ltd., Yucheng Industrial Park, Danyang, Jiangsu, China*
*Corresponding author: mazheng123@ujs.edu.cn

different, including high water content of maize kernel, inconsistent planting row spacing, and different agronomic requirements in various regions. The maize harvesting technology and equipment in developed countries are only applicable to some regions of China. For example, the Huang-Huai-Hai region is one of the main maizes producing areas in China where two cropping systems are usually employed (Liu et al., 2015). Due to a short farming season, the moisture content of maize kernels is higher than 28% during actual harvest, and the harvest has great damage to maize kernel at maturity stage. It has been pointed out in some studies that the average moisture content of maize kernels in China reaches 26.65%, and the average breakage rate of maize kernels during direct harvesting reaches 8.56%, which is higher than the ≤5% national standard (China Machinery Industry Federation, 2008) high damage rate of maize kernels not only reduces maize quality and commercial price, but also decreases difficulties of drying costs and introduces storage. Evidently, the high kernel breakage rate restricts the promotion of maize direct harvesting technology in China (Fan et al., 2019; Yang et al., 2018).

Many previous studies have investigated the primary and secondary factors of maize kernel damage. Some people studied the effect of mechanical threshing on the quality of maize seed threshed at different moisture contents (MC). The results showed that the damage percentage increased and the seed vigor parameters decreased with increasing seed MC during threshing in both cultivars (Gu et al., 2019; Petkevichius et al., 2008). Through experimental analysis, concluded that different threshing concave structures would have an important effect on maize kernel breakage during threshing (Pužauskas et al., 2016; Steponavičius et al., 2018). The maize threshing test was conducted, their results indicated that the breaking rate increased as water content increased and the threshing cylinder speed significantly affected the breaking rate (Srison et al., 2016). Some scholars discussed the effects of corn variety, moisture content and ear type on kernel mechanical crack (Zhang et al., 2019). Some people studied the correlation between key factors such as thresher speed, concave clearance and feeding speed and crushing entrainment loss during high humidity maize harvest. The results showed that the importance of drum speed, feeding speed and concave clearance on corn crushing rate and entrainment loss rate decreased in turn (Zhu et al., 2020). The mechanism underlying the effect of water content was explored on maize threshing, their results highlighted grain breakage strength and threshing force as major factors (Gao et al., 2011). The difference of grain water content was studied before and after maize harvest, then found that the grain water content after harvest was positively correlated with the water content and the crushing rate before harvest. The results showed that the higher water content of crops led to the easy crushing of kernel (Li et al., 2021). The study that the damage rate of maize kernels with high moisture content on the surface was significantly higher during threshing and separation. Therefore, the drum speed and concave clearance were optimized in the threshing link of maize kernels with high moisture content to reduce the damage rate of maize kernels (Fu et al., 2020).

Overall, previous research has indicated that maize moisture content, cylinder speed, feeding mode, feeding amount, and threshing clearance affect maize kernel breakage and un-threshing rates. However, most previous studies focused on the threshing mechanism, overall breakage rate of direct harvesting, fracture morphology and related influencing factors, which rarely damage individual maize kernels. We consider that maize kernel damage should be quantified and characterized before undertaking specific investigations of the causes and primary and secondary factors of maize damage.

The combination of image processing technology and machine learning has satisfactory speed and accuracy in grain characteristic analysis, detection, classification, and evaluation (Chen & Yu, 2021a, b), which provides an effective tool for studying grain damage detection and evaluation. Some scholars have established a vision system based on image processing technology to detect and evaluate the appearance quality and varieties of rice, and accurately distinguish the whole grain and broken grain of rice (Payman et al., 2018). Distinguishing features were extracted through image processing, and support vector machine (SVM) was used to classify and evaluate the quality and defects of different rice (Mittal et al., 2019). The size and shape characteristics of lentils were measured by image processing technology, and the shelling efficiency of lentils was further predicted by the regression model based on the measured values (Shahin et al., 2012). An image processing system (MATLAB) was proposed to judge the quality of grain. The grain samples were classified according to color, shape and size, the impurities such as stones, damaged seeds and broken particles were identified (Sharma & Sawant, 2017). Some people proposed a method based on digital image analysis, which could automatically quantify the percentage of defective corn and highlight the defective maize area in the image (Orlandi et al., 2018). An image processing and feature extraction algorithm of barley grain automatic detection system was proposed and optimized, which was an important part of barley grain defect classification system (Kociołek et al., 2017). Some scholars used texture analyzer and artificial neural network to classify and recognize the texture features of test objects (Zhu & Wu, 2019). Some researchers indicated that artificial neural network was used to classify and identify the test objects by material components (Pranoto et al., 2022) or predict the characteristics of the test objects quality (Abdelbasset et al., 2022). Some scholars extracted the color features of corn leaves based on image processing, and used artificial neural network to classify the maturity of maize (Peter et al., 2017). Previous studies have shown that image processing and neural network technology have strong application potential in the research of crop characteristics and feature extraction and recognition.

The above research mainly used image processing and machine learning technology to realize the automatic evaluation of corn quality and the recognition of corn varieties. Although the results of previous studies were sufficient for calculating the total damage rate of maize grains in direct harvesting, they were insufficient for quantifying damage in a single maize kernel. In the present study, samples were collected from direct harvesting field experiments to extract maize kernel damage under different conditions by image processing, the quantitative model of maize kernel damage was established based on BP neural network, and the parameters were optimized. This will provide an important help for the development of maize kernel direct harvest technology, and improve kernel harvest quality to satisfy food processing industry demands.

2 Materials and methods

2.1 Materials and equipment

Damaged maize kernel samples were collected in Shiyezhou, Zhenjiang city, Jiangsu province, China (32°12'21.4"N, 119°18'34.8"E) in October 2018. The maize variety was "Zhengdan 958", which has an average growth period of 96 days, an average quality of 264 g per ear, a kernel moisture content of 27.75%, and an average of 100 g of 100 grains. The test equipment included a maize kernel combine harvester (Figure 1a), with an engine power of 117 kW, and equipped with a maize picking head with 6 rows and a width of 3990 mm. A schematic diagram of the combine harvester and a partially enlarged view of both sides were shown in Figure 1b. Adjustment of the cylinder speed was realized by hydraulic stepless speed change. The external drive and speed regulating device of the tangential flow threshing cylinder were located on the right side of the machine. The clearance adjusting device of the tangential concave was located on the left side of the machine.

Some maize kernel samples were collected from each group (Figure 1c), and 5 damaged maize kernels (Figure 1d) were randomly selected for specificity analysis. The image acquisition system was set up as shown in Figure 1e. The system comprised a computer and USB digital microscope (UMU1000XIR). The digital microscope and computer were connected by the USB cable, and the focus could be adjusted by turning the focusing roller. The digital microscope was linked to the software AMCap and measurements. A darker background could improve imaging owing to the inherent color of the maize kernels, namely yellow or yellowish-white. Therefore, images were acquired in front of a black background with an LED annular light source. The focal length and sample position were adjusted to optimize imaging for the first image, and then fixed parameters were convenient for subsequent imaging. Next, images of 30 damaged maize kernels of samples for 6 groups were captured in turn, then files were numbered and stored.

Table 1. Field test operation parameters.

Test group number	Entrance clearance (mm)	Export clearance (mm)	Cylinder speed (rpm)
1	35	15	300
2	35	15	350
3	30	10	300
4	30	10	350
5	25	5	350
6	25	5	300

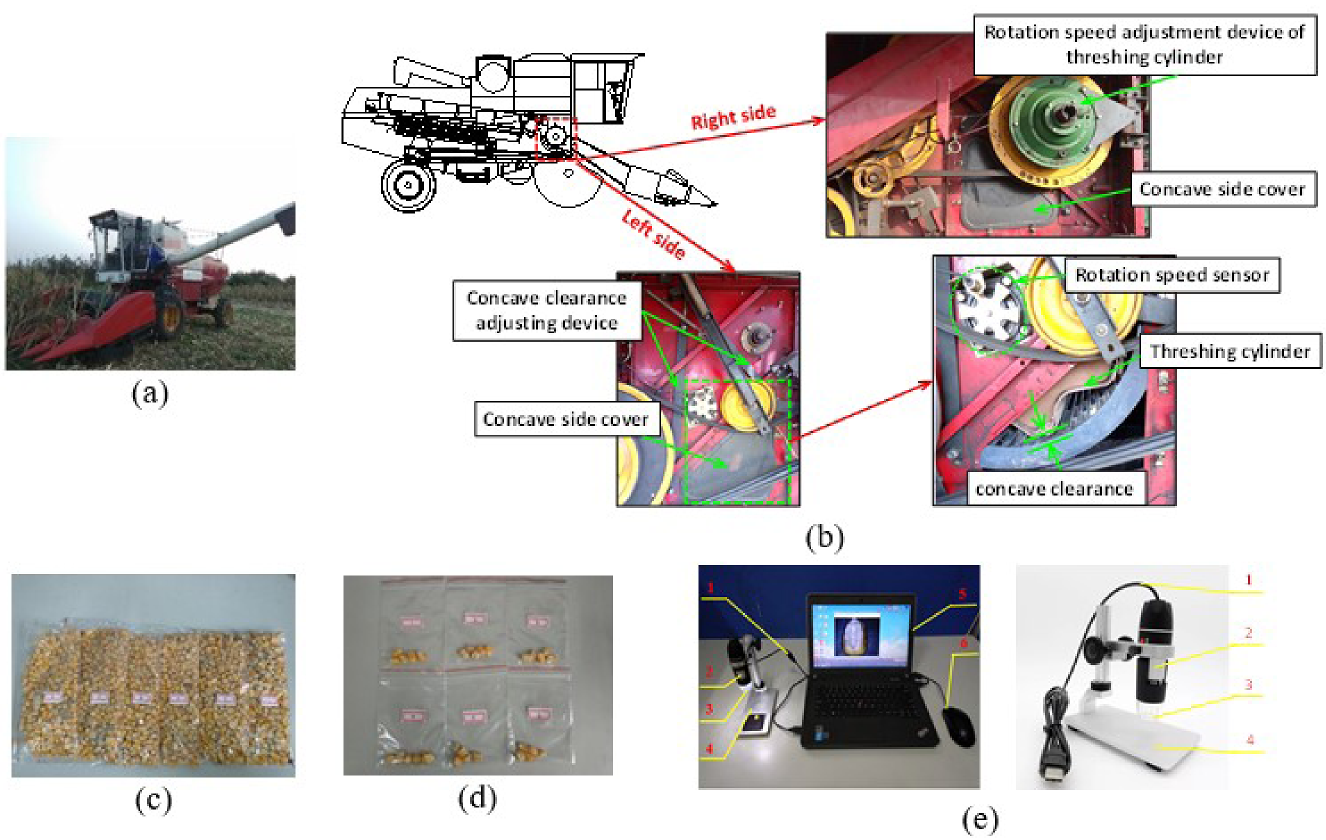

Figure 1. Equipment and materials: (a) Maize kernel combine harvester, (b) Schematic diagram and partial enlargement of the maize kernel combine harvester, (c) Maize kernel samples, (d) Five damaged kernel samples in each group, (e) Image acquisition system (1. USB cable, 2. Focusing roller, 3. LED lamp cover, 4. Metal base, 5. Computer, and 6. Mouse).

6 groups of field experiments with different operation parameters (Table 1) were designed to compare the differences in kernel damage from changing one parameter and keeping the other parameters the same.

2.2 Image preprocessing methods and establishment of BPNN kernel quantitative damage model

The software *Measurement* was used to measure the maize kernel images preliminarily and roughly, which was brought by UMU1000XIR. Firstly, the average number of pixels corresponding to 1 mm was obtained by measuring the calibration scale several times. Then, the maize crack was measured roughly, and the maximum length was recorded (Figure 2a).

Images were preprocessed using grayscale, binarization, filtering and morphological operations (Figure 2b) (Li et al., 2009). A reasonable gray image could be obtained using the weighted average method for RGB (Figure 2b).

a) The gray thresh function provided was used to find the appropriate image threshold using the maximum variance between clusters. Then the optimal binary image was obtained by manual adjustment (Figure 2b);

b) Some noise contained in the image after binarization was removed using median filtering technology, the filter window was 3 × 3 (Figure 2b);

c) The imdilate function was used to expand or the imerode function was used to corrode the binary image. The choice between expansion (Figure 2b);

d) or corrosion (Figure 2b);

e) depended on whether the main crack could be highlighted.

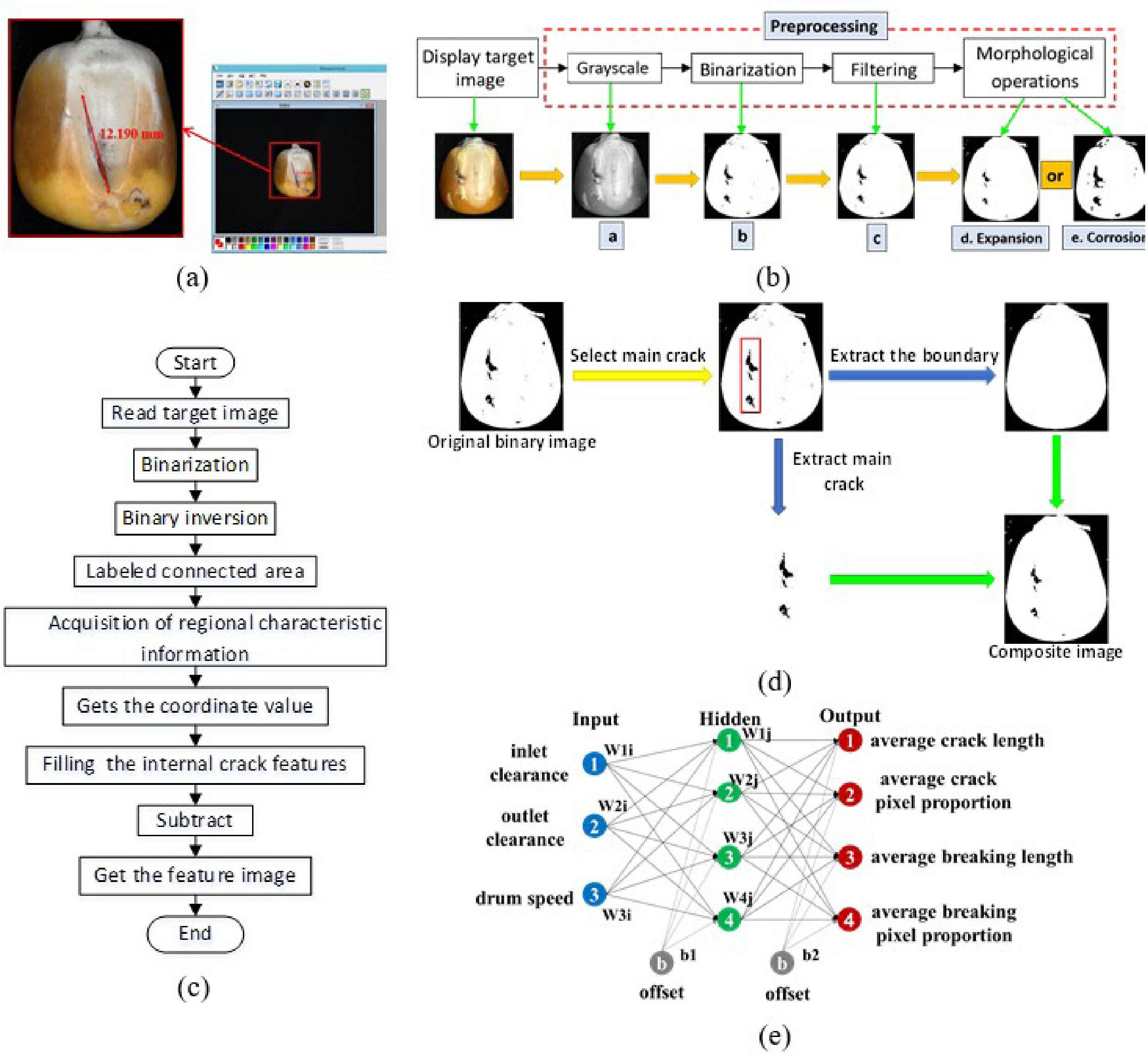

Figure 2. Image processing and BPNN model structure: (a) Crack length measurement, (b) Image preprocessing flow chart, (c) The flow chart of feature extraction process, (d) Image feature extraction, and (e) BPNN model.

The clear cracks and boundaries were extracted and then synthesized to directly calculate the pixel area to obtain the contour area. A flow chart of the feature extraction process was shown in Figure 2c. The crack image and boundary image extracted by the steps in the flowchart were shown in Figure 2d. The pixel area was further counted by region props function. The kernel contour area and damage area were calculated.

The quantitative model of maize kernel damage established for BPNN in MATLAB 17.0 (Figure 2e). The total number of samples had 6 (the average value of 5 damaged kernels in each group), the training set, test set, and verification set account for 70%, 15%, and 15% respectively. The model was composed of 3 input, 4 output, and 4 hidden layer units. The data of 6 groups for threshing drum operating parameters (Inlet clearance, outlet clearance, and drum speed) were the input matrix data of the neural network. According to the image processing (Grayscale, binarization, filtering, and expansion / corrosion), the crack image and contour image were obtained (Figure 2d). Then the crack image was inversed, the bwlabel function marked the connection area of the crack inversion image and contour image, and the regional feature information (Crack / fracture length, crack / fracture area, and grain contour area) were acquired by the regionprops function. The ratio of crack / fracture area to grain contour area were calculated, then obtained the crack pixel proportion and breaking pixel proportion respectively. The image processing data of 5 grains in each group were averaged to obtain 6 groups of average data, which formed the output matrix of the neural network (Average crack length, average crack pixel proportion, average breaking length, and average breaking pixel proportion). According to "the number of neurons in the hidden layer is about two-thirds of the sum of the number of neurons in the input layer and the output layer", the number of hidden layers was determined to be 4 or 5. After many times of training, the effect was better when the number of the hidden layer was 4. Levenberg-Marquardt was selected as the training function. The prediction error would be reduced in reverse by automatically adjusting the weight and threshold. The prediction model was established, and the output of the prediction model were obtained and compared with experiment data.

3 Results and discussions

3.1 Overall analysis of kernel damage

The change in threshing strength was caused by the different test conditions of the respective groups during the field test, which leaded to difference in damage intensity. Some kernels were only slightly cracked, while others were broken. The number of cracked kernels gradually decreased, the proportion of broken kernels gradually increased as the threshing clearance decreased, and the threshing strength increased at the same cylinder rotation speed (Figure 3a). We found that the proportion of broken kernels increased with increasing rotational speed by comparing groups 1-2 and 3-4 with the same threshing clearance. The kernel breakage rate increased with increasing cylinder rotation speed when threshing clearance was fixed. There were fewer cracked kernels in the high-speed rotation group than in the low-speed rotation group, but the ratio of broken kernels was larger in the former than the latter, because the threshing clearance and the cylinder rotation speed were different (Figure 3a). Thus, the change in cylinder rotation speed was a key factor affecting the kernel breakage rate when the threshing clearance and the cylinder rotational speed changed within a certain range. The order of threshing intensity was: 5 > 4 > 6 > 2 > 3 > 1.

The damage types observed in the collected maize kernel samples mainly included cracks, breakages, or a combination of both. The maximum crack length and breakage area were measured by Measurement, and a broken line graph based on the calculated mean and variance with error bars (Figure 3b). The order of average values for crack or breakage length in each group was 1 < 3 < 2 < 6 < 4 < 5. This indicated that kernel damage becomes increasingly serious with increasing threshing intensity. The proportion of damaged area to total area of each kernel in the six groups of samples was calculated, and then the average of the proportions was calculated (Figure 3c). The order of proportions was: 5 > 4 > 6 > 2 > 3 > 1. The larger proportion represented a longer crack or that more parts of the kernel were broken, which meant the damage was more serious. We concluded that decreasing the threshing intensity properly could effectively decrease the damage.

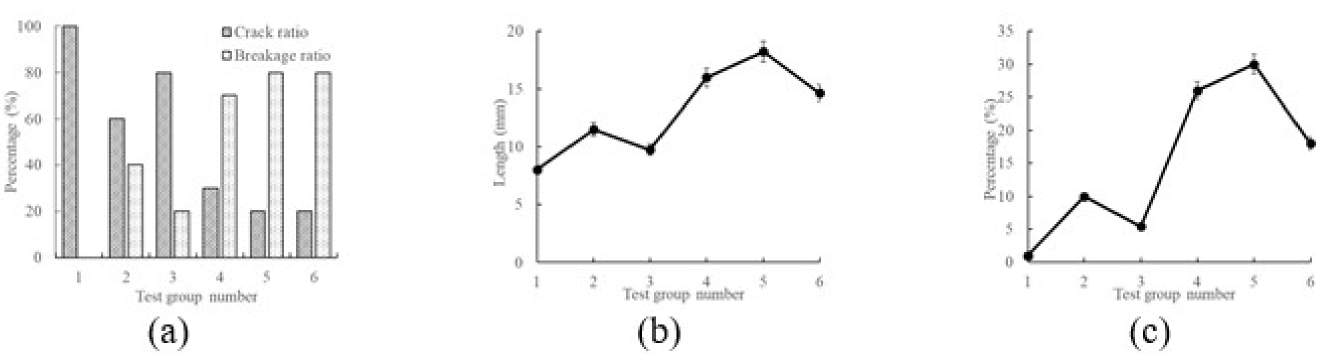

Figure 3. Overall analysis of grain damage: (a) The ratio of cracked kernels to broken kernels, (b) Total mean length of damage in each group, and (c) The total mean of the proportion of pixels in each group of damage to the total pixels.

3.2 Model of kernel quantitative damage

In Figure 4a, when the BPNN model converged in 3 epochs, the training ended. the BPNN error was mainly concentrated -0.024 ~ 0.006, the error was small (Figure 4b). The R was above 0.95 in Figure 4c, which meant that the established model had high reliability.

In Table 2, it was found that there were large errors in N1 (groups 1, 2), N2 (groups 6), and the errors of other groups were around 10% under different combinations of operating parameters. The accuracy of BPNN kernel damage quantitative model in judging all kernel damage characteristics was above 85%, the BP neural network model of kernel quantitative damage was certainly feasible and relatively accurate and reliable.

3.3 Analysis of kernel crack and breakage length and pixels

The cracked and broken kernels were analyzed separately. The means of crack length were used to plot the graph in Figure 5a. The order of average crack length in each group was 1 < 3 < 2 < 4 < 5 < 6 (Figure 5a). The average crack length of groups 1, 2, and 3 was similar, because the changes in threshing intensity were small. Because the cylinder rotation speed increased and the threshing clearance of groups 5 and 6 decreased. There were significantly more broken kernels in groups 5 and 6 than cracked kernels, the minimum threshing clearance resulted in a relatively large threshing intensity. As shown in Figure 5b, we concluded the ratios that the maximum cracked area was about one fifth of the total area. The cracks in groups 1-3 was usually from abrasion or slight cracking due to the relatively weak threshing intensity. the total area of cracks was relatively small. The cracks in groups 4 and 5 were relatively large due to high threshing intensity, leading to a high proportion of cracks, it was not recommended to directly harvest maize kernel under the parameters.

The only form of damage observed in this group 1 was cracks. The maximum length was relatively small in the case of some small breakages in the crown or side of the kernel. As shown in Figure 5c, groups 2-4, and 6 were similar in maximum height. The length of group 5 was overall large since the cylinder rotation speed was relatively large, and the threshing clearance was small leading to breakages. In order to further analyze and judge the size of the breakage area, and thus the damage level was obtained (Figure 5d). The trend was basically the same as that seen in Figure 5c, but with evident differences between the groups in the chart. Kernel breakages increased as threshing intensity increased, and the proportion was larger as a result. The difference range between BPNN model and test results was 0%-10.4% (Figure 5a), 0.02%-1.52% (Figure 5b), 0%-20.5% (Figure 5c), and 0%-6.9% (Figure 5d). This showed the prediction results of BPNN for different kernel damage categories and their quantification were good, and the kernel damage quantification model was relatively reliable. When the inlet clearance was 30-35 mm, the outlet clearance was 10-15 mm and the drum speed was 300-350 rpm under different combinations of operating

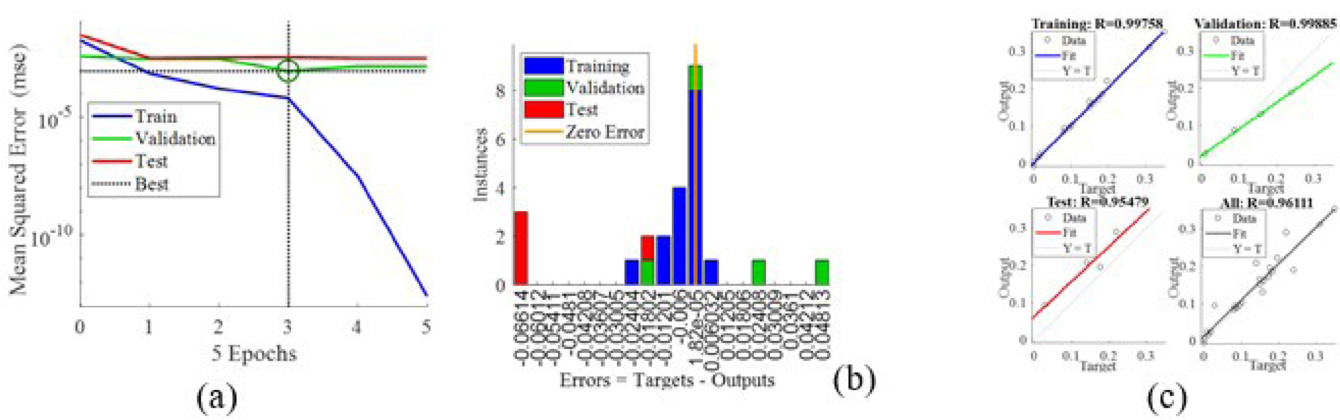

Figure 4. BPNN model training results. (a) Performance; (b) Error; (c) Regression.

Table 2. Comparison of kernel quantitative damage between BPNN model and experiment.

Number	Operating parameters			Experiment				BPNN model			
	Inlet clearance (mm)	Outlet clearance (mm)	Drum speed (rpm)	K_1 (mm)	N_1 (%)	K_2 (mm)	N_2 (%)	K_1 (mm)	N_1 (%)	K_2 (mm)	N_2 (%)
1	35	15	300	8.00	1.20	0.00	0.00	8.30	1.56	0.00	0.40
2	35	15	350	8.67	0.80	15.67	24.00	8.70	2.32	13.00	18.90
3	30	10	300	8.33	1.80	15.00	19.67	9.30	2.33	16.50	22.10
4	30	10	350	15.00	9.50	16.00	31.00	15.00	9.39	16.00	31.00
5	25	5	350	17.33	10.20	18.33	35.00	17.20	10.18	18.50	35.20
6	25	5	300	17.67	2.90	14.00	22.00	19.50	5.30	16.90	28.90

Note: K_1: average crack length; N_1: average crack pixel proportion; K_2: average breaking length; N_2: average breaking pixel proportion.

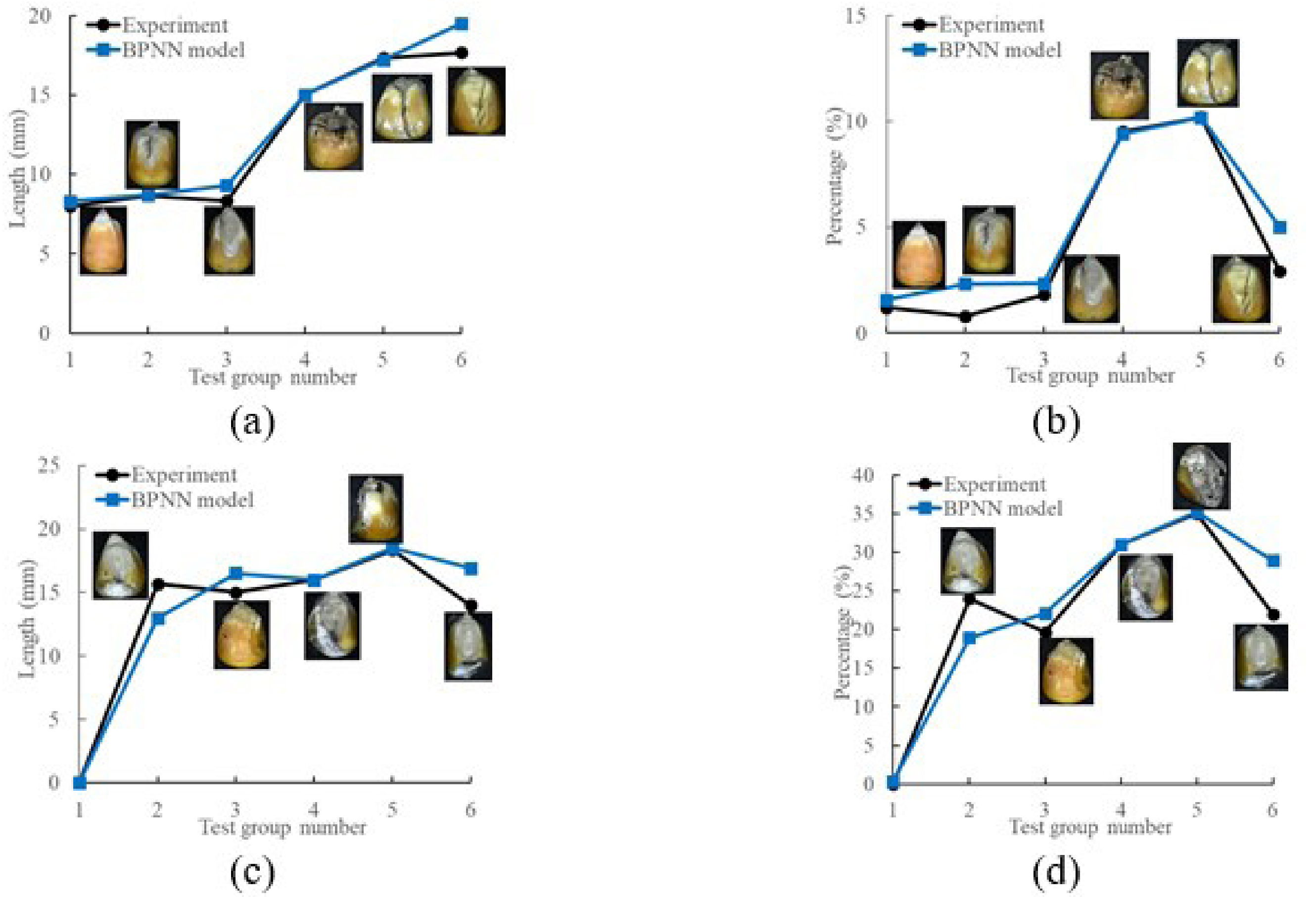

Figure 5. Quantification of grain damage characteristics: (a) Average crack length of each group, (b) The average proportion of cracked pixels to total pixels, (c) Lengths of the breakage area, and (d) The ratio of pixels in the breakage area to total pixels.

parameters, the damage length and damage area of maize kernel surface in groups 1, 2 and 3 were small. The inlet clearance was 35mm, the outlet clearance was 15mm, and the drum speed was 300 rpm, the kernel surface damage was less.

4 Conclusions

In order to provide assistance for maize kernel direct harvesting technology, reduce kernel damage, and improve harvest quality to content food processing industry demands. In this study, we extracted the key features based on the imaging method, established the quantitative model of kernel damage under different operating parameters through BPNN, and optimized the parameters. Our main findings can be summarized as follows:

(1) Rotation speed was the key factor affecting the kernel breakage rate in the process of maize threshing. The length and width of cracks increased with increasing threshing intensity. the area and maximum length of breakage area increased with increasing threshing intensity;

(2) The R of the kernel damage quantitative model was more than 0.95, the accuracy was above 85%. When the inlet clearance was 35 mm, outlet clearance was 15 mm, and drum speed was 300 rpm, the damage of maize kernel was small;

(3) We only collected relatively few samples to test the feasibility of image and machine learning technology for quantitative research on kernel damage. Therefore, increasing the amount of sample is important for research aiming to further quantitative research on damage.

Acknowledgements

This work is supported by National Natural Science Foundation of China [51975256], Jiangsu Modern Agricultural Machinery Equipment and Technology Demonstration and Promotion Project [NJ2021-07], a project funded by the Priority Academic Program of the Development of Jiangsu Higher Education Institutions [PAPD], Jiangsu Province and Education Ministry Co-sponsored Synergistic Innovation Center of Modern Agricultural Equipment [XTCX2011].

References

Abdelbasset, W. K., Nambi, G., Elkholi, S. M., Eid, M. M., Alrawaili, S. M., & Mahmoud, M. Z. (2022). Application of neural networks in predicting the qualitative characteristics of fruits. *Food Science and Technology*, 42, e118821. http://dx.doi.org/10.1590/fst.118821.

Chen, T. C., & Yu, S. Y. (2021a). The review of food safety inspection system based on artificial intelligence, image processing, and robotic. *Food Science and Technology*, 42, e35421. http://dx.doi.org/10.1590/fst.35421.

Chen, T. C., & Yu, S. Y. (2021b). Research on food safety sampling inspection system based on deep learning. *Food Science and Technology*, 42, e29121. http://dx.doi.org/10.1590/fst.29121.

Chen, Z., Hao, F. P., Wang, D. F., Su, W. F., & Cui, J. W. (2012). Development of technology and equipment of corn harvester in China. *Nongye Jixie Xuebao*, 43(12), 44-50. [In Chinese].

China Machinery Industry Federation, General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China, Standardization Administration of the People's Republic of China. (2008). *GB/T 21962-2008: technical conditions for maize harvesting machinery.* Retrieved from https://kns.cnki.net/kcms/detail/detail.aspx?FileName=SCSF00065679&DbName=SCSF

Fan, C. L., Cui, T., Zhang, D. X., & Qu, Z. (2019). Design of feeding head spiral angle longitudinal axis corn threshing separation device based on EDEM. In *Proceedings of the 2019 ASABE Annual International Meeting*. St. Joseph, Michigan: American Society of Agricultural and Biological Engineers. http://dx.doi.org/10.13031/aim.201900077

Fu, J., Yuan, H. K., Zhang, D. P., Chen, Z., & Ren, L. Q. (2020). Multi-objective optimization of process parameters of longitudinal axial threshing cylinder for frozen corn using RSM and NSGA-II. *Applied Sciences (Basel, Switzerland)*, 10(5), 1646. http://dx.doi.org/10.3390/app10051646.

Gao, L. X., Li, F., Zhang, X. W., Zhang, Y. L., Liu, X., & Jiao, W. P. (2011). Mechanism of moisture content affect on corn seed threshing. *Nongye Jixie Xuebao*, 42(12), 92-42. [In Chinese].

Gu, R. L., Huang, R., Jia, G. Y., Yuan, Z. P., Ren, L. S., Li, L. I., & Wang, J. H. (2019). Effect of mechanical threshing on damage and vigor of maize seed threshed at different moisture contents. *Journal of Integrative Agriculture*, 18(7), 1571-1578. http://dx.doi.org/10.1016/S2095-3119(18)62026-X.

Hiregoudar, S., Udhaykumar, R., Ramappa, K. T., Shreshta, B., Meda, V., & Anantachar, M. (2011). Artificial neural network for assessment of grain losses for paddy combine harvester a novel approach. In *International Conference on Logic, Information, Control and Computation*. Berlin, Heidelberg: Springer. http://dx.doi.org/10.1007/978-3-642-19263-0_27

Kociołek, M., Szczypiński, P. M., & Klepaczko, A. (2017). Preprocessing of barley grain images for defect identification. In *2017 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA)*. USA: IEEE. https://doi.org/10.23919/SPA.2017.8166894.

Li, L. L., Ming, B., Xue, J., Gao, S., Wang, K. R., Xie, R. Z., Hou, P., & Li, S. K. (2021). Difference in corn kernel moisture content between pre-and post-harvest. *Journal of Integrative Agriculture*, 20(7), 1775-1782. http://dx.doi.org/10.1016/S2095-3119(20)63245-2.

Li, W., Yu, Z. D., Chen, T., & Xun, Y. (2009). Identification and Detection for Surface Damages of Cottonseed Based on Morphology. *Nongye Jixie Xuebao*, 40(04), 169-172. [In Chinese].

Liu, Z., Tang, R. J., Zhao, Z. L., Li, S. M., Zhu, D. H., & Zhang, X. D. (2015). Regionalization of maize cultivars cultivated in Huang-Huai-Hai Plain of China. *Nongye Jixie Xuebao*, 46(08), 281-288. [In Chinese].

Mathanker, S. K., & Hansen, A. C. (2014). Harvesting system design and performance. In Y. Shastri, A. Hansen, L. Rodríguez, & K. Ting (Eds.), *Engineering and science of biomass feedstock production and provision* (pp. 85-139). New York: Springer. https://doi.org/10.1007/978-1-4899-8014-4_5.

Mittal, S., Dutta, M. K., & Issac, A. (2019). Non-destructive image processing based system for assessment of rice quality and defects for classification according to inferred commercial value. *Measurement*, 148, 106969. http://dx.doi.org/10.1016/j.measurement.2019.106969.

National Bureau of Statistics. (2018). *Announcement of the National Bureau of Statistics on Grain Yield in 2018*. Beijing: National Bureau of Statistics China. Retrieved from http://www.stats.gov.cn/tjsj./zxfb/201812/t20181214_1639544.html

Orlandi, G., Calvini, R., Foca, G., & Ulrici, A. (2018). Automated quantification of defective maize kernels by means of multivariate image analysis. *Food Control*, 85, 259-268. http://dx.doi.org/10.1016/j.foodcont.2017.10.008.

Pastukhov, A. G., Bakharev, D. N., & Parnikova, T. V. (2021). Differentiated threshing of seed corn with minimal grain crushing. In *IOP Conference Series: Earth and Environmental Science*. Bristol: IOP Publishing. http://dx.doi.org/10.1088/1755-1315/659/1/012095

Payman, S. H., Bakhshipour, A., & Zareiforoush, H. (2018). Development of an expert vision-based system for inspecting rice quality indices. *Quality Assurance and Safety of Crops & Foods*, 10(1), 103-114. http://dx.doi.org/10.3920/QAS2017.1109.

Peter, A., Abdulkadir, S., & Abdulhamid, U. F. (2017). Detection of optimum maturity of maize using image processing and artificial neural networks. *TheScientificWorldJournal*, 12(2)

Petkevichius, S., Shpokas, L., & Kutzbach, H. D. (2008). Investigation of the maize ear threshing process. *Biosystems Engineering*, 99(4), 532-539. http://dx.doi.org/10.1016/j.biosystemseng.2008.01.002.

Pranoto, W. J., Al-Shawi, S. G., Chetthamrongchai, P., Chen, T.-C., Petukhova, E., Nikolaeva, N., Abdelbasset, W. K., Yushchenko, N. A., & Aravindhan, S. (2022). Employing artificial neural networks and fluorescence spectrum for food vegetable oils identification. *Food Science and Technology*, 42, e80921. http://dx.doi.org/10.1590/fst.80921.

Pužauskas, E., Steponavičius, D., Jotautienė, E., Petkevičius, S., & Kemzūraitė, A. (2016). Substantiation of concave crossbar shape for corn ear threshing. *Mechanics*, 22(6), 553-561. http://dx.doi.org/10.5755/j01.mech.22.6.16370.

Shahin, M. A., Symons, S. J., & Wang, N. (2012). Predicting dehulling efficiency of lentils based on seed size and shape characteristics measured with image analysis. *Quality Assurance and Safety of Crops & Foods*, 4(1), 9-16. http://dx.doi.org/10.1111/j.1757-837X.2011.00119.x.

Sharma, D., & Sawant, S. D. (2017). Grain quality detection by using image processing for public distribution. *In 2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*. New York: IEEE. http://dx.doi.org/10.1109/ICCONS.2017.8250640

Srison, W., Chuan-Udom, S., & Saengprachatanarak, K. (2016). Effects of operating factors for an axial-flow corn shelling unit on losses and power consumption. *Agriculture and Natural Resources*, 50(5), 421-425. http://dx.doi.org/10.1016/j.anres.2016.05.002.

Steponavičius, D., Pužauskas, E., Špokas, L., Jotautienė, E., Kemzūraitė, A., & Petkevičius, S. (2018). Concave design for high-moisture corn ear threshing. *Mechanika*, 24(1), 80-91. http://dx.doi.org/10.5755/j01.mech.24.1.18345.

Yang, L. Q., Wang, W. Z., Zhang, H. M., Li, L. H., Wang, M. M., & Hou, M. T. (2018). Improved design and bench test based on tangential flow-transverse axial flow maize threshing system. *Nongye Gongcheng Xuebao*, 34(1), 35-43. [In Chinese].

Zhang, X. W., Yi, K. C., Liu, X. D., & Zhao, X. G. (2019). Analysis on the generating mechanism and causes of stress cracks in maize seed. *Journal of Yangtze University*, 16(5), 59-68. [In Chinese].

Zhu, L., & Wu, W. (2019). Artificial neural network for determining the hedonic score of texture of and distinguishing different grades of ham sausages. *Food Science and Technology*, 40(1), 46-54. http://dx.doi.org/10.1590/fst.31018.

Zhu, X. L., Chi, R. J., Du, Y. F., Qin, J. H., Xiong, Z. X., Zhang, W. T., & Li, X. Y. (2020). Experimental study on the key factors of low-loss threshing of high-moisture maize. *International Journal of Agricultural and Biological Engineering*, 13(5), 23-31. http://dx.doi.org/10.25165/j.ijabe.20201305.5653.