

To cite this article: TanJinting (2023). IMPERFECT GRAIN IDENTIFICATION OF WHEAT BASED ON IMAGE PROCESSING AND CNN, International Journal of Education and Social Science Research (IJESSR) 6 (3): 50-57
Article No. 772, Sub Id 1231

IMPERFECT GRAIN IDENTIFICATION OF WHEAT BASED ON IMAGE PROCESSING AND CNN

TanJinting

Shenyang Ligong University

DOI: <https://doi.org/10.37500/IJESSR.2023.6305>

ABSTRACT

In order to realize the rapid, comprehensive and nondestructive identification of imperfect grains of wheat, image processing and CNN recognition methods can be applied by collecting the imperfect grains and perfect grains mentioned in the national quality standard of wheat. Image processing can make the output image have better effect, which is convenient for image analysis and recognition. Image preprocessing includes image acquisition, graying, median filtering, image segmentation and so on. The classical classification network LeNet-5 in convolutional neural network (CNN) takes the preprocessed image as the input and adds batch normalization (BN). BN algorithm can speed up the decline speed of training gradient, increase the convergence speed of the model, and increase the stability of the model. It can recognize the image and evaluate the performance with the accuracy of the test set. It avoids complex feature extraction steps and effectively improves the recognition rate of wheat grains, which is of great significance to the intelligent detection and recognition of wheat.

KEYWORDS: Imperfect grain of Wheat Image processing, CNN Batch Normalization (BN)

INTRODUCTION

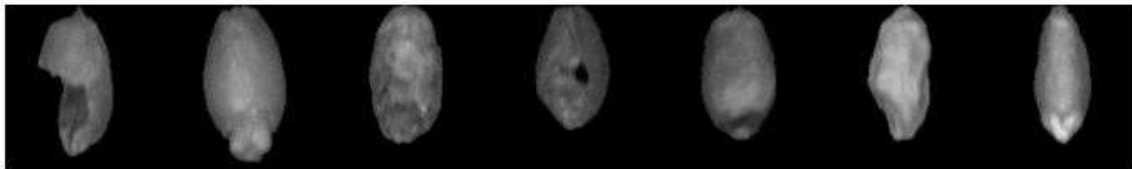
Wheat imperfect grain refers to wheat grain with certain damage, and there are five types of damage, namely disease plaque grain (gibberella grain and black germ grain), germination grain, mildew grain, insect erosion grain, broken grain. Its essence is wheat whose embryo or endosperm has been damaged or caused by physiological changes and defects caused by microorganisms, and still has certain use value. Wheat imperfect grain is an important indicator of wheat quality measurement, and correct and accurate detection and identification of wheat imperfect grain is conducive to ensuring China's food security and market circulation^[1].

At present, because the detection of imperfect wheat grains mainly relies on manual detection, but the manual inspection and detection error is large and the efficiency is low, with the rapid development of computer technology and artificial intelligence, the research on intelligent identification of imperfect wheat grains based on image processing and CNN is becoming more and more extensive. The method of CNN deep model avoids feature extraction algorithms that rely on prior knowledge, and it has the advantages of independent feature learning and self-improvement. It

provides an important detection and identification method for the rapid and intelligent automatic identification of imperfect wheat grains and the determination of wheat grade.

1. Wheat grain image acquisition

Wheat grain images are the most basic source of data for image processing, and this step will directly affect the accuracy of the subsequent processing process. The images of six types of wheat disease grains (gibberella disease grains and nigra grains), germinated grains, mildew grains, insect erosion grains, and broken grains are shown in Figure 1. The wheat grain is placed on the type orifice plate, and the brush located above the type orifice plate carries out linear movement under the drive device to evenly spread the wheat grain in the type hole of the type orifice plate, and remove the excess grain, and obtain the wheat grain image through the fixed CCD camera^[2]. Clear and non-sticking wheat grain images are stored in computer memory, and then a certain algorithm is used to extract the characteristics of the images to facilitate the extraction of useful information.



(a) Broken grain (b) Germination grain (c) Mildew granule (D) Insect etching grain (e) Black germ grain (f) Gibberella grain (g) Complete grain

Fig. 1 Image of imperfect grain species of wheat

2. Seed image preprocessing

Grain image preprocessing is based on the needs of detection and identification, highlighting the useful information of wheat grain images, facilitating feature extraction, and deleting redundant information. The overall distribution of wheat grain color images is uneven, and image preprocessing is required, first after grayscale processing and image enhancement, then threshold segmentation, morphological processing and other operations are carried out to eliminate the noise interference caused by background and ambient light, and finally the smallest external rectangle method is used to segment to obtain single-grain images, and all images are dimensionally unified. The original image is free of noise interference and the image quality is enhanced^[3].

2.1 Grayscale processing

When the image is recognized and processed, the first thing to do is grayscale processing, the red, green and blue channels constitute a color image, the color image has a large amount of information, occupying more memory space, but in fact contains a limited amount of useful information, because the color cannot reflect the characteristics of the picture, texture, just the grayscale image to modify,

grayscale map is a special color image, grayscale change range is 0-255, containing brightness level information, so there will be excess calculations when computer processing, as shown in Figure 2 (a), (b) Raw and grayscale images are shown.

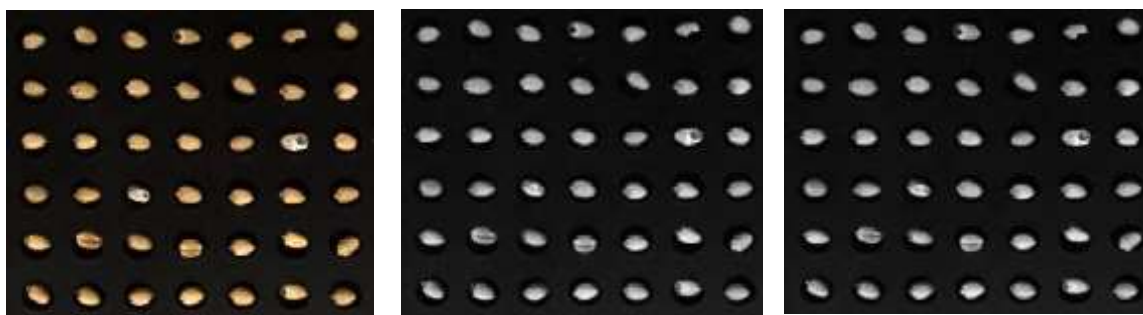
Image grayscale commonly used component method, maximum value method, average method, weighted average method, this paper uses the weighted average method. According to the different sensitivity of the human eye to the three colors and some other factors, different coefficients are used to weight the three components of RGB and then average, and a more reasonable grayscale image can be obtained than the first four, the formula is as follows:

$$\text{Gray}(i, j) = 0.299 * R(i, j) + 0.578 * G(i, j) + 0.114 * B(i, j)$$

2.2 Image Enhancement

Image enhancement can be divided into spatial domain enhancement and frequency domain enhancement, among which grayscale histogram equalization is a very effective spatial domain enhancement technique to make the image uniform or basically uniform. Median filtering enhancement is commonly used in frequency domain enhancement, which is a nonlinear smoothing filtering technique that effectively filters out noise and has relatively good edge preservation characteristics^[4].

The median filter is a statistically sorted nonlinear spatial filter, which first sorts the pixels covered by the filter template, and then replaces the central pixel value of the sorting result with the intermediate value of the sorting result, which has a strong filtering effect on the noise, plays the purpose of image enhancement, and effectively saves the details and edge information of the image, as shown in Figure 2(c), the noise is obviously filtered.



Raw image

(b) Grayscale image

(c) Median filtered image

Figure 2 Original image, grayscale plot and median filtered image

2.3 Image segmentation

The characteristics of fast calculation speed, stable performance, simple and diverse methods, and strong applicability of threshold segmentation have become a common

method used in agricultural products. Especially when there is a big difference between the gray value of the physical object and the background gray of the image, it can simplify the processing process and simplify the data. The principle of segmentation is to divide the graphic into several parts according to the grayscale change of the figure ^[5]. An image has a background image, a target image, a noise image, etc., and the gray level between the object and the background is not the same, and the objects representing different areas are divided according to the change of the gray scale of the image. Among them, there are many ways to divide the threshold, and the most commonly used methods are bimodal, iterative, OTSU, discriminant analysis, etc. The OTSU algorithm is simple, computationally efficient, and not affected by brightness, contrast, etc., as shown in Figure 3 is the segmentation effect, when the gap between the target area and the background area is large, it will also have a better effect, and its adaptability is stronger.

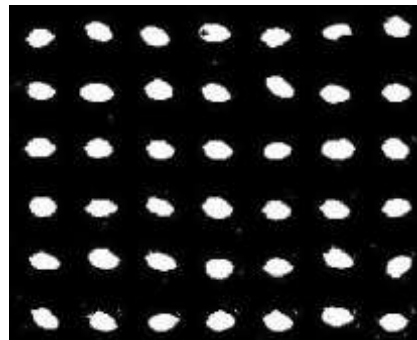


Figure 3 Threshold segmentation image

2.4 Minimum circumscribed rectangle method

The minimum circumscribed rectangle method is to mark each grain in the image, obtain the maximum and minimum values of each grain horizontally and vertically, and then crop it through the smallest circumscribed rectangle to quickly segment a single grain target from the original image. The general method used is equal interval rotation iteration, that is, the grain image is rotated at a fixed angle within the acute angle, and the size of the rectangle is determined which is the smallest according to the size of the rectangle at different angles. Taking the center of the grain image as the fixed point, the grain image is rotated according to the set angle value, and the horizontal and vertical coordinate values of the outline point of the rectangle are calculated according to the position in the coordinate

system. The rotation is oriented to the vertical axis of the image, and each angle of rotation is fitted to the edge of the grain with a rectangle tangent to it, and after the end of rotation, the smallest rectangle

and the corresponding horizontal and vertical distances are selected, which are recorded as the length and width of the smallest rectangle, and gradually rotate to find the smallest circumscribed rectangle for clipping. As shown in Figure 4, the grain characteristics of each type of wheat grain are obvious, so the various samples with uniform size can be directly input to the deep learning model for classification^[6].

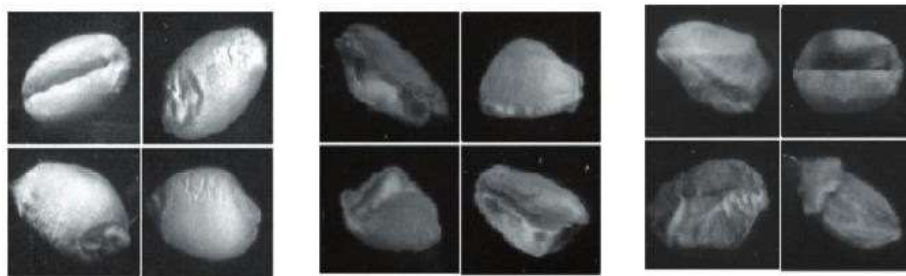


Figure 4 Image of a single grain after segmentation

3. CNN-based imperfect grain identification of wheat

Convolutional neural networks (CNNs) are one of the most commonly used classification recognition neural networks in deep learning. CNN is a deep neural network model applied to image processing and recognition, consisting of five parts, namely Input (input layer), Concolutions (convolutional layer), Subsampling (sampling layer), Full connection (fully connected layer), Output (Output layer). In the process of image processing and recognition, the input amount is wheat two-dimensional image information, which passes through the convolutional layer to the pooling layer, then passes through the fully connected layer, and finally uses a classifier in the output layer for classification and recognition. All parameters in CNN need to be adjusted layer by layer by minimizing the loss function by gradient descent algorithm, and the accuracy of the model is continuously improved through multiple iterations^[7]. CNN adopts local joining and weight sharing techniques to reduce the number of parameters of the convolutional neural network model. Classic CNN models include LeNet, ResNet, AlexNet, VGG, GoogLe Net, ResNet and so on.

CNN makes the spatial structure information of the original image completely preserved, avoids the complex manual extraction process, and uses a large number of different convolution kernels suitable for image features to extract different image features, thereby saving detection time and has very good feature extraction and data analysis capabilities^[8]. LeNet-5 is a convolutional network structure with wide applicability and strong scalability, as shown in Figure 5. The dataset is set with the processed image as input, and 3000 images are taken from each of the seven types of wheat grain to establish the wheat imperfect grain identification dataset, of which 2500 are used as the training set and 500 are used as the test set.

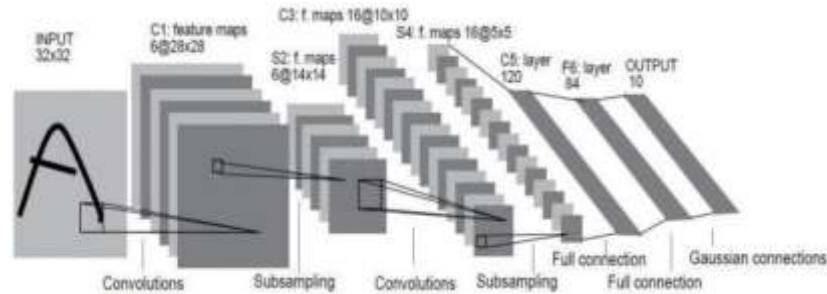


Figure 5 LeNet-5 structure diagram

3.1 Selection of activation functions

Activation functions are used when performing convolution operations, and different activation functions will affect the efficiency of feature extraction from convolutional layers [9]. At present, common activation functions include the Sigmoid function, the tanh function, and the Relu function. The mathematical expression of the Relu function is the simplest, with pure linear and unsaturated forms, while the first two have a relatively saturated form, when the input is greater than 0, it remains variable, and the output is 0 in other cases, so the activation function used here is the Relu function.

3.2 Batch standardization

Adding a BN after each convolutional layer of the CNN prevents gradient diffusion, suppresses overfitting, accelerates convergence, and enhances the generalization ability of the model, as shown in Figure 6.

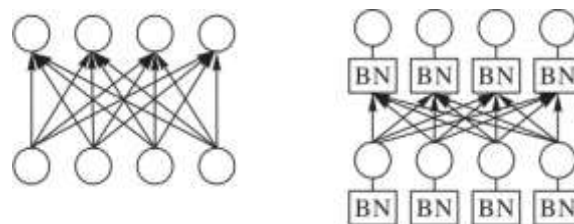


Figure 6 The structure before and after CNN is added

BN is essentially when each layer is input, insert a normalization layer, first do a normalization processing, and then enter the next layer of the network, normalize the input data according to its variance, so that the model will be more stable, so that it is concentrated near the mean with a small variance, batch mean, batch variance, batch normalization, shift calculation formula is shown in Equation 1-4.

$$\mu_B = \frac{1}{m} \sum_{i=1}^m x_i \quad (1)$$

$$\sigma_B^2 = \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2 \quad (2)$$

$$\hat{x} = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + s}} \quad (3)$$

$$y_i = \gamma \hat{x} + \beta \quad (4)$$

where m is the number of batches, x_i is the input value, μ_B is the mean, σ_B^2 is the variance, ε is the constant, γ , β are the learning parameters, \hat{x}_i is the normalization, and y_i is the output value. The BN layer takes the mean and variance of all training data as the mean and variance of batch normalization when testing data, increases the convergence speed of the convolutional layer, reduces the parameters in the convolutional layer, and improves the quality of the extracted features of the convolutional layer, which provides theoretical support for the application of imperfect grain identification in wheat^[10].

SUMMARY

China is a major producer of wheat, and wheat, as one of the world's major food crops, plays a pivotal role in promoting national economic development and world food trade. With the improvement of people's living standards, the requirements for wheat flour quality have gradually improved, in 2008, China's General Administration of Quality Supervision, Inspection and Quarantine promulgated the wheat national standard GB1351-2008, for different grades of wheat imperfect grain content has clear regulations and quality standards, so wheat imperfect grain content seriously affects the circulation and consumption of wheat. Therefore, the detection method of imperfect grain of wheat has great practical significance for the correct assessment of wheat quality grade.

The traditional wheat imperfect grain detection method is manual detection, but it has the disadvantages of large workload, time-consuming and labor-intensive, strong subjectivity and slow speed. However, the detection method of volatile substances in imperfect grains of wheat has lag, and the terahertz detection method is easily affected by the environment. The imperfect wheat grain detection method based on computer image processing and CNN has the advantages of high precision, fast speed, strong reliability, real-time, unaffected by the environment, and repeatable, which is very feasible for the grade evaluation of wheat grain. Compared with traditional machine vision methods, deep learning models can perform feature extraction autonomously, avoiding the tedious process of manual feature extraction. Therefore, CNN-based imperfect grain recognition technology for wheat will become a trend in future research. There are still many shortcomings in this paper, and further research is needed on grading algorithms and recognition methods.

REFERENCE

- [1] RUß G, KRUSE R, SCHNEIDER M, et al. Data mining with neural networks for wheat

- yield prediction; proceedings of the Advances in Data Mining Medical Applications, E-Commerce, Marketing, and Theoretical Aspects: 8th Industrial Conference, ICDM 2008 Leipzig, Germany, July 16-18, 2008 Proceedings 8, F, 2008 [C]. Springer.
- [2] HOSSEINI-MOTLAGH S-M, SAMANI M R G, SAADI F A. A novel hybrid approach for synchronized development of sustainability and resiliency in the wheat network [J]. Computers and Electronics in Agriculture, 2020, 168(C).
- [3] HUANG L, LI T, DING C, et al. Diagnosis of the Severity of Fusarium Head Blight of Wheat Ears on the Basis of Image and Spectral Feature Fusion [J]. Sensors, 2020,20(10).
- [4] YANG Y, SONG H, SUN S, et al. A fast and effective video vehicle detection method leveraging feature fusion and proposal temporal link [J]. Journal of Real- Time Image Processing, 2021, (prepublish).
- [5] MIAO Z, XIAOWEN B, SHUAI L, et al. The novel polyfluoroalkyl benzenesulfonate OBS exposure induces cell cycle arrest and senescence of rat pituitary cell GH3 via the p53/p21/RB pathway [J]. Toxicology, 2023, 490.
- [6] MANLEY M, DU TOIT G, GELADI P. Tracking diffusion of conditioning water in single wheat kernels of different harnesses by near infrared hyperspectral imaging [J]. Analytica Chimica Acta, 2011, 686(1-2): 64-75.
- [7] YU J-H, SIM K-B. Face classification using cascade facial detection and convolutional neural network [J]. Journal of the Korean Institute of Intelligent Systems, 2016, 26(1): 70-5.
- [8] GATYS L A, ECKER A S, BETHGE M. Image style transfer using convolutional neural networks; proceedings of the Proceedings of the IEEE conference on computer vision and pattern recognition, F, 2016 [C].
- [9] POLISHETTY R, ROOPA EI M, RAD P. A next-generation secure cloud-based deep learning license plate recognition for smart cities; proceedings of the 2016 15th IEEE international conference on machine learning and applications (ICMLA), F, 2016 [C]. IEEE.
- [10] SINGH C B, JAYAS D S, PALIWAL J, et al. Identification of insect-damaged wheat kernels using short-wave near-infrared hyperspectral and digital colour imaging [J]. Computers and electronics in agriculture, 2010, 73(2): 118-25.