Study on egg sorting model based on visible-near infrared spectroscopy

Xiaoping Han\textsuperscript{a}, Yan-Hong Liu\textsuperscript{b}, Xuyuan Zhang\textsuperscript{c}, Zhiyong Zhang\textsuperscript{a} and Hua Yang\textsuperscript{b}

\textsuperscript{a}College of Agricultural Engineering, Shanxi Agricultural University, Shanxi, People’s Republic of China; \textsuperscript{b}College of Information Science and Engineering, Shanxi Agricultural University, Shanxi, People’s Republic of China; \textsuperscript{c}Hainan Vocational University of Science and Technology, Haikou, People’s Republic of China

\textbf{ABSTRACT}

To realize the automatic sorting of eggs, the sorting models are established in this paper by using the visible-near infrared spectroscopy technique and taking the eggshell colour, integrity, as well as the feeding mode as sorting indexes. A variety of methods are selected to remove the noise and systematic error by preprocess the spectral information. The backpropagation neural network (BP), the Principal Component Analysis (PCA) coupled with BP and the Soft Independent Modeling of Class Analogy (SIMCA) sorting method are used to identify the eggshell colours (white, pink, green), eggshell integrity (intact, cracked) and laying hen feeding mode (caged and cage-free) by their characteristic band, respectively. The prediction correlation coefficient ($R_v$), the prediction mean square error (RMSEP), the prediction standard error (SEP), the recognition rate ($R_r\_1$) and the rejection rate ($R_r\_2$) are used to evaluate the established models. The results show that the established classification models have high prediction accuracy and small errors. The non-destructive testing (NDT) technology has great potential for large-scale intelligent laying hen farms.

\textbf{ARTICLE HISTORY}

Received 1 June 2022
Accepted 7 August 2022

\textbf{KEYWORDS}

Eggshell colours; eggshell integrity; feeding mode; characteristic spectrum; sorting models

\section{1. Introduction}

With the increasing of consumption and the development of modern agriculture, the large-scale and intelligent production of eggs will become an inevitable trend. The pre-sale classification of eggs is one of the important procedures in the large-scale production. The appearance quality of eggs and the way they are raised will be the first two factors in the pre-sale classification of eggs, which are of great significance in quality control of eggs from the source.

Eggshell colour is the most intuitive external feature of eggs and is also a direct reference for consumers to judge the quality of eggs (Mertens et al., 2010; Sun et al., 2015). Studies have shown that the eggshell strength and the egg white antioxidant activity of coloured eggs are higher than those of white shell eggs, and the eggshell colour can reflect the physiological state of the laying hens (Mertens et al., 2010). At present, research on eggshell colour mainly focus on the formation mechanism, quality analysis and storage methods (Cen, 2006; Li, 2016; Shen et al., 2017; Ye et al., 2020), with little consideration given to classification. Classifying eggs by colour is convenient to the management and selling, and hence improving the business value and brand effect of eggs.

Crack identification is a crucial part of the inspection of egg appearance quality. Machine vision technology (Cen, 2006; Wang, 2014) and acoustic information technology (Qin et al., 2019) are used to identify the egg crack. Using machine vision technology to extract eggshell crack features requires specific lighting condition, professional photographic equipment (Pourreza et al., 2008), a series of complex calculations and image processing techniques (Ouyang & Liu, 2012; Pourreza et al., 2008), which makes it not easy to meet the real-time and online requirements. When using acoustic wave technology to detect eggshell crack, a specialized sound signal extraction device is needed (Luo et al., 2016). Nevertheless, the acoustic wave technology has strict requirements on environmental noises, which makes it unsuitable for using in production.

The feeding modes, including caged mode and cage-free mode, of laying hens are also a crucial factor for egg quality and high grade gene transmission. There is a strong correlation between the egg quality and feeding mode of laying hens (Ji et al., 2019; Zhao et al., 2016). Compared with caged eggs, cage-free eggs have higher nutritional value and lower hormones, pesticides, and various heavy metals. The lecithin and protein content in cage-free eggs are higher than those in caged eggs (Zhao, 2004), while the cage-free eggs have thinker eggshell and yellower yolk than caged eggs. Electronic nose and electronic tongue are used to identify cooked...
and fresh cage-free eggs (Sun et al., 2018). The result shows that the combination of these two technologies is better than one technology alone, and the recognition rate for fresh eggs is lower than that for cooked eggs. In above-mentioned studies, non-destructive identification of eggs is not considered enough to meet the practical application needs.

In conclusion, motivated by the status of egg grading and the needs of large-scale production, this paper will fill in the gaps in egg colour classification and insufficient consideration of the non-destructive testing (NDT) technology. In this paper, the near-infrared spectroscopy is used which is a non-destructive, non-contact, and fast response detection technology. The eggshell colour, integrity, and the feeding modes of laying hens are selected as target to establish eggs sorting models by using the information of visible-near infrared spectral. The main contributions of this paper can be highlighted as follows: (1) the visible-near infrared spectroscopy is used in automatic sorting of eggs; (2) the proposed classification models have the advantages of simple structure, fast response and high recognition rate; and (3) the theoretical foundation is laid in this paper of a simple near infrared egg classifier.

The rest of this paper is organized as follows. In Section 2, the sample spectral information acquisition system and the data processing method are introduced. In Section 3, the process of establishing egg classification models is demonstrated. Finally, conclusion is drawn and the possible future research directions are pointed out in Section 4.

2. Materials and method

2.1. Samples

The egg samples are selected from farmers in Taigu which are all fresh eggs within 1 week. The egg shape index of all samples is distributed between 1.3 and 1.35, while the weight index is between 50 g and 65 g. All samples are wiped off the surface dirt with a slightly wet clean towel before testing. The cracked egg samples are obtained by lightly bumping eggs against the tabletop. The test sample is shown in Table 1.

| Table 1. Test sample. | White | Pink | Green |
|-----------------------|-------|------|-------|
| Egg sample            | Intact| Crack| Intact| Crack | Intact| Crack |
| Number of samples     | 120   | 120  | 120   | 120   | 120   | 120   |
| Label                 | A1    | A2   | B1    | B2    | C1    | C2    |

2.2. Spectral information acquisition

The spectral information in this study is collected by Field Spec3 portable spectrometer designed and produced by ASD Company of the United States. The light source, fibre-optics probe and sample are settled in a cuboid box with a black inner surface. The light source comes from a bromine tungsten lamp with a power of 30 W. The light source and the fibre-optics probe are located on left and right sides of the tested samples, respectively. The probe and the irradiation direction of the light source form an angle of 45° with the equatorial position measurement surface of the sample (Shen et al., 2017). The sample is fixed on a plane with a hole of 2 cm diameter. See Figure 1 for details.

2.3. Data preprocessing and feature band extraction

To eliminate the influence of system error and baseline drift, in the whole wavelength range, averaging, multivariate scatter correction (MSC), standard normal variate (SNV), Savitzky–Golay (SG) smoothing filter and their combinations are used to preprocess the spectral information. The average reflectance spectrum of each type of sample is showed in Figure 2.

Figure 2(a) shows the average reflectivity of three egg colours (white, pink and green). The differences among reflectivity are clear in the visible spectral region (350–780 nm), and green and pink eggs have lower reflectivity than white. There is severe shaking and lots of noises in the region of 350–440 nm and this band will not take as the contributing band in this study. Studies have shown that the colour difference
of eggshells lies in the type and content of porphyrin pigments contained in eggshell (Mertens et al., 2010). In the near-infrared spectrum, the absorption interval of porphyrin compounds in eggshells is 400–500 nm (Hu, 2009). Combined with Figure 2(a), 440–690 nm is selected as the characteristic band for identifying eggshell colour.

In Figure 2(b), eggs of the same colour have similar change rules. The difference of reflectivity is apparent in the 350–1600 nm band. In addition, the waveband of 1600–2500 nm has more peaks and troughs. To eliminate the influence of colour on crack and intact egg sorting, the waveband of the visible spectrum 350–780 nm is dismissed. In the near-infrared spectral region, the peaks, the troughs and their combinations are adopted to screen the characteristic bands.

From Figure 2(c), it is known that the spectral reflectance of cage-free eggs, compared with caged eggs, changes gently in the whole wavelength range and the difference is distinct. The content of water and cholesterol in cage-free eggs are lower than those in caged eggs (Yang, 2011). For the water molecules, the first-order frequency doubling is around 1450–1460 nm, the second-order frequency doubling is around 975–985 nm, the third-order frequency doubling is around 740–750 nm, and the combined frequency is around 1375–1385 nm (Siesler et al., 2002). The cholesterol frequency doubling is around 1750 nm (Wu et al., 2011). The reflectivity of cage-free eggs at these bands is all lower than that of caged eggs.

3. Sorting models

In the classification model, learning rate, as an important parameter in supervised learning, determines whether and when the objective function converges to the local minimum. When the learning rate is too large, the training process will shock, and when it falls to a certain degree, the training set cannot converge. When the learning rate is small, the convergence speed will be greatly reduced. Usually, the learning rate is set within 0.01–1.0. In this study, it is 0.05. The proper learning rate can make the objective function converge to the local minimum in the proper time (Zhang, 2020).

Taking 2/3 samples as validation set and 1/3 samples as test set, the sorting models of egg colour, integrity and feeding mode are established.

3.1. The back propagation (BP) sorting model of eggshell colour

BP neural network is one of the most widely used neural networks (Chai, 2007). The structure of BP neural network is shown in Figure 3 (Wang et al., 2020).

\[ \text{Figure 2. Average spectral reflectance: (a) white, pink, green eggs, (b) intact and crack eggs and (c) caged and cage-free eggs.} \]
In Figure 3, \( X = \{x_1, x_2, \ldots, x_n\} \) is the input vector, \( Y = \{y_1, y_2, \ldots, y_k\} \) is the output vector. \( \omega_{ij} \) is the weights between input layer and hidden layer, \( \omega_{jk} \) is the weights between hidden layer and output layer.

The sorting model of eggshell colour using BP neural network is given as follows:

\[
Y_k = \sum_{j=1}^{n} \sum_{i=1}^{m} (x_i \omega_{ij} + b_i) \omega_{jk} \quad (k = 1, 2, \ldots, m) \tag{1}
\]

where \( b_i \) is a deviation.

According to the theory of BP neural network, the number of hidden layers can be calculated to be 5–14 in this model. To choose the optimal model, the BP neural networks are established with hidden layers of 5–14, respectively. The evaluation parameters are got by the average value of the model running 10 times continuously. The prediction correlation coefficient (Rv), the prediction mean square error (RMSEP) and the prediction standard error (SEP) are showed in Figure 4.

As shown in Figure 4, for 5–14 hidden layers, all the Rv is higher than 0.994 which has reached the goal of complete identification. The SEP has a similar waveform with Rv and shows a linear negative correlation relationship. When the hidden layer is 6 and 12, better prediction results can be achieved, and the RMSEP and SEP are less than 0.035.

To further compare the 6 hidden layer model and 12 hidden layer model, the operating and evaluation parameters of the two models are compared in Table 2 and Figure 5. Compared with 6 hidden layer model, the operation parameters with 12 hidden layer model are better except for the long running time.

In Figure 5, the average Rv value of the model running continuously for 10 times is taken as the standard (zero line), and the absolute deviation of Rv is taken as the evaluation parameter of the model stability.

The model with 12 hidden layers shows better stability. However, the model with 6 hidden layers has a relatively simple structure and fast running speed and can also identify samples absolutely. When adding 6 more hidden layers in the model with 12 hidden layers, the improvement of evaluation parameters is not distinct.

Therefore, the BP neural network with six hidden layers is chosen as the eggshell colour discrimination model. The prediction result is shown in Figure 6. Where ‘0’ stands for white eggs, ‘1’ stands for pink eggs and ‘2’ stands for green eggs. The model can fully identify three kinds of eggs. Although there is a little bit difference between the standard and predicted values of white eggs, it does not affect the classification of their categories.

### 3.2. Principal component analysis (PCA)-BP sorting model of cracked and intact eggs

PCA is to decompose the original spectral data matrix into the product of the score matrix and the load matrix (Li, 2014).

\[
X_{n \times p} = T_{n \times d} \times (L_{p \times d})^T \tag{2}
\]

where \( X_{n \times p} \) is the original spectrum, \( n \) is the number of samples and \( p \) is the characteristic information of samples. \( T_{n \times d} \) is the score matrix, \( d \) is the number of principal components; \( L_{p \times d} \) is the load matrix.

The vector set obtained by PCA is independent of each other. The number of principal components is determined according to the criterion of maximum variance. The first principal component contains the largest part of the variance of data, and the following principal components are arranged in sequence according to the variance (Li, 2016).

In this section, PCA is carried to reduce the data dimension and extract the characteristics band. The BP neural
network is selected to establish optimization models. The transfer functions of both neuroid and hidden layer are ‘tansig’, the training function adopts gradient descent backpropagation-trainlm, the maximum training times is 500, and the training accuracy is $10^{-4}$. The other information is showed in Table 3.

There are same characteristic bands (1100 − 1260 nm, 1648 − 1698 nm and 2380 − 2410 nm), principal component fractions (2) and hidden layers (6) gained by PCA. Therefore, the sorting models of these three groups of samples can be unified into one model, that is, the PCA-BP neural network discrimination model with six hidden
Table 3. PCA-BP optimization models and evaluation parameters.

| Sample   | Characteristic band (nm) | Principal component fraction | Hidden layer | Prediction accuracy | Rv     | SEP    | RMSEP  |
|----------|--------------------------|-----------------------------|--------------|---------------------|--------|--------|--------|
| A(A1, A2)| 1100 – 1260 mm           | 2                           | 6            | 98.75%              | 0.9673 | 0.1339 | 0.1362 |
|          | 1648 – 1698 mm           |                             |              |                     |        |        |        |
|          | 2380 – 2410 mm           |                             |              |                     |        |        |        |
| B(B1, B2)| 1100 – 1260 mm           | 2                           | 6            | 100%                | 1      | 0      | 0.0033 |
|          | 1648 – 1698 mm           |                             |              |                     |        |        |        |
|          | 2380 – 2410 mm           |                             |              |                     |        |        |        |
| C(C1, C2)| 1100 – 1260 mm           | 2                           | 6            | 100%                | 0.9999 | 0      | 0.0035 |
|          | 1648 – 1698 mm           |                             |              |                     |        |        |        |
|          | 2380 – 2410 mm           |                             |              |                     |        |        |        |

Figure 7. Prediction results of crack and intact egg: (a) white egg forecast results, (b) pink egg forecast results and (c) green egg forecast results.

layers for cracked and intact eggs. Although the prediction effect is different due to the egg colour, the model can still meet the needs of cracked egg sorting. The prediction results of three groups of egg samples are showed in Figure 7.

In the results, ‘0’ represents intact eggs and ‘1’ represents cracked eggs. All the samples can be correctly graded except for a few of white cracked samples deviating greatly from the standard value. The order of sorting effect of the three groups is group B (pink) > group C (green) > group A (white). The reason for the deviation in group A is that the high reflectivity of white eggshell leads to the loss of spectral information.

3.3. Soft independent modelling of class analogy (SIMCA) sorting model of cage and cage-free eggs

SIMCA is a supervised pattern recognition method, which belongs to binary decision method.

The specific execution process is as follows (Li et al., 2010):

1. Principal component analysis is performed on each type of samples in the training set.
2. Mathematical model of each kind samples is established by PCA.
3. The distance is calculated between the unknown sample point and the training set.
The class is found by the closest distance.

In this study, the Mahalanobis distance is calculated to establish the discriminant model. The model evaluation parameters are expressed by recognition rate \( R_{r1} \) and rejection rate \( R_{r2} \). \( R_{r1} \) refers to the number of unknown samples falling in this kind of model. In contrast, \( R_{r2} \) refers to the rejection degree to unknown samples that do not belong to this kind of model, as shown in formula (3) and (4) (Ma et al., 2011).

\[
R_{r1} (%) = \frac{d_1}{s_1} \times 100 \tag{3}
\]
\[
R_{r2} (%) = \frac{d_2}{s_2} \times 100 \tag{4}
\]

where \( s_1 \) represents the total number of some kind of samples, \( s_2 \) represents the total number of another kind of samples, \( d_1 \) represents the number of recognition to this sample in this model and \( d_2 \) represents the number of rejection to other sample in this model.

The SIMCA recognition models for caged and cage-free eggs are built by using different data preprocessing methods (Table 4). Using the parameters \( R_{r1} \) and \( R_{r2} \) as the criterion for judgment, the result indicates that the best prediction effect has been got by SNV. The \( R_{r1} \) and \( R_{r2} \) of caged model are all reached 100%, and the \( R_{r1} \) and \( R_{r2} \) of the cage-free model are 100% and 85%, respectively.

By SNV, five principal component fractions are acquired, and the contribution rate has reached 97%, which represents the original spectral information of the sample. The first and second principal component scores are showed in Figure 8. Their cumulative variance contribution rate reaches 96%. Therefore, these two principal component scores are very representative. In this figure, ‘0’ represents caged eggs and ‘1’ represents cage-free eggs. There are two ‘1’ that fall within the range of ‘0’. Nevertheless, all scores of caged eggs are clustered in a small area. It is inevitable that caged eggs can be identified preferably.

In Figure 9, the Mahalanobis distances are showed under the 5% significance level, and the two red lines are confirmed by the significant level. The blue circles are the classification samples of caged eggs and the red circles are the caged eggs identified samples. The green circles at lower right corner are the cage-free eggs identified samples and the green circles at low left corner are unrecognized samples. It can be seen that there is a smaller Mahalanobis distance in caged egg sample, so caged eggs gain a better sorting result.

Table 4. Data preprocessing results comparison.

| Data preprocessing | Principal component fraction | Contribution rate (%) | Recognition rate | Rejection rate | Recognition rate | Rejection rate |
|--------------------|-----------------------------|-----------------------|------------------|---------------|------------------|---------------|
| Original spectrum  | 3                           | 99%                   | 100%             | 71.7%         | 100%             | 85%           |
| SNV                | 5                           | 97%                   | 100%             | 100%          | 100%             | 85%           |
| MSC                | 5                           | 95%                   | 100%             | 90%           | 100%             | 73.3%         |
| SNV+MSC            | 3                           | 95%                   | 100%             | 91.7%         | 100%             | 73.3%         |
| SG                 | 3                           | 99%                   | 100%             | 75%           | 100%             | 75%           |
| SG+SNV             | 5                           | 96%                   | 100%             | 70%           | 100%             | 81.7%         |
| SG+MSC             | 4                           | 97%                   | 100%             | 78.3%         | 100%             | 83.3%         |

Figure 8. Principle component score.
4. Conclusion and prospects

In this paper, the sorting models are established by using visible-near infrared spectroscopy NDT technology based on egg colour, integrity and feeding mode to meet the large-scale egg production needs.

A sorting model based on egg colour is established by BP neural network. The reflectivity of characteristic band (440 − 690 nm) is selected as the input variable of the model with six hidden layers. All the test samples are correctly identified and the Rv, RMSEP and SEP are 0.9975, 0.0277 and 0.0159, respectively.

An identification model based on egg integrity is built by PCA-BP. The bands 1100 − 1260 nm, 1648 − 1698 nm and 2380 − 2410 nm are extracted as characteristic. The result shows that the identification model of three colours (pink, green and white) can be unified into one model with six hidden layers. The prediction results show that the sorting accuracy rates for pink, green and white are 100%, 100% and 98.75%, respectively. For colour pink, the Rv is 1, the RMSEP is 0.0033 and the SEP is 0. For colour green, the Rv is 0.9999, the RMSEP is 0.0035 and the SEP is 0. For colour white, the Rv is 0.9673, the RMSEP is 0.1362 and the SEP is 0.1339.

A model based on egg feeding mode is constructed by SIMCA. The best prediction results are achieved by data pre-processing of SNV. The test samples of caged egg get a better identification rate than the test samples of cage-free egg at the significance level of 5%.

In this paper, visible-near infrared spectroscopy technology is used to establish a rapid egg sorting model. To make a final decision on the possibility of commercialization of the presented method, further research topics include to perform tests on a larger number of samples (more colours, different origin, varying degrees of damage, etc.), to further verify the stability and generalization of the established models.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This article is funded by the Basic Research Program of Shanxi Province (grant number 20210302123408).

References

Bi, H. J., Li, G. Q., & Yang, N. (2016). Genetic Research Progress of Eggshell Color. Acta Veterinaria Et Zootechnica Sinica, 47(12), 2325–2330. https://doi.org/10.11843/j.issn.0366-6964.2016.12.001
Cen, Y. K. (2006). Research on the method of egg quality detection based on machine vision. Zhejiang University.
Chai, S. B. (2007). Research on data classification based on neural network. Dalian University of Technology. https://doi.org/10.7666/d.y1225909.
Cruz-Tirado, J. P., Lucimar da Silva Medeiros, M., & Barbin, D. F. (2021). On-line monitoring of egg freshness using a portable NIR spectrometer in tandem with machine learning. Journal of Food Engineering, 306(10), 1–9. https://doi.org/10.1016/j.jfoodeng.2021.110643
Hu, M. B. (2009). Study on ion recognition function of chlorophyll porphyrin compounds. Shandong Normal University.
Ji, X. F., Yang, H., Li, R., Zheng, F. Y., Shan, L. Y., Xu, J. X., & Qian, M. R. (2019). Comparative study on egg quality and nutritional composition in different feeding modes. Quality and Safety of Agricultural Products, 4, 65–68.
Li, J., Fan, L., Bi, Y. L., Qu, L. B., Zhou, Z. M., & Wu, C. R. (2010). Combining infrared, near infrared with soft independent modeling of class analogy for identification of vegetable blend oil. Chinese Journal of Analytical Chemistry, 4(28), 475–482. https://doi.org/10.3724/SP.J.1096.2010.00475
Li, M. (2014). Infrared spectrum analysis of microwave heating food. University of Electronic Science and Technology of China.
Li, X. (2016). Study on potato variety identification and dry matter content detection method based on near infrared spectroscopy. Heilongjiang Bayi Agricultural University.
Luo, H., Yan, S. M., & Dai, D. J. (2016). An on-line detection method of eggs micro-cracks based on mechanical-acoustic characteristics. Acta Agri-Mechanica Sinica, 47(11), 224–230. https://doi.org/10.6041/ij.issn.1000-1298.2016.11.031
Ma, D. H., Wang, X. C., Liu, L. P., & Li, Y. (2011). Research progress of near-infrared spectroscopy in food origin traceability. Spectroscopy and Spectral Analysis, 31(4), 15–19.
Mertens, K., Vaesen, I., Loffel, J., Kemps, B., Kamers, B., Perianu, C., Zoons, J., Darius, P., Decuyere, E., De Baerdemaeker, J., & De Ketelaere, B. (2010). The transmission color value: a novel egg quality measure for recording shell color used for monitoring the stress and health status of a brown layer flock. Poultry Science, 89(3), 609–617. https://doi.org/10.3382/ps.2009-00261
Ouyang, J. Y., & Liu, M. H. (2012). Research on egg crack detection method based on computer vision. *Agricultural Mechanization Research*, 34(3), 91–93. https://doi.org/10.13427/j.cnki.njyi.2012.03.026

Pourreza, H. R., Pourreza-Shahri, R., Fazeli, S., & Taghizadeh, B. (2008). Automatic detection of eggshell defects based on machine vision. *Journal of Animal and Veterinary Advances*, 7(10), 1200–1203. https://doi.org/10.2460/javma.233.7.1127

Qin, Y. Y., Wang, S. C., & Li, S. F. (2019). Detection of egg cracks based on sound signal recursion graph. *Journal of Huazhong Agricultural University*, 38(2), 102–108. https://doi.org/10.13300/j.cnki.hnlkxb.2019.02.014

Shen, J., Zheng, C. W., Pan, A. L., Liang, Z. H., Wu, Y., Du, J. P., Zhang, H., Pu, Y. J., & Pi, J. S. (2017). Color pigment analysis and gene expression of Jianghan eggshell. *Hubei Agricultural Sciences*, 56(3), 508–510+. https://doi.org/10.14088/j.cnki.issn0439-8114.2017.03.029

Siesler, H. W., Ozaki, Y., Kawata, S., & Heise, H. M. (2002). Near-infrared spectroscopy – principles, instruments, applications (pp. 335–339). Wiley-VCH.

Sun, L., Cai, J. R., Li, Y. Q., Yuan, L. M., & Xu, D. C. (2015). Research progress on nondestructive testing methods for eggshell quality. *China Agricultural Science and Technology Herald*, 17(5), 11–17. https://doi.org/10.13304/j.nyjdzh.2015.508

Wang, C., Han, F., Zhang, Y., & Lu, J. Y. (2020). An SAE-based resampling SVM ensemble learning paradigm for pipeline leakage detection. *Neurocomputing*, 403, 237–246. https://doi.org/10.1016/j.neucom.2020.04.105

Wang, Y. (2014). Research on the computer vision cracked eggs detecting method. *International Journal of Computer Applications in Technology*, 50(3/4), 215. https://doi.org/10.1504/IJCAT.2014.066730

Wu, J. Z., Li, H., & Wang, K. D. (2011). Study on the application of spectral pretreatment in near infrared model optimization of agricultural products. *Agricultural Mechanization Research*, 33(3), 178–181. https://doi.org/10.3969/j.issn.1003-188X.2011.03.045

Xu, L., Yu, L. H., Sun, J. X., Wang, B. W., & Wang, S. B. (2018). Study on identification and detection of free-range/caged eggs based on electronic nose and electronic tongue. In *Proceedings of the 15th annual meeting of Chinese Institute of Food Science and Technology*.

Yang, H. M. (2011). Study on the influence of instrument conditions on non-invasive biochemical detection by near-infrared spectroscopy. Graduate School of Chinese Academy of Sciences (Changchun Institute of Optics, Precision Mechanics and Physics).

Ye, L., Huang, X. H., Yang, L. J., Zhao, Y. M., Liang, X. T., Luo, W. J., Wang, X., & Wei, H. (2020). Effects of storage methods and time on the quality of eggs with different colors. *China Feed*, 9, 52–58.

Zhang, T. (2020). Research on hyperparameter optimization method of deep learning based on learning rate attenuation. Central China Normal University.

Zhao, C. (2004). Study on the effect of different laying Hen breeds, feeding methods and feeding types on egg quality. Hebei Agricultural University.

Zhao, Q. Y., Li, B. L., Wang, L., Yu, J. M., & Liu, S. J. (2016). Effects of cage rearing and courtyard rearing on egg quality. *Journal of Heilongjiang Bayi Nongken University*, 28(1), 28–30.