Study on Egg Freshness Detection Based on Inception and Attention

Min-lan Jiang(✉), Li-yun Mo, and Pei-lun Wu

College of Physics and Electronic Information Engineering, Zhejiang Normal University, Jinhua 321004, China
xx99@zjnu.cn

Abstract. Egg freshness is an important economic index to measure egg quality, and it is also the main factor affecting egg sales. In this paper, aiming at the problem of small number of training and testing samples in current research, a sample collection device was set up, and 1173 pictures of egg samples with three different levels of freshness were collected, which greatly expanded the number of samples. On this basis, aiming at the problems of strong subjectivity and low accuracy of the obtained model when extracting features manually in the current research, the CBAM module is used in combination with the Inception module to construct a network model, and attention mechanism was introduced to assign adaptive weights to the collected multi-scale features, which further improved the accuracy of the network and the problem of network over-fitting, and establishes a high-precision egg freshness detection model. The test results showed that the average test accuracy of GoogLeNet-A reaches 94.05%, and the highest test accuracy reaches 98.44%. At the same time, compared with other existing deep learning models, the experimental results showed that the detection model proposed in this paper has the highest accuracy, which provided a new idea and method for egg freshness detection.

Keywords: Egg freshness classification · Inception · CBAM

1 Introduction

Eggs are one of the most frequently eaten eggs, which contain a large amount of vitamins and minerals and are a good source of dietary nutrition. According to the statistics of the World Food and Agriculture Organization, in 2018, there were more than 137 million metric tons of eggs produced globally. The output of the top five egg-laying countries accounted for 56% of the total demand, of which China ranked first in the world. If eggs can be classified according to freshness in the process of production and consumption, it will not only be helpful for producers and operators to adopt scientific management methods to ensure the quality of eggs and their by-products, but also safeguard the rights and interests of consumers and protect the health of consumers [1]. So how to select a good egg is one of the urgent problems to be solved. At present, the artificial selection method of observing the internal quality of eggs by using an egg illuminator

D. Jiang and H. Song (Eds.): SIMUtools 2021, LNICST 424, pp. 613–626, 2022.
https://doi.org/10.1007/978-3-030-97124-3_47

in a darkroom is widely used. This method is inefficient, and the results are based on the experience of workers, with strong subjectivity and low accuracy.

Since the beginning of the 21st century, many researches have been put forward by domestic and foreign scholars on the non-destructive detection of egg freshness. At present, the main research directions are: non-destructive detection based on machine vision [2–5], non-destructive detection based on acoustic impact characteristics [6, 7], non-destructive detection based on optical characteristics [8–10], non-destructive detection based on dielectric properties, etc. The non-invasive detection technology based on machine vision mostly uses extracting the inside and outside characteristics of eggs, such as egg weight, yolk size, air chamber diameter ratio, to detect the freshness of eggs. Wang Qiaohua et al. [11] Constructed the model of the Haugh value of eggs and the optical information parameters of eggs by using the BP network. The non-destructive detection and grading of the freshness of eggs were carried out, and the detection accuracy reached 89%. Li Xincheng et al. [12] separated four characteristic parameters from the egg light transmittance chart, which were yolk area ratio, air chamber area ratio, air chamber height ratio and air chamber diameter ratio, and used them as independent variables, and established a univariate regression model with the egg Haugh value to detect the egg freshness, in which the goodness of fit between the egg yolk area ratio and the Haugh value reached 0.62. Li Jiating et al. [13] established the relationship model between the electronic nose response signal and the physical and chemical indexes of eggs by using the BP network analysis method. The detection accuracy of egg freshness reached 90.19%. Liu Yan et al. [14] established a ternary model for egg freshness detection by extracting the three characteristics of the air chamber size, egg yolk size and ovality in the light transmission image of eggs. The model correlation coefficient R^2 reached 0.952.

The above studies show that it is feasible to establish an egg freshness detection model through the corresponding relationship between the characteristic parameters such as the ratio of chamber diameter in the egg translucent picture and the Haugh value. Current studies usually use the method of extracting the characteristics of egg translucency map manually, which is a complex image preprocessing method with a small number of samples and a strong subjectivity. With the development of deep learning in recent years, convolution neural network has made many breakthroughs in the field of image analysis and processing, avoiding the complex pre-processing of images. Convolution, pooling and filling replace the subjectivity of traditional machine learning in extracting image features manually. However, as the network depth increases, the network parameters increase exponentially, resulting in the disappearance of gradients, over-fitting, and so on.

Inception modular structure proposed by Christian Szegedy [15] et al. can further improve network performance within limited computing resources. Therefore, in order to improve the generalization ability and speed of operation, it is easy to overfit the artificial neural network. In this paper, the Inception module is used to optimize the network structure while enlarging the number of samples, and multiscale convolution is introduced to acquire the required convolution kernel size for autonomous learning of the input image features. At the same time, this paper introduces the attention mechanism to assign adaptive weights to it, which makes the network focus on the characteristics related to egg freshness, such as yolk size, air chamber diameter ratio, to further improve the accuracy of the network, and establishes a high-precision ICBAM egg freshness detection network model.

2 ICBAM Network Model

2.1 Inception Module

The performance improvement of convolution neural network depends on increasing the depth of the network and the number of hidden layer neurons, which will result in a larger network parameter space, making the network more prone to over-fitting, computational load, slow operation, and so on. Moreover, as the network depth increases, the gradient disappears during the model building process. The solution to this problem is to introduce the sparse nature and convert the full connection layer to sparse connection, even if convolution is used instead of full connection, but hardware optimization for dense matrices only results in inefficient computation of asymmetric sparse data in the network. Christian Szegedy et al. proposed an Inception module to solve the above problems. The convolution network is designed as an optimal local sparse structure, which can be implemented with existing density matrix computing hardware. This structure improves the performance of the network and guarantees the computational efficiency of the network.

The three Inception module structures used in this paper are shown in Figs. 1, 2 and 3. These three modules contain multiple convolution core branches of 1×1, 3×3, $3 \times$

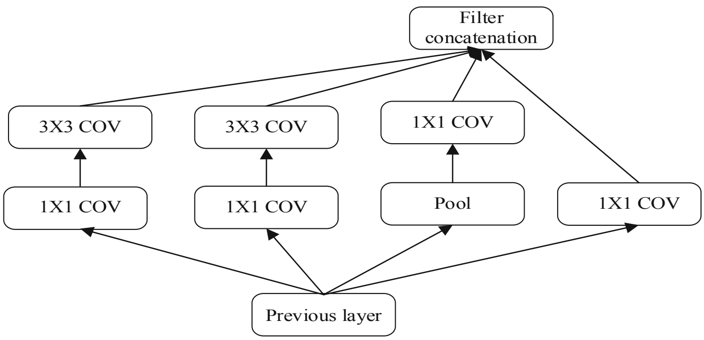

Fig. 1. Inception module structure 1. The module uses 1×1 and 3×3 convolution cores to extract image features.

1, 1 × 7, and 7 × 1. The multicore structure can extract and learn the features of different forms of eggs. At the same time, this multiscale convolution makes it unnecessary to design the convolution core size manually or to determine whether convolution and pooling layers need to be created in the module, which reduces the influence of human factors on the network.

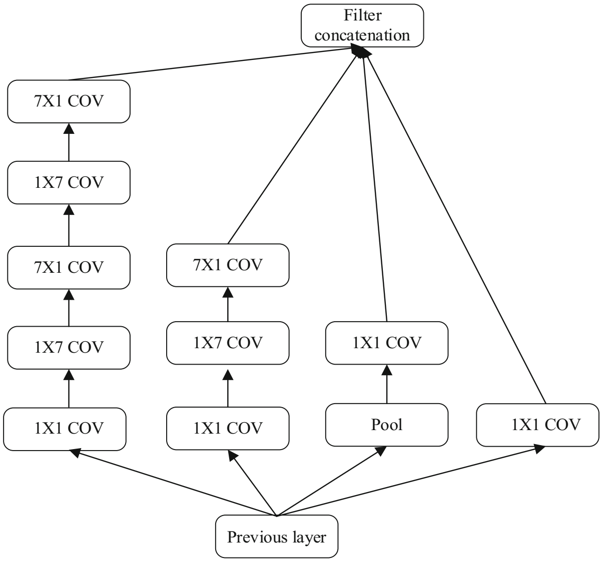

Fig. 2. Inception module structure 2. The module decomposes the 7 × 7 convolution kernel asymmetrically into 1 × 7 and 7 × 1, which greatly reduces the network calculation parameters and adds a non-linear layer to handle richer spatial characteristics.

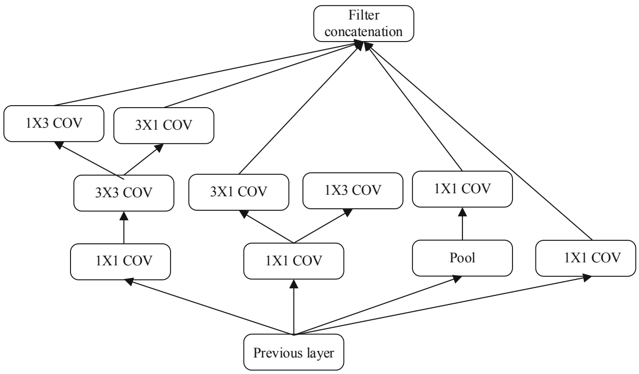

Fig. 3. Inception module structure 3. In this module, the 3 × 3 convolution kernel is decomposed asymmetrically into 1 × 3 and 3 × 1, which reduces the network calculation parameters significantly while adding a non-linear layer to deal with richer spatial characteristics.

2.2 CBAM (Convolutional Block Attention Module) Module

Attention Model, originally used for machine translation, has become an important concept in the field of neural networks. In the field of artificial intelligence, attention can better capture the visual structure by focusing on some scenes and selectively on the prominent parts, and has now become an important part of the structure of neural networks. Because convolution extracts information features by mixing cross-channel and spatial information, Sanghyun Woo et al. [16] used a CBAM module to infer attention mapping from two independent dimensions: channel and spatial order, and then multiplies the attention mapping into an input feature mapping with adaptive feature refinement, which improves the performance of the convolution neural network classification task.

Channel Attention Mapping compresses the convoluted image features on the channel dimension by averaging and maximizing the pooling of the image features, then using the same simple MLP network structure, and finally adding the corresponding elements of the features together as the channel Attention Mapping, as shown in Fig. 4.

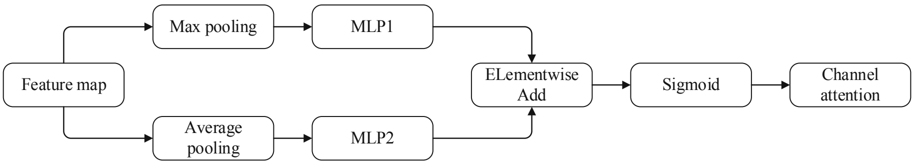

Fig. 4. Channel Attention Mapping

Sanghyun Woo et al. not only generated channel attention mappings on channels, but also established spatial attention mappings on image features in spatial dimensions. Sanghyun Woo et al. first compressed channel attention features using average pooling and maximum pooling, respectively, to get two two-dimensional features and stitch them together in channel dimensions. A 1×1 convolution layer is then used to convolute it, as shown in Fig. 5.

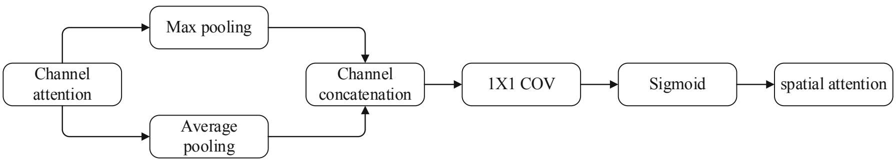

Fig. 5. Spatial Attention Mapping

Channel Attention and Spatial Attention solve the problem of equal processing of all image features by neural network models during training. Channel attention enables the neural network to distinguish what is meaningful in a sample picture, and spatial attention supplements the missing location information in channel attention. The CBAM module used in this paper learns channel attention and spatial attention separately while maintaining good network performance and reducing the amount of parameters used in calculating 3D feature maps. In the input feature map multiplied by the attention map, the network focus is on the features related to egg freshness, which reduces the impact of background on sample collection and improves network performance. The CBAM flowchart is shown in Fig. 6.

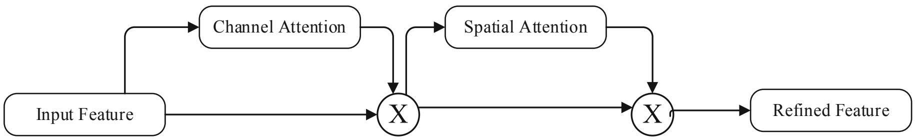

Fig. 6. CBAM flow chart

2.3 ICBAM Model

ICBAM Module. In this paper, the advantages of the Inception module and the CBAM module are used to combine the Inception module and the CBAM module. The Inception module was used to convolute the input egg freshness feature map with multi-scale, and the multi-scale image features were used as the input of CBAM. The CBAM module infers attention mapping from two independent dimensions, channel and space, and multiplies it by input features, which enables the whole network to selectively focus on the highlights and improves the accuracy of egg freshness classification tasks. The ICBAM module flow is shown in the dashed wireframe section of Fig. 7.

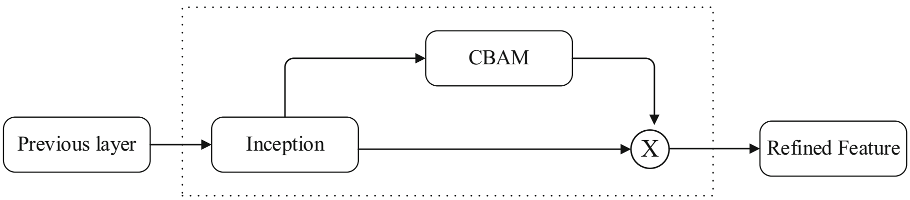

Fig. 7. ICBAM module structure

ICBAM Model Structure. The GoogLeNet-A network built in this paper has four ICBAM modules, six convolution layers, four Dropout layers and one softmax layer. The parameters required for convolution layer design are step (s), convolution kernel size (f), number of convolution cores (n), and activation function. The activation function selected in this paper is Relu, and the parameters for each convolution layer are shown in

Table 1. The sample collected in this paper is 1173. In the case of non-massive samples, dropout layer can effectively prevent over-fitting problem, so dropout layer is added after convolution layer in the ICBAM model structure for egg freshness detection in this paper. The GoogLeNet-A model is shown in Fig. 8.

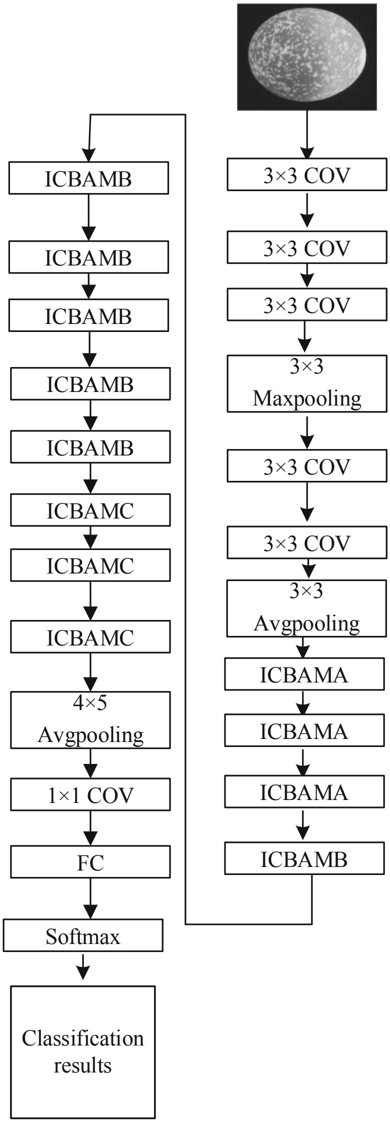

Fig. 8. GoogLeNet-A model

Table 1. Model structure diagram

Number of layers	Layer type	Enter dimension
1	Input layer	144 × 192 × 3
2	COV, f=3, s=2, n=32	144 × 192 × 3
3	COV, f=3, s=1, n=32	71 × 95 × 32
4	COV, f=3, s=1, n=64	69 × 93 × 32
5	Maxpooling, f=3, s=2	69 × 93 × 64
6	COV, f=3, s=1, n=80	34 × 46 × 64
7	COV, f=3, s=2, n=192	32 × 44 × 80
8	Maxpooling, f=3, s=1	16 × 22 × 192
9	3 ICBAM, The structure is shown in Fig. 1.	16 × 22 × 288
10	Dropout	
11	5 ICBAM, The structure is shown in Fig. 2.	8 × 11 × 768
12	Dropout	
13	3 ICBAM, The structure is shown in Fig. 3.	4 × 5 × 1280
14	Dropout	
15	Maxpooling, f=4 × 5, s=1	4 × 5 × 1280
16	Dropout	
17	FC	1 × 1 × 3
18	Softmax	1 × 1 × 3

3 Experimental Design

3.1 Image Acquisition Device

In order to collect eggs pictures, an image sampling device is designed as shown in Fig. 9. The light source uses OPT-RID-150 spherical integral light source, and a flat mirror is placed at the bottom of the light source, so that the light emitted by the light source is reflected through the top transparent hole through the flat mirror, and the light intensity on the eggs is better than using incandescent light source directly in previous studies, and select industrial color CMOS camera (effective pixel 2592 × 1944), the camera has 5 megapixels, 12 mm lens. When collecting egg pictures, you need to limit the light intensity of the collecting environment to 2–10 lx, collect RGB three-channel color image with an image resolution of 1920 × 1440.

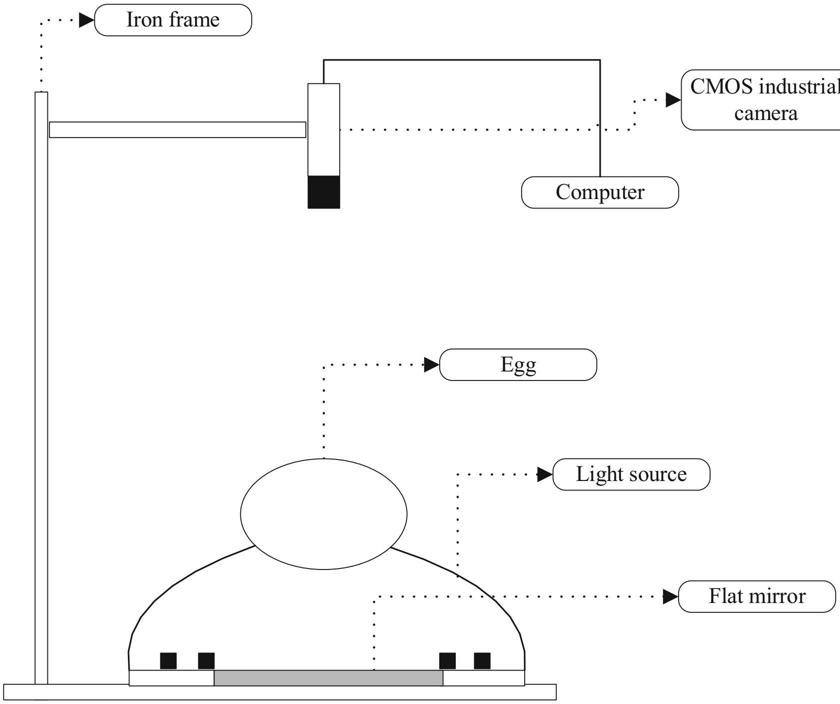

Fig. 9. Image acquisition device

3.2 Image Preprocessing

The color of egg picture collected in Fig. 9 is yellow to red, the chamber that can highlight the egg characteristics and the yolk color is dark red to black. The color contrast between them is not high. After color enhancement experiments, it is found that the G component in RGB space is easier to highlight the egg feature [17], so the G component in sample picture is enhanced four times. The interpolation algorithm is then used to reduce the G-enhanced image size to 1/10 of the original sample to meet the requirements of fast training and testing of CNN network models.

3.3 Determination of Haugh Value

The Haugh unit value is an index established by USDA to synthesize two factors, egg protein height and egg weight, to characterize the freshness of eggs. Fresh egg Haugh unit is usually between 70 and 82, and its formula is as follows:

$$Ha = 100 \times \lg\left(H + 7.57 - 1.7 \times w^{0.37}\right) \tag{1}$$

In formula H is the protein height in mm and W is the egg mass in g.

According to the relationship between egg freshness level and Haugh value in the domestic trade industry standard of the People's Republic of China (SB/T 10683–2011), the tested eggs are divided into three levels: AA, A, B, as shown in Table 2.

Table 2. Haugh value and freshness level

Haugh value	Freshness level	Protein stability
$Ha \geq 72$	AA	High freshness, high nutritional value, suitable for consumers
$60 \leq Ha \leq 72$	A	Consumer edible
$Ha \leq 60$	B	Not suitable for consumers

3.4 Experimental Process

The experimental materials used in this paper are 500 fresh Jingbai 939 powdered-shell eggs provided by Lanxi poultry and egg-rich farm in Jinhua city. They are stored at 26–28 °C and 70–80% relative humidity in indoor environment.

During the experiment, the damaged, dark-spotted eggs caused by storage were removed every day. All remaining eggs were collected using the device shown in Fig. 9. 20 eggs were randomly selected from the eggs to detect the Haugh value. The Haugh value of 20 eggs was used instead of that of all samples (500 eggs) on the same day and the eggs were classified according to the classification method shown in Table 2.

The above collection was repeated every 1 day for a sampling period of 19 days. The first and second day's eggs were all AA grade by Haugh value test. The eggs on days 6–8 were all Class A eggs. All eggs on days 12–19 were Class B. Because eggs of different freshness levels were mixed on days 3–5 and 9–11, the images collected during these two periods were not used in subsequent experiments.

After removing the samples with unclear images due to shooting and other problems, 366 AA grade samples, 402 A grade samples and 405 B grade samples were obtained. 43 (129 total) samples were selected from each freshness sample as test samples, and 1044 samples were all used as training samples. First, the training samples are pre-processed by quadrupling the channel and one-hot encoding is used to code the labels of three freshness levels. Then, the training samples and their labels are substituted into the ICBAM model in Sect. 2.4. The weights are updated by the random gradient descent algorithm to obtain the egg freshness detection model. The detection process is shown in Fig. 10.

4 Experimental Result

This paper is based on Python 3.7 programming environment. The deep learning framework is Tensorflow framework. 1044 training samples are used as input data of the model, and one-hot code of sample label is used as output data of the model. When each training starts, 64 samples are randomly selected from the training set as input data for one training, and 64 samples are labeled as output data for the model. When a training is completed, 64 samples from 129 test samples are randomly selected to test the trained model. The test accuracy and loss function are shown in Fig. 11 and Fig. 12.

It can be seen from Fig. 11 and Fig. 12, as the number of training iterations increases, the loss function of training decreases and tends to be stable, while the accuracy of training increases. This shows that the network model is continuously optimized during

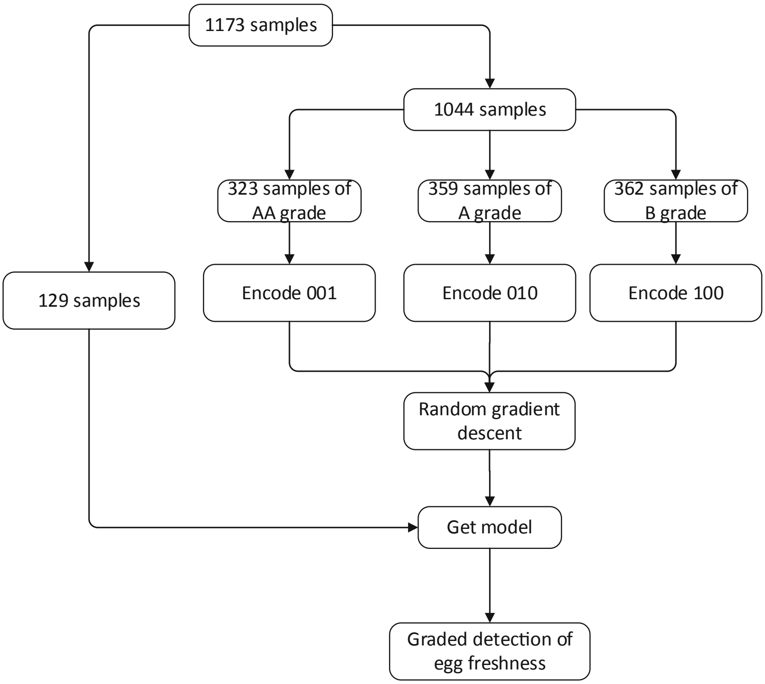

Fig. 10. Test flow chart

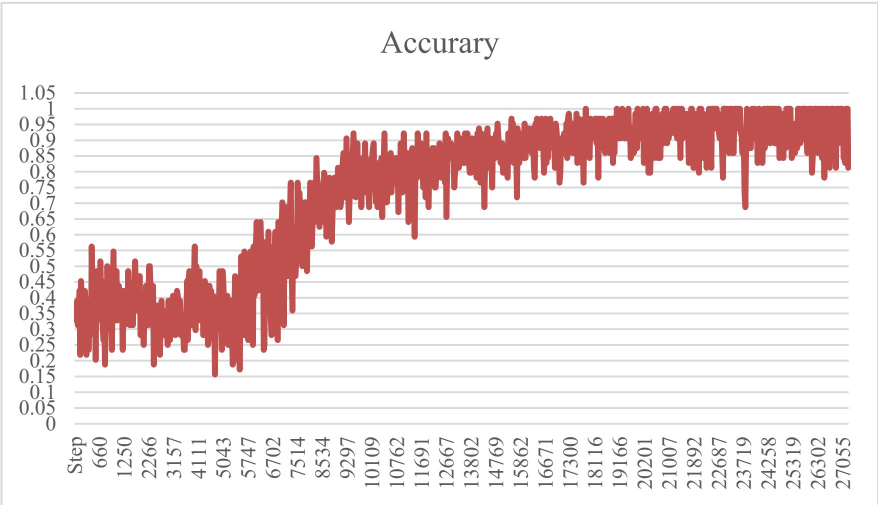

Fig. 11. Accuracy

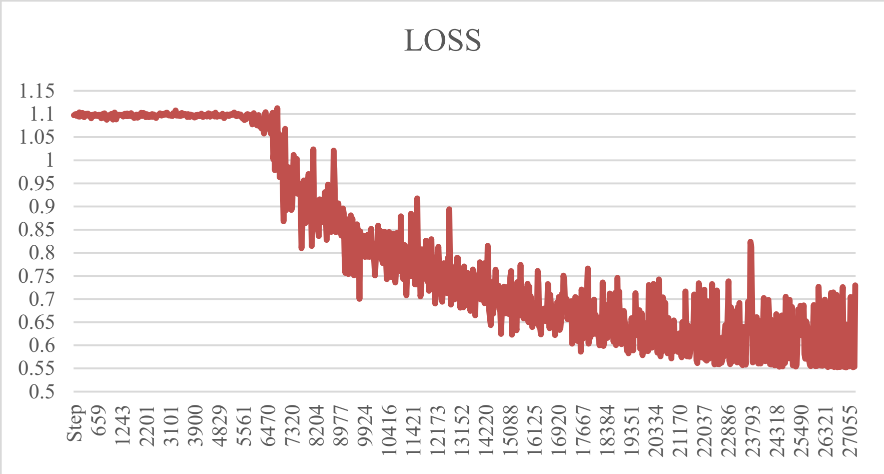

Fig. 12. Loss function value

training, and the classification effect is improved. Finally, when the number of iterations reaches 27037, the basic convergence occurs, and the average detection accuracy of the last 100 iterations is 94.05%. The highest detection accuracy was 98.44%.

To further verify the validity and accuracy of the egg freshness detection model proposed in this paper, three kinds of network models, GoogLeNet, VGG16 and VGG19, were introduced and compared with each other using the same dataset with the same experimental settings. The experimental results are shown in Table 3. Table 3 gives the average and maximum detection rates of GoogLeNet, VGG16 and VGG19, and the highest detection rates of BP network and grey network (the average detection rates are not given in the relevant literature).

Table 3. Comparison of egg freshness detection methods

Network model	Feature extraction method	Average accuracy	Highest accuracy
GoogLeNet	Inception	93.54%	98.44%
GoogLeNet-A	ICBAM	94.05%	98.44%
VGG16	Feature extraction by convolution layer	92.30%	96.88%
VGG19	Feature extraction by convolution layer	92.03%	93.75%
BP neural network	Color feature parameter extraction	/	89.03%
Grey neural network	Color feature parameter extraction	/	92.70%

The results from Table 3 show that the method of extracting egg freshness features by self-selection of the model is more accurate and comprehensive than the method of extracting egg freshness features by artificial network model. The highest accuracy of GoogLeNet, GoogLeNet-A, VGG16 and VGG19 networks using convolution neural network instead of manual selection of image features is higher than that of BP network and grey neural network using manual selection of image features. Among all the deep learning models tested, ICBAM module extracts the most comprehensive features with an average test accuracy of 94.05%. Extraction of multiscale features from GoogLeNet and GoogLeNet-A networks results in higher average and highest accuracy than VGG16 and VGG19 networks using a single convolution core. After introducing the attention mechanism, the focus of the network is more on the characteristics of egg freshness. The average accuracy of the GoogLeNet-A network is 0.49% higher than that of GoogLeNet under several tests, which verifies that GoogLeNet-A has better network performance and better stability in practical application.

5 Conclusion

Non-destructive grading of egg freshness can be used to detect the freshness level online without destroying the sample, which is of great significance in the process of actual sales, production and supervision. In previous studies, the method of extracting egg freshness characteristics manually is often used for egg freshness level classification, and then the classification model is built by machine learning. The precision of the model established by this method is limited, and only a few dozen or one or two hundred samples are used for training and testing. It is easy to fit the extracted features. In this paper, the training and testing samples are expanded first. 1173 samples collected by the collection device are used for model building and testing. At the same time, the model structure is improved. CBAM module is embedded after Inception module, and the extracted image features are weighted by attention mechanism. The average test accuracy of the model is increased to 94.05%, and the maximum test accuracy is increased to 98.44%. In comparison experiments, the accuracy of VGG16, VGG19 and GoogLeNet is not as good as that of GoogLeNet-A model using ICBAM module, which verifies the validity of the proposed model and has great significance for the economic benefits of actual production, sales and market supervision.

References

1. Zhang, W., Zhou, W., et al.: Research progress in detection of egg freshness. J. Human Univ. Sci. Technol. **32**(12), 54–56 (2011)
2. Wang, Q., Xiong, L., Ding, Y., et al.: Study on neural network detection system of egg freshness. J. Huazhong Agric. Univ. **24**(6), 630–632 (2005)
3. Wang, Q., Wen, Y., et al.: Correlation between morphological characteristics of transmitted light image and freshness of eggs. J. Agric. Eng. **24**(03), 179–183 (2008)
4. Zheng, L., Yang, X., Xu, G., et al.: Nondestructive detection of egg freshness based on computer vision. J. Agric. Eng. **25**(2), 335–339 (2009)
5. Wei, X., Wang, S.: Model and experiment of comprehensive nondestructive testing of egg freshness. J. Agric. Eng. **25**(3), 242–2479 (2009)

6. Wang, S., Wei, X.: Correlation between egg beating response characteristics and freshness. J. Huazhong Agric. Univ. **28**(3), 373–376 (2009)
7. Long, X., Li, Y., Luo, X.: Research and design of egg freshness nondestructive testing system. J. Comput. Dig. Eng. **38**(5), 155–158 (2010)
8. Lin, H., Zhao, J., Sun, L., et al.: Freshness measurement of eggs using near infrared (NIR) spectroscopy and multivariate data analysis. J. Innov. Food Sci. Emerg. Technol. **12**(2), 182–186 (2011)
9. Giunchi, A., Berardinelli, A., Ragni, L., et al.: Non-destructive freshness assessment of shell eggs using FT-NIR spectroscopy. J. Food Eng. **89**(2),142–148 (2008)
10. Kemps, B., Bamelis, F., Ketelaere, D., et al.: Visible transmission spectroscopy for the assessment of egg freshness. J. Sci. Food. Agric. **86**(9), 1399–1406 (2006)
11. Wang, Q., Reng, Y., Wen, Y.: Nondestructive detection method of egg freshness based on BP neural network. J. Agric. Mach. **37**(01), 104–106 (2006)
12. Li, X., Zhao, D., Shi, H., Yuan, Y.: Nondestructive testing method for egg quality based on machine vision. J. Food Saf. Qual . **10**(2), 408–493 (2019)
13. Li, J., Wang, J., Li, Y., Wei, Y.: Detection of egg freshness based on electronic nose. J. Mod. Food Sci. Technol. **33**(4), 300–305+188 (2017)
14. Liu, Y., Li, Q., Huang, X., et al.: Study on feature extraction and freshness detection model of egg transparency image. Sci. Technol. Eng. **15**(25), 72–77 (2015)
15. Szegedy, C., Liu, W., Jia, Y.Q., et al.: Going deeper with convolutions. In: IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA (2015)
16. Woo, S., Park, J., Lee, J., et al.: CBAM: convolutional block attention module. Computer Vision Foundation. ArXiv,1807.06521v2 (2018)
17. Li, X., Zhao, D., Shi, H.: Non-destructive testing method of egg quality based on machine vision. J. Food Saf. Qual. **10**(2), 408–493 (2019)