# Detecting Dark Spot Eggs Based on CNN GoogLeNet Model

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**Abstract.** Aiming at the problems of high labor intensity and low efficiency in detecting dark spot eggs, a method of detecting dark spot eggs based on GoogLeNet model is proposed. This method uses Inception convolution module in GoogLeNet model to automatically extract dark spot eggs features and realize the detection. A device for collecting transparent images of eggs was set up in the experiment, and the sample collection experiments were designed to acquire samples. A total of 1200 dark spot eggs images and 8850 normal eggs images were obtained. Selecting 1200 samples of these two kinds for network modeling. The experimental results show that the detection accuracy of dark spotted eggs based on CNN GoogLeNet model is 98.19%. In order to further verify the GoogLeNet model, this paper repeats the above experiments using the VGG16 and VGG19 models of CNN model, and compares the accuracy. To further validate the GoogLeNet model, this paper repeats the above experiments using VGG16 and VGG19 models, and compares the accuracy. The results show that the three CNN models together have high detection accuracy, and the GoogLeNet model is highest, which provides a new method for egg quality detection.

**Keywords:** Dark spot eggs · Convolutional Neural Network · GoogLeNet model · HOG-SVM model

## 1 Introduction

Chicken egg's dark spots are dark spots formed when water in the egg contents permeates and accumulates on the eggshell. The appearance of dark spots is a manifestation of the decline in egg quality. Dark spot eggs lose water quickly, decrease freshness quickly and are more susceptible to microbial contamination, which have adverse effects on egg storage performance. Eggs are the national preferred nutritional food. It is an inevitable trend to accurately detect and remove dark spots of eggs, and to detect and grade the quality of eggs before they are put on shelves [2], which can ensure the health and safety of food.

At present, the detection of dark spot eggs is mainly completed by humans. It is of practical significance to find a high-efficiency detection method for the reasons such as the great difference in the coverage rate of the dark spots on the eggshell, the unstable


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position, the insignificant color of some dark spots, and the high intensity of labor. The detection method of machine vision combined with machine learning has been widely studied in egg quality detection due to its advantages of low cost and high convenience. For example, wang qiaohua [3–6] collected the light-transmitting image of eggs, extracted the color information inside the eggs and detected the freshness of the eggs by using the morphological features such as the yolk area ratio and the air chamber area ratio. Tu kang et al. [7] marked egg surface stains with threshold segmentation method to realize nondestructive detection of egg stains. Li xincheng et al. [8] use four characteristic parameters of egg freshness including ratio of egg yolk area, air chamber area, chamber height and chamber diameter and established single-element regression model with Haff values. The above research has made some progress in egg quality detection, however there are also some limitations. For example, only tens or hundreds of samples of egg translucent images were collected in the experimental which are easy to lead to over-fitting. Also, the distribution of small samples is uneven and the distribution of features is unbalanced which lead to in the freshness test, the samples are concentrated in grade b eggs and the number of super and grade a sample is far less than grade b. In addition, traditional machine learning methods such as BP neural network and support vector machine (SVM) are mostly used in the above studies. BP neural network needs to update network parameters repeatedly and SVM is excessively dependent on parameter adjustment. What's more, there are many pretreatment steps and large interference of the extraction methods based on color and morphological characteristics, so the accuracy of the existing egg quality detection methods is not high and there is a big gap with the actual production.

The Convolutional Neural Network (CNN) model [9] of deep learning uses the common operation of "Convolutional" and "descending sampling" to process and classify the multi-dimensional sample features, which has the advantage of processing multiple data. It has been widely used in the field of image recognition and detection, however, there are only a few studies use the CNN model to detect the quality of eggs. In this paper, normal eggs and dark spot eggs were taken as classified samples, and the method of combining machine vision with CNN was applied to dark spot eggs detection. The GoogLeNet [10] model was put forward for learning the characteristics of dark spot eggs to establish the dark spotted egg detection model, and to verify the effectiveness and accuracy of the model. The detection method proposed in this paper solves the problems existing in previous studies and provides a reference for the detection of dark spot eggs.

## 2 Materials and Methods

### 2.1 Experimental Materials

The test materials were 500 fresh JingBai 939 powdered-shell eggs provided by lanxi poultry farm in JinHua, China. In this experiment, the eggs were numbered, placed horizontally in the egg tray, and stored in indoor environment with temperature of 26–28 C and relative humidity of 70%–80%.

### 2.2 Instruments and Equipment

In order to obtain the transparent image of eggs, an egg transparent image acquisition system as shown in Fig. 1. The light source is OPT-RID-150 sphere integrated light source that is used in the process of image acquisition to supplement the light of the collected objects. In this experiment, a plane mirror was placed at the bottom of the light source, and the light from the original light source convergent at the bottom of the device. In this experiment, a plane mirror is placed at the bottom of the light source, so that the light originally collected at the bottom of the device pass through the top light transmission hole after being reflected through the plane mirror. The light obtained in the experiment is uniform, the light intensity is better and transmission effect are far better than those of incandescent light sources used in previous studies. The camera uses an industrial color CMOS camera (effective pixels: 2592 × 1944) with a 5-megapixel 12 mm lens. The illumination intensity in the image acquisition environment is 2–10 lx, and the collected images are RGB color images with a resolution of 1920 × 1440. Firstly, the brightness of light source was adjusted to highlight the dark spots of eggs. The process of collecting experimental images is as follows: firstly, adjust the brightness of the light source to the maximum; secondly, adjust the height of the camera by the iron frame, so that the whole egg is just of a moderate size and can be clearly photographed; then, the egg is placed in the light hole at the top of the light source in sequence according to its' number; finally, the image is collected by using the computer acquisition software.

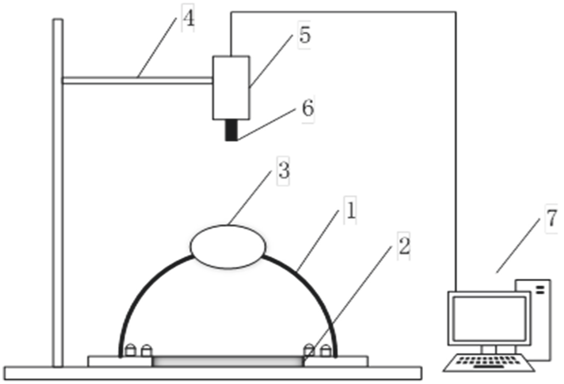


**Fig. 1.** Egg picture collecting device. 1. Spherical integral light source; 2. Plane mirror; 3. Egg; 4. Iron frame; 5. Industrial color CMOS camera; 6. Camera lens; 7. Computer image acquisition

### 2.3 Sample Collection

In the actual detection, eggs pass through the camera at a random Angle. If an image is collected from a single egg, dark spots on the egg shell cannot be completely collected, also the sample size cannot meet the modeling requirements. In order to get close to the practical application scene, this experiment adopts the multi-angle collection method for dark spotted eggs. After the egg image collection, it is turned over to 90° and repeated collection. If there is no dark spot on the eggshell at a certain angle, it is not collected. Normal eggs are collected one image sample individually. Studies have shown that [11] with the extension of storage time, dark spots will gradually increase and expand and appear on normal eggs. In order to learn the dark spot characteristics, the experiment repeated the above collection every day with a sampling period of 20 days. A total of 1200 images of dark speckled eggs and 8850 images of normal eggs were obtained.

## 2.4 Image Processing

The color of transmitted light image of eggs collected in this paper is yellow to red, and the color of dark spots of eggs is dark red. The color contrast between the two is not high. Previous studies have suggested that [12] color enhancement of RGB images can enhance color contrast. After color enhancement experiments, it was found that the G component in RGB space was easier to recognize the dark spots of eggs, so the G component in the sample picture was enhanced four times. Then, an interpolation algorithm is used to reduce the size of the enhanced image to 1/8 of the original size to meet the fast training and testing of the CNN network model. The resulting image is shown in Fig. 2.

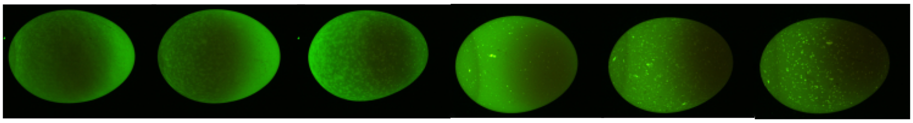

**Fig. 2.** Sample images of partial dark spot eggs

## 2.5 Model Description

CNN network, as a deep neural network model [13], can automatically learn and extract features from data, avoiding complex image preprocessing in the early stage, and has been widely used in such fields as pattern classification, object detection and object recognition. CNN network composed of input layer, feature extraction, the fully connection layer and output layer. The feature extraction layer is the core of the network, the more layers there are, the stronger the feature extraction capability is. It mainly includes convolution layer and lower sampling layer. The convolution layer is used to extract features of input images. Features extracted from different convolution cores are different. The more the number of cores in the convolution layer, the more the features extracted. The lower sampling layer can reduce the amount of data processing and ensure the computing speed.

As a CNN network model, GoogLeNet uses Inception module as a convolutional layer to introduce multi-scale convolution to extract multi-scale local features. Its structure is shown in Fig. 3. The module contains several $1 \times 1$, $3 \times 3$ and $5 \times 5$ convolution kernel branches, the multi-core structure can extract and learn the features of different forms of egg spots, which is suitable for the dispersed, multi-morphological and multi-scale characteristics of egg spots [14]. Moreover, an additional $1 \times 1$ convolution kernel is added to the structure, which not only increases the network depth, but also improves the nonlinear degree of the network. It also reduces the dimensions of convolution objects in other convolution kernel and reduces the computation. The CNN GoogLeNet model structure used in this article is shown in Fig. 4.

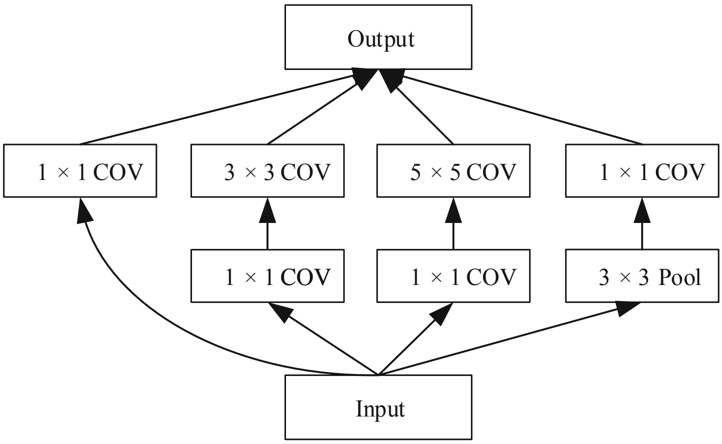


**Fig. 3.** Inception module structure

It can be seen from Fig. 4 that the basic modules of traditional CNN network, namely convolution layer and pooling layer, are adopted near the image input layer. Considering that the characteristics of the middle layer have been able to identify to a certain extent, and considering that the gradient vanishing in the optimization process of random gradient descent algorithm is easily caused by the excessively deep network layer, GoogLeNet added two additional full-connected SoftMax classifiers to the side of the trunk network.In the process of model optimization, network model parameters are updated by adding the gradient of loss function of trunk and branch classifier. In the test process, the branch classifier was removed and only the trunk classifier was used for dark spot egg detection and grading.

### 2.6 Testing Process

A total of 1200 dark spot egg images and 8850 normal egg images were obtained. To balance the number of two types of samples, 1200 samples were randomly selected from the normal egg samples, and the two types of samples were processed with the above image processing. Secondly, the number of training sets and test sets is selected, according to the ratio of 1:3. This paper randomly takes 900 samples from each category as model training samples and 300 as test samples. The labels of dark spot eggs and normal eggs are coded as 0001 and 0010 by one-hot code. Then, the training samples and labels are substituted into the input and output of the CNN GoogLeNet model for training, and the random gradient descent algorithm (SGD) is adopted for weight update. When the error or iteration number reaches the threshold value, the training stops. Finally,

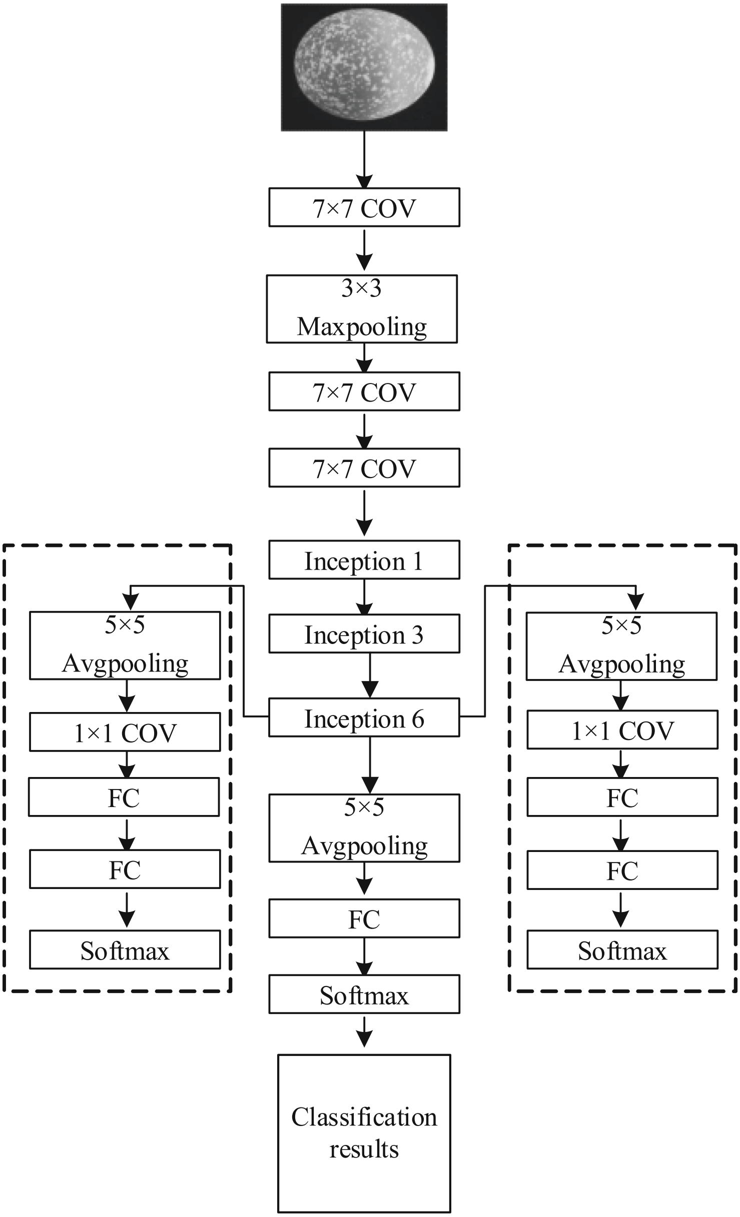


**Fig. 4.** GoogLeNet model

test samples are substituted into the trained network and test results are obtained. The flow chart is shown in Fig. 5.

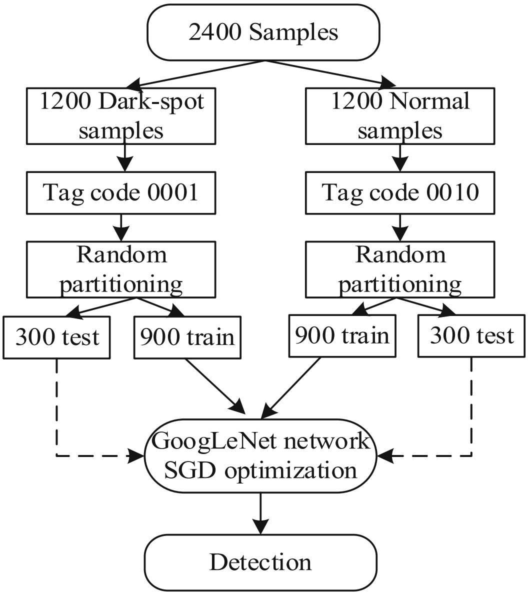


**Fig. 5.** Flow chart of detection of dark spot eggs

## 3 Results and Discussion

In the experiment, the classification accuracy was selected as evaluation index and optimized by SGD algorithm. According to the principle of optimal test accuracy, momentum parameter of convolutional network was set as 0.7, initial learning rate was set as 1e-4, the number of sample batch included in each iteration of gradient descent was set as 32, and the number of epochs was set as 20. The trend of test accuracy and loss function during model optimization is analyzed experimentally with increasing iterations. The detection accuracy of this method is compared with that of the directional gradient histogram (HOG) combined with the support vector machine (SVM) method. To further validate the GoogLeNet model, we repeated the above experiments using the VGG16 and VGG19 models for accuracy comparison.

### 3.1 Experimental Results

The GoogLeNet model was established in this experiment, and the experimental platform was MATLAB2017b, CPU: Intel Xeon (R) (R) X5650CPU@2.67 GHz@2.67 GHz; Memory size: 48 GB. When training the model in this experiment, the training situation of the model is evaluated according to the loss and accuracy curves, and the network parameters are adjusted accordingly, as shown in Fig. 6.

It can be seen from Fig. 6 that the training loss function presents a downward trend in the training process, and the prediction loss deviation of the response model gradually decreases in the optimization process by updating the loss function gradient. Meanwhile, as the number of iterations increases, the prediction accuracy of the model on the test set

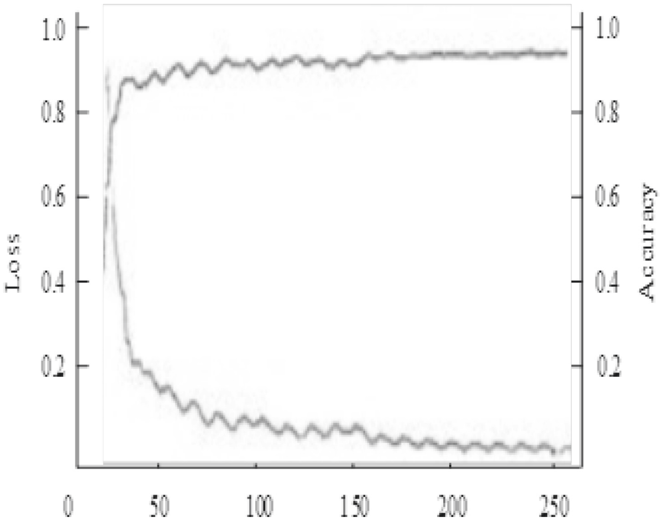


**Fig. 6.** Loss function and accuracy

increases as a whole. The performance of the response model can be optimized in the process of constantly updating the parameters. When the number of iterations reaches 260, it basically converges. The detection accuracy of dark spot eggs was 97.04%, that of normal eggs was 98.89%, and the total detection accuracy of test samples was 98.19%.

### 3.2 Model Validation

In order to verify the effectiveness and credibility of this method, the GoogLeNet model and HOG-SVM method are compared. As a widely used image feature extraction method, HOG feature [16] can describe image morphology by using the density distribution of gradient and edge direction in the sample to be measured. To extract HOG feature, firstly, color normalization of the image is required. In this paper, the optimal threshold value is obtained by combining with the traditional large law, and the optimal adaptive threshold value is 0. 294. Then the color sample image is binarized. After that, the sample of 240 $\times$ 180 pixels is divided into several blocks of 2 $\times$ 2 cells, each cell is 8 $\times$ 8 pixels in size. Histogram statistics of the gradient directions facing all pixels in each cell is conducted to obtain a multi-dimensional feature vector. Finally, the feature vectors of adjacent units are connected to get higher-dimensional feature vectors, and the HOG feature of the entire sample is obtained. The process is shown in Fig. 7.

SVM [15] model, as a classical machine learning method, can produce better classification results under high-dimensional data. This paper combines SVM with HOG and applies HOG-SVM to dark spot egg detection. The SVM toolbox is the least squares support vector machine (LS-SVM) toolbox and the kernel function is RBF kernel function. The combination of grid search and crossover verification is used to find the best kernel parameter. The experimental results are shown in Table 1. It can be seen from Table 1 that GoogLeNet detection accuracy is more than 10% higher than that of the

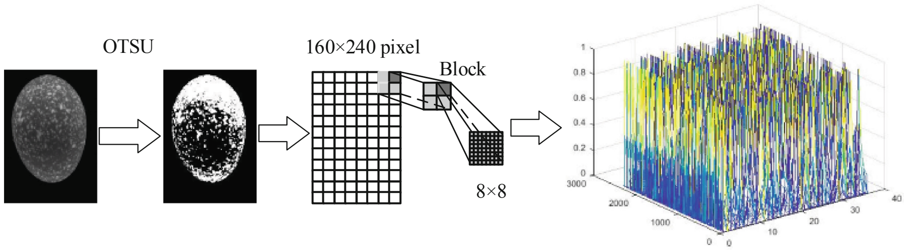


**Fig. 7.** HOG feature extraction process

Hog-SVM model, which proves the validity and credibility of the GoogLeNet model. To evaluate the detection accuracy of GoogLeNet model, it was compared with VGG16 and VGG19 models. The experimental samples were consistent, and the parameters of convolutional network optimization algorithm were also the same.

**Table 1.** Comparison of test results of four models

| Network model | Feature extraction | Test set accuracy/% | Dark-spots eggs accuracy/% | Normal eggs accuracy/% |
|---|---|---|---|---|
| GoogLeNet | Inception | 98.19 | 97.04 | 98.89 |
| SVM | HOG | 86.12 | 85.34 | 88.73 |
| VGG16 | Conv | 96.99 | 95.83 | 97.64 |
| VGG19 | Conv | 96.76 | 95.53 | 97.52 |

As can be seen from Table 1, the CNN based dark spot egg detection method proposed in this paper is feasible and reliable. The accuracy of the three CNN models can reach over 96%, among which the GoogLeNet model has a better detection accuracy of 98.19%. It can be concluded from the experiment that the detection method based on GoogLeNet model is feasible and has highest detection accuracy.

## 4 Conclusion

This paper presents a method of dark spot eggs detection based on the convolutional neural network GoogLeNet model. Aiming at the problems of too few samples, too many pretreatment steps and low precision of model in the previous research on egg quality detection. This paper improves the egg image acquisition experiment which greatly expanding the number of samples and balancing the number of samples of two kinds of egg images. The GoogLeNet model, which can automatically learn and extract features, is applied to the detection of egg dark spots. The experiment dividing training and testing samples were used in GoogLeNet model training. The result shows that the detection accuracy of dark spot eggs is 98.19%. This proves that the method based on CNN network can detect dark spot eggs with high detection accuracy without too many pre-processing steps. In order to verify the effectiveness and credibility of this method, the GoogLeNet model is compared with the HOG-SVM model and the other two CNN models. The results show that the detection results of the three CNN models are far superior to the traditional image classification algorithm HOG-SVM model, while the GoogLeNet model is more accurate than other CNN models.

In this paper, although machine vision combined with CNN model has been applied to the detection of dark spotted eggs and good results have been obtained, there are still researches to be further carried out: firstly, In order to highlight the characteristics of samples, the illumination intensity of the collected environment in this paper is low. In order to enhance the adaptability of the detection method to the illumination changes, the diversity of samples under different illumination conditions should be increased; Secondly, This paper proposes that the detection method is still in the laboratory stage, and further research on egg transfer and sorting device should be carried out if it is to be put into production. Thirdly, the detection method proposed in this paper is not only limited to the detection of dark spots, but also applicable to the detection of egg freshness in a wide range of studies, and the detection of other poultry eggs can also be tried, which is worthy of further research.

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