Egg freshness recognition based on a fuzzy radial-basis-function neural network technology

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Abstract. There are often mobile, unconscientious vendors in China who sell stale or even rotten eggs in produce markets, earning money by dishonest means. To prevent the entry of substandard eggs into the market that endanger the health of consumers, we designed an egg freshness recognition system based on a fuzzy radial-basis-function (RBF) neural network. This system acquires the color characteristic parameters red (R), green (G), and blue (B) of the transmitted light of eggs through a computer vision device. The system converts the RGB values into HIS (hue, intensity, and saturation) values, uses the egg transmitted light color characteristic parameter HIS as an input value and employs the Huff value coding as an output. A test sample was used to verify the identification system. Our experimental results show that when using a fuzzy RBF neural network and simple RBF neural network algorithm, the average recognition accuracy of the system is 96.35% and 92.72%, respectively, both of which are higher than the average recognition accuracy of 88.14% when using the back propagation neural network algorithm. The feasibility and superiority of the identification system proposed in this paper were verified; therefore, this system may serve as a reference for future research on egg freshness recognition.

1. Introduction
Eggs contain a variety of nutrients that are beneficial to the human body and are one of the most common foods consumed by society. However, some mobile and unconscientious vendors sell stale or even rotten eggs in grocery markets, thereby threatening the health of consumers. Figure 1 is a comparison of various eggs, including the shape of the yolk of a fresh egg. If the yolk is loose, then the egg is not fresh. If the egg yolk sticks to the interior of the eggshell or if the interior of the eggshell is black in color, the egg is rotten. Therefore, it is necessary to study egg freshness recognition.

When we purchase eggs, we typically hold the eggs close to our ear and forcefully shake them up and down. Hearing a sound while shaking the egg indicates that it is not fresh, whereas the absence of sound reveals egg freshness. In general, the recognition accuracy of this method is poor, and vendors often prevent consumers from shaking the eggs they sell, as the vendors are concerned that shaking further loosens the yolk inside the egg. In recent years, several scholars worldwide have studied egg freshness recognition. The main methods used include near-infrared spectroscopy [1-3], electronic nose detection [4], hyperspectral detection [5,6], microwave spectroscopy [7], and gas...
chromatography detection [8]. The applicability of near-infrared spectroscopy is relatively limited, as the position and number of selected points are relatively random and one-sided. Electronic nose detection is suitable for sampling detection but is relatively time-consuming when compared to the optical method. Hyperspectral detection and microwave spectroscopy are susceptible to instrument noise and are affected by the uneven surfaces of eggs, and gas chromatography detection cannot directly generate qualitative analytical results as it requires derivation. Computer vision technology has been successfully applied to agricultural product testing [9-11], including the integration of back propagation (BP) neural network and computer vision technology to identify egg freshness [9]. However, the established system does not have a high recognition accuracy for egg freshness, which is mainly due to slow convergence speed, long training time, and low approximation accuracy of the BP neural network; there are also local optimization problems. Relative to the numerous shortcomings of BP neural network, RBF neural network can approximate arbitrary nonlinear functions with arbitrary precision and display a global approximation ability, which fundamentally solves the local optimization problem inherent to BP network. RBF neural network also have rapid convergence speeds and a shorter training time [12,13]. However, studies on the application of combined RBF neural network and computer vision technology for egg freshness recognition are rare. According to the optical properties of eggs, the transmittance of fresh eggs to light decreases with storage time [9,14]. Changes in the transmittance of light indicate alterations in the internal egg quality, which can be reflected as modifications of color inside the egg. Here, a fuzzy RBF neural network and computer vision technology were combined to construct an automatic system for the recognition of egg freshness. The experimental device used in this paper has been successfully applied in the recognition of artificial ripening tomatoes [15], it is a low cost and easy-to-use device, and the RBF neural network algorithm itself is mature, so any person can apply it immediately.

2. Material and methods

2.1. Materials
600 fresh eggs, provided by xiantao food corporation in China’s Hubei province on March 1, 2019.

2.2. Methods formulation
There are multiple color models for describing the color of an object. In practical applications, the commonly used models include the RGB and HIS color models. Based on the requirements of our test, the HIS color model was selected [15]. The conversion formula from the RGB model to the HIS model is [15]:

Figure 1. Eggs of different degrees of freshness. (a) Fresh egg, (b) Loose yolk eggs and (c) Rotten eggs.
where R is red, G is green, B is blue, H is hue, I is intensity, and S is saturation.

The test device consists of a light source, an egg tray, a video camera, an image acquisition card and a computer, as shown in figure 2. During the test, it is critical to ensure that there is no gap between the egg and the light-transmitting hole to prevent light from entering the light box directly from the gap. Both sides of the egg are equipped with two mirrors at an angle of 45° to the horizontal plane, which ensures that the charge-coupled device (CCD) camera can capture the transmitted light image information of three sides of each egg at a time, which satisfies the comprehensive requirements of color detection.

![Figure 2. Schematic diagram of test drive for egg freshness recognition.](image)

The operation process of system identification is as follows: (1) select 200 pieces each of brown- and white-shell eggs, and label all eggs to facilitate test data collection; (2) place each egg in the egg holder of the test device, collect the images (R, G, B) of the transmitted light of the eggs in the light box and transfer the images to a computer, in order to process the image through a test procedure to obtain color information of the egg content (H, I, S); (3) weigh each egg on an electronic balance after the images are obtained; and (4) break each egg after the images are obtained and measure the Huff value as an indicator of the freshness of the egg. The formula for calculating the Huff value is as follows [9]:

\[
H_w = 100 \log(h + 7.57 - 1.7w^{0.37})
\]  

In the formula, \(H_w\) represents the Huff value. The Huff value is a test specified by the U.S. Department of Agriculture as the egg standard and serves as a factor indicating the freshness of eggs. The Huff value of a fresh egg is usually between 75 and 82, with relatively high values up to 90; edible eggs must have a Huff value above 72. According to the requirements of this test, the Huff value is divided into three grades according to international standards and are coded as different codes (table 1). In equation (2), \(w\) (g) indicates the mass of the egg and \(h\) (mm) indicates the height of the albumen, which can be measured using the device in figure 3 [14].
Table 1. Huff value coding.

| Egg freshness grade          | Huff value coding |
|-------------------------------|-------------------|
| Special ($H_a \geq 72$)      | [1,0,0]           |
| Grade A ($60 \leq H_a < 72$) | [0,1,0]           |
| Grade B ($30 < H_a < 60$)    | [0,0,1]           |

Figure 3. Measurement of albumen height.

The method of measuring albumen height involves placing a cracked egg on a horizontal glass plate, identifying the height values of four different parts of the egg with a ruler, namely, $h_1$, $h_2$, $h_3$, and $h_4$, and computing the average value, which is designated as albumen height $h$. In the experiments, we respectively obtained 196 and 190 groups of brown- and white-shell egg color data (H, I, S). The corresponding Huff value data indicated freshness grade, which we used as sample data to train the fuzzy RBF neural network. Finally, we identified each test sample by employing the trained network model.

3. Construction of fuzzy RBF neural network

The RBF neural network has a strong self-learning function and self-adaptive ability, and can effectively learn and adjust to the sample; however, its internal mapping rules are invisible and difficult to understand. Fuzzy control has the characteristics of strong reasoning ability, and the control rules of fuzzy control are summarized and determined based on the experience of experts or skilled professionals, so the rules are easy to understand and intuitive. Therefore, we combined fuzzy control and a RBF neural network to form a fuzzy RBF neural network.

3.1. Neural network structure

The structure of the fuzzy RBF neural network is shown in figure 4 [16]. The network consists of an input layer, a fuzzification layer, a fuzzy inference layer, and an output layer. The functions of each layer are as follows:

- The first layer is the input layer. This layer has three nodes, each node is directly connected to each component of the input quantity, and the input quantity is passed to the next layer. The input and output of each node of the layer is expressed as follows:

  \[ f_i(i) = X = [x_1, x_2, x_3] = [H, I, S] \]  

  (3)

  where the input and output of the layer are equal and represent the color data H, I, and S.

- The second layer is the fuzzification layer. According to the principle of least membership function [16], three nodes are selected in this layer to divide the three inputs into three fuzzy sets, and the Gaussian function is used as the membership function. $c_{ij}$ and $b_{ij}$ are the mean and standard deviation of the membership function of the $i$ th input variable and the $j$ th fuzzy...
set, respectively:

\[
H \quad I \quad S
\]

\[
y_1 
\]

\[
y_2 
\]

\[
y_3 
\]

Figure 4. Fuzzy RBF neural network structure.

\[
f_2(i, j) = \exp \left\{ - \frac{(f_i(i) - c_{ij})^2}{(b_{ij})^2} \right\}
\]

where \( i = 1, 2, 3 \) and \( j = 1, 2, 3 \).

- The third layer is the fuzzy inference layer. The number of nodes in this layer is \( 3^3 \times 3 = 81 \) [17], and the fuzzy operation is implemented between each node. Specifically, the corresponding ignition intensity is obtained by the combination of each fuzzy node. The output of each node \( j \) is the product of all input signals of the node, namely:

\[
f_3(j) = \prod_{i=1}^{N} f_2(i, j)
\]

In the formula, \( N = \prod_{i=1}^{n} N_i \), where \( N_i \) is the fuzzy segmentation number of the \( i \)th input.

- The fourth layer is the output layer. This layer has three nodes and the output is a three-dimensional Huff value coding \([y_1, y_2, y_3]\), i.e.:

\[
f_y(i) = W \cdot f_3 = \sum_{j=1}^{N} W(i, j) \cdot f_3(j)(i = 1, 2, 3)
\]

where \( W_y(i = 1, 2, 3) \) is the connection weight matrix of the output node and each node of the third layer.

The fields of input quantities, H, I, and S, are all \([-1, 1]\), and the fuzzy sets are all \{NB, ZO, PB\}, indicating that the input is \{small, moderate, and large\}; the output values are all 0 or 1. The membership functions of the input quantities (H, I, and S) are shown in figure 5. After several trials, the fuzzy control rules were developed as shown in table 2. Figure 6 shows the fuzzy relationship between the inputs (H, I, S) and output \( y_2 \) of the system (the fuzzy relationships between the three inputs of the system and the other two outputs are not listed).
Figure 5. Membership function.

Table 2. Fuzzy control rules.

| H   | I  | S  | Huff value       |
|-----|----|----|------------------|
| NB  | NB | NB | \[0,0,1\]        |
| NB  | ZO | NB | \[0,0,1\]        |
| NB  | PB | NB | \[0,0,1\]        |
| ZO  | NB | ZO | \[0,0,1\]        |
| ZO  | ZO | ZO | \[0,0,1\]        |
| ZO  | PB | ZO | \[1,0,1\]        |
| PB  | NB | PB | \[0,1,0\]        |
| PB  | ZO | PB | \[0,0,1\]        |
| PB  | PB | PB | \[0,1,0\]        |

Figure 6. Fuzzy relationships between input and output. (a) Fuzzy relationship between H, I, and output $y_2$, (b) Fuzzy relationship between H, S, and output $y_2$, and (c) Fuzzy relationship between...
I, S, and output $y_2$.

3.2. Network training

Using Matlab (2017a) as network training software. Figures 7-9 illustrate the network training errors when using a BP neural network, simple RBF neural network, and fuzzy RBF neural network, respectively. Figure 7 shows that the network training error is 0.01193 when the network training is iterated to 40 steps and the training is stopped at 238 steps. Figure 8 shows that when the network training is iterated to 11 steps, the network training error is 0.01193; the training is stopped when the network training is iterated to 78 steps. Figure 9 shows network training iterated only to the 4th step, and the network training error reached 0.01424; the network training was stopped only when it was iterated to the 21st step. Therefore, compared to the BP and simple RBF neural network, when the fuzzy RBF neural network is adopted, the system has a faster convergence speed, shorter training time, and higher approximation accuracy.

![Figure 7](image1.png)  
**Figure 7.** Network training error when using BP neural network.

![Figure 8](image2.png)  
**Figure 8.** Network training error when using simple RBF neural network.

![Figure 9](image3.png)  
**Figure 9.** Network training error when using fuzzy RBF neural network.

4. System design

Matlab (2017a) was used as the development software in the Win7 environment in the system, and detection was conducted using a computer vision device. Eggs with different shell colors and the same
freshness have different image color characteristics, whereas eggs of various shell colors and freshness sometimes have similar image color characteristics. Therefore, to avoid the influence of shell color on egg freshness detection, we detected freshness according to different shell color classifications to be efficient and accurate. Since the color of the egg shell is related to the color information of the yolk area (H, I, S), the fuzzy identification is conducted using the I value with greater influence. The membership functions A(I) and B(I) of the fuzzy set of brown-shell and white-shell eggs was established, and the I value of the tested egg was substituted into A(I) and B(I), respectively. According to the principle of maximum membership, if A(I) > B(I), then the egg is considered to have a brown-shell, and vice versa [9]. The system identification flow chart is shown in figure 10.

5. Results
To detect the performance and efficiency of the network, several batches of brown- and white-shell eggs of the same variety as the previous test were randomly selected, and the test conditions were kept the same. First, we extracted color information from the egg to be tested on the test device. Next, we broke the egg, measured and calculated the true freshness of the egg, and then input the color information parameters (H, I, S) of the egg into the network. Then, we assessed the freshness grade of the egg using the network and recorded the test and network results of each egg separately. The system detection results as shown in table 3.

Figure 10. System identification flow chart.
Table 3. Recognition accuracy.

| Algorithm                  | Brown-shell egg | White-shell egg |
|---------------------------|-----------------|-----------------|
| BP neural network         | 87.258%         | 89.029%         |
| Simple RBF neural network | 91.682%         | 93.758%         |
| Fuzzy RBF neural network  | 95.175%         | 97.525%         |

6. Conclusions
We developed a novel fuzzy RBF neural network egg freshness recognition system to address the problem of poor recognition accuracy of egg freshness using a BP neural network. To avoid the influence of shell color on egg freshness detection, we detected egg freshness according to different shell color classifications, and our experimental results show that the average recognition accuracy of the fuzzy RBF neural network detection system is 96.35%, which is higher than that of the simple RBF neural network detection system (92.72%) and the BP neural network detection system (88.14%).

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References
[1] Duan Y F, Wang Q H, Ma M H, Lu X and Wang C Y 2016 Study on non-destructive detection method for egg freshness based on LLE-SVR and visible/near-infrared spectrum Spectrosc. Spectr. Anal. 34 981-5
[2] Aboonajmi M, Saberi A, Najafabadi T A and Kondo N 2016 Quality assessment of poultry egg based on visible-near infrared spectroscopy and radial basis function networks Int. J. Food Prop. 19 1163-72
[3] Li X M 2017 Study on on-line detection of egg freshness based on visible-nearinfrared spectrum (Wuhan, China: Huazhong Agriculture University)
[4] Li J T, Zhu S S, Jiang S and Wang J 2017 Prediction of egg storage time and yolk index based on electronic nose combined with chemometric methods LWT 82 369-76
[5] Fu D D and Wang Q H 2016 Predictive models for the detection of egg freshness, acidity and viscosity using hyper-spectral imaging Food Sc. 37 173-9
[6] Wang Q H, Zhou K, Wu L L and Wang C Y 2016 Egg freshness detection based on hyper spectr Spectrosc. Spectr. Anal. 36 2596-600
[7] Akbarzadeh N, Mireei S A and Askari G 2019 Microwave spectroscopy based on the waveguide technique for the nondestructive freshness evaluation of egg Food Chem. 277 558-65
[8] Cavanna D, Zanardi S, Dall'Asta C and Suman M 2019 Ion mobility spectrometry coupled to gas chromatography: A rapid tool to assess eggs freshness Food Chem. 271 691-6
[9] Wang Q, Ren Y and Wen Y 2006 Study on non-destructive detection method for fresh degree of eggs based on BP neural network Trans. Chin. Soc. Agricul. Machinery 37 104-6
[10] Pan L, Tu K, Zhan G, Liu M and Zou X 2010 Eggshell crack detection based on information fusion between computer vision and acoustic response Trans. CSAE 26 332-7
[11] Zhao H and Zhou X 2013 Recognition of artificial ripening tomato and nature mature tomato based on the double parallel genetic neural network Adv. J. Food Sci. Technol. 5 482-7
[12] Song Q, Meng G J, Yang L, Du D Q and Mao X F 2014 Comparison between BP and RBF neural network pattern recognition process applied in the droplet analyzer International Conference on Vehicle and Mechanical Engineering and Information Technology (VMEIT), Beijing, China pp 2333-6
[13] Wang H, Kong C, Li D, Qin N, Fan H, Hong H and Luo Y 2015 Modeling quality changes in brined bream (Megalobrama amblycephala) fillets during storage: comparison of the arrhenius model, BP, and RBF neural network Food. Bioprocess Technol. 8 2429-43
[14] Wang Q 2004 The study of recognition of egg fresh degree by BP neural network (Wuhan, China: Huazhong Agricultural University)

[15] Zhao H B and Zhou X H 2013 Recognition of artificial ripening tomato and nature mature tomato based on the double parallel genetic neural network Adv. J. Food Sci. Technol. 5 482-7

[16] Zhang Y and Lv H 2016 Study on PID controller based on fuzzy RBF neural network in rolling mill hydraulic AGC system Proceedings of the 28th Chinese Control and Decision Conference (Yinchuan, China) pp 4616-20

[17] Cao H, Sun B, Duan J, Pan D and Li T 2000 Principle of determining the minimum reasoning rules in fuzzy control Veh. Engin. 5 24-7