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Research Article

Application of Artificial Neural Network in the Baking Process of Salmon

Pengfei Jiang,[1] **Kaiyue Zhu**,[1] **Shan Shang**,[1] **Wengang Jin**,[2] **Wanying Yu**,[1] **Shuang Li**,[1] **Shen Wang**,[1,3] **and Xiuping Dong**[1]

[1]*School of Food Science and Technology, Dalian Polytechnic University, Dalian 116034, Liaoning, China*
[2]*Key Laboratory of Bio-resources of Shaanxi Province, School of Biological Science and Engineering, Shaanxi University of Technology, Hanzhong 723001, China*
[3]*Qingdao Agricultural Products Quality and Safety Center, Qingdao 266041, China*

Correspondence should be addressed to Xiuping Dong; dxiuping@163.com

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The global production of farmed Atlantic salmon amounts to over 2 million tons per year. Consumed all over the world, salmon is not only delicious but also nutritious. This paper deals with the relationship between moisture content, low-field nuclear magnetic resonance (LF-NMR), scanning electron microscope (SEM), and sensory evaluation in the baking process of salmon. An artificial neural network (ANN) model has been established to simulate the change of moisture content and energy consumed in the baking process. Through the study of LF-NMR, SEM, and sensory evaluation, it was found that the change of sensory indexes was consistent with the results observed by LF-NMR and SEM. With the increase of temperature, muscle fibers contracted, the interstices increased, the rate of water loss increased, and the sensory score decreased. Initial moisture content, baking time, baking temperature, baking humidity, and baking air velocity were employed as the baking control parameters for the ANN. ANN can be used to determine the moisture content and energy consumed of baking salmon. The best network topology occurred with 5 input layer neurons, 17 hidden layer neurons, and 2 output layer neurons, and the MSE was 0.00153, and Rall was 0.99661. According to the experiment, it was demonstrated that the ANN is a reliable software-based method.

1. Introduction

Salmon is a large- and medium-sized cold water migratory fish, mainly distributed in the northern Pacific Ocean and the boundary between the Atlantic Ocean and the Arctic Ocean [1]. Salmon is not only delicious but also nutritious [2]. The global production of farmed Atlantic salmon (*Salmo salar* L.) reached 2.36 million tons in 2017 [3].

The salmon market was dominated by raw food and smoked products [4]. Veiseth-Kent et al. [5] studied the effect of sensory assessment and texture assessment on the postmortem process of raw salmon by sensory and instrumental methods. Birkeland et al. [6] researched cold smoking procedures and raw material characteristics on product yield and quality parameters of cold smoked fillets. Other scholars also studied raw salmon and cold smoked salmon preservation technology [7, 8], processing technology [9], food safety [10], and other aspects. With the improvement of people's living standard, higher requirements have been put forward for salmon products.

Baking was a common cooking method which induces water loss in the food [11, 12]. Evaporation of water was one of the several fundamental complex physical processes during baking [13]. The main conditions affecting baking include baking temperature, air velocity, and humidity.

Artificial neural network (ANN) is one of the black-box modeling approaches, which is a heuristic soft computing method used for the nonlinear and complex systems [14, 15]. ANN has been used in the food industry for modeling many processes, such as estimation of antioxidant activity of foods, recognition in the drying of guava pieces in the spouted bed, and prediction of paddy drying a fluidized-bed drier [16–18].

Generally speaking, ANN was used to predict product indicators (moisture content, crumb temperature, color change, and relative volume) with the inputs of drying parameters (jet temperature, jet velocity, and baking time) [19]. Similar study was conducted to predict the modified moisture ratio of pepper-tree fruits with two inputs of mass, air temperature, and air velocity [20]. In addition, there were many researchers who used different variables to predict the performance of moisture content [21–23]. Current research studies generally had taken a single parameter (such as moisture, active ingredients, and color) as the output layer to establish the ANN model. When studying multiple indicators, multiple models were generally established to study one by one. Therefore, if the ANN model can be established by simultaneously studying two parameters as output layers, such as moisture content and energy consumed in this paper, it will be more conducive to the wider application of ANN in food research, which is also the significance of this paper.

2. Materials and Methods

2.1. Materials and Drying Equipment. The salmon used in this experiment was Pacific salmon. Chilled salmons were purchased from a local market and were transported to the laboratory using refrigerated transportation. At the beginning of the experiment, salmons were removed the head, scales, skin, and bones and taken the anterior back muscles of the salmon to be the materials. The salmons were cut manually using the cubic device with dimensions of 1 cm × 1 cm with a thickness of 4 cm. The baking experiment was conducted using the universal steam oven (model SCC WE 101, Rational Co., Ltd., Germany).

2.2. Experimental Procedure. The initial moisture content of the experiment materials was controlled at about 59.91 ± 0.27%. The baking temperature, time, humidity, and air velocity are given in Table 1. The levels for the process variables were decided based on trial experiments.

The prepared samples were picked in the seasoning solution for 2 hours at 4°C. In the first half minutes, the sample moisture content was measured at an interval of 2 min. After 30 minutes, the sample moisture content was measured at an interval of 5 min.

2.3. Measurement of Energy Consumption. Fifty-four groups of salmons were investigated for energy consumption measurement. An energy meter (model DTS 7738 3 × 220/380 V, Shanghai Huali Co., Ltd., China) bridging the connection between a voltage stabilizer and the universal steam oven was installed. Energy consumed per experiment was estimated in kilowatt hours.

2.4. Low-Field Nuclear Magnetic Resonance (LF-NMR) Imaging Technology. The samples were prepared according to the treatment method of the fish in method 2.1. The salmon samples were divided into 54 groups with 3 parallel for each group. Samples were baked at different temperatures (100°C, 110°C, 120°C, 130°C, 140°C, and 150°C), and each temperature was set for different times (2 min, 4 min, 6 min, 8 min, 10 min, 12 min, 14 min, and 16 min).

The processed sample was detected by using an LF-NMR imaging analyzer. The resonance frequency of the proton was 22.7 mhz, the temperature of the magnet was 32°C, and the strength of the magnet was 0.47 T. The salmon sample was placed in a cylindrical feeding tube, with imaging parameters settings as follows: TW = 1500 ms, TE = 20 ms, average = 2, slice width = 2.5 mm, and slice = 1 [24].

2.5. Scanning Electron Microscope (SEM). The SEM was used to analyze the microstructure of salmons after baking 16 min. The sample microstructure was observed by JEOL model JSM-7800F, Tokyo, Japan. The specimen fragments for SEM were taken from the center of baked sample and dehydrated by freeze-drying. Small piece of about 4 × 4 × 1 mm was cut from the dried samples and fixed on the SEM stub, which were coated with gold to provide a reflective surface for electron beam. The gold-coated samples were viewed under the microscope, and a 50× magnification was used in all SEM observations [25].

2.6. Sensory Evaluation. The sensory qualities of different salmons were analyzed in terms of taste (1–10 points), odour (1–10 points), color (1–10 points), hard (1–10 points), and springiness (1–10 points). An eight-member panel, all of whom were experienced in the sensory evaluation of salmon foods, scored the five parts. The judges were asked to give their remarks about each of the samples [26].

2.7. Artificial Neural Network (ANN) Implementation. The ANN is a multilayer feedforward neural network trained according to the error back propagation algorithm with a momentum adjustment and an adaptive learning rate [27–29].

The ANN implemented a three-layer ANN like the one shown in Figure 1(a). The three kinds of layers in our ANN are known as input, hidden, and output layers. Equation (1) through (3) express the inputs of the input layer:

$$\begin{aligned} H_I^{i1} &= \left[\left(I_1 \times w_{11}\right) + b_{11}\right] + \left[\left(I_2 \times v_{21}\right) + b_{21}\right] \\ &\quad + \cdots + \left[\left(I_i \times u_{i1}\right) + b_{i1}\right], \end{aligned} \tag{1}$$

$$\begin{aligned} H_I^{i2} &= \left[\left(I_1 \times w_{12}\right) + b_{12}\right] + \left[\left(I_2 \times v_{22}\right) + b_{22}\right] \\ &\quad + \cdots + \left[\left(I_i \times u_{i2}\right) + b_{i2}\right], \end{aligned} \tag{2}$$

$$\begin{aligned} H_I^{ij} &= \left[\left(I_1 \times w_{1j}\right) + b_{1j}\right] + \left[\left(I_2 \times v_{2j}\right) + b_{2j}\right] \\ &\quad + \cdots + \left[\left(I_i \times u_{ij}\right) + b_{ij}\right]. \end{aligned} \tag{3}$$

Equation (4) expresses the outputs of the hidden layer:

$$H_O^{jk} = f\left(H_I^{ij}\right). \tag{4}$$

The input signal to the output layer is estimated using

Table 1: Responses obtained for experimental runs.

Run no.	M_0 (% w.b.)	Baking time (min)	Baking temperature (°C)	Baking humidity (%)	Baking air velocity (m/s)	Final M (% w.b.)	Energy consumed (kW)	Sensory Evaluation (point)
1	59.94	55	100	0	8	40.19	2.2	34.13
2	60.32	45	100	0	16	39.23	1.8	34.75
3	59.71	35	100	0	25	39.74	1.7	36.69
4	59.87	40	100	10	8	39.53	1.6	33.88
5	59.76	35	100	10	16	38.53	1.7	30.25
6	59.82	45	100	10	25	39.99	1.8	31.88
7	59.98	45	100	20	8	39.32	1.8	34.88
8	59.56	40	100	20	16	38.12	1.7	33.13
9	59.78	40	100	20	25	39.24	1.8	32.38
10	59.83	45	110	0	8	39.27	1.8	38.13
11	59.54	35	110	0	16	39.17	1.8	34.13
12	60.26	35	110	0	25	40.76	1.8	34.5
13	59.58	40	110	10	8	39.86	1.9	36
14	59.62	35	110	10	16	39.18	1.8	34.38
15	59.82	40	110	10	25	39.48	2	35.38
16	60.12	30	110	20	8	39.86	1.7	36.5
17	59.59	55	110	20	16	40.04	2.2	33.88
18	59.66	30	110	20	25	40.16	1.7	34
19	60.21	30	120	0	8	41.12	1.8	35.88
20	59.85	28	120	0	16	40.43	2	32.63
21	59.88	26	120	0	25	40.01	1.9	31
22	59.88	35	120	10	8	40.17	1.9	34.88
23	59.66	28	120	10	16	38.35	2	32.25
24	60.3	30	120	10	25	41.83	2.1	31.88
25	59.67	22	120	20	8	39.37	1.2	35
26	60.19	26	120	20	16	41.29	1.9	35.75
27	60.03	28	120	20	25	40.54	2.2	34.88
28	60.19	28	130	0	8	40.37	2.2	35.38
29	59.85	26	130	0	16	39.67	2.1	34.13
30	59.67	28	130	0	25	39.45	2	32.25
31	60.57	26	130	10	8	41.35	2	31.13
32	60	28	130	10	16	40.56	2	33.5
33	59.84	24	130	10	25	39.73	1.9	32.88
34	59.91	28	130	20	8	40.52	2.3	33.88
35	60.08	40	130	20	16	37.92	2.4	32.3
36	59.9	26	130	20	25	39.35	2.1	32.5
37	59.69	30	140	0	8	40.29	2.4	34.25
38	60.05	28	140	0	16	39.36	2	34.13
39	59.99	22	140	0	25	39.27	2	36.5
40	60.1	30	140	10	8	40.4	2.3	34.13
41	60.31	30	140	10	16	39.48	2.4	32.38
42	59.85	20	140	10	25	39.17	1.9	36.13
43	60.2	22	140	20	8	41.81	1.8	33.13
44	59.75	22	140	20	16	40.2	1.8	35.5
45	59.97	22	140	20	25	38.9	1.9	36.38
46	60.14	28	150	0	8	39.29	2.5	35.88
47	60.52	28	150	0	16	38.94	2.4	35.31
48	59.04	18	150	0	25	40.05	1.4	31.75
49	59.65	20	150	10	8	38.62	2	34.13
50	59.86	28	150	10	16	37.56	2.1	35.88
51	59.86	18	150	10	25	40.32	1.4	37.25
52	59.9	24	150	20	8	38.53	2.1	33.38
53	60.17	20	150	20	16	40.03	1.6	32.63
54	59.82	18	150	20	25	38.36	1.8	35.88

where M_0 was initial moisture content and final M was final moisture content.

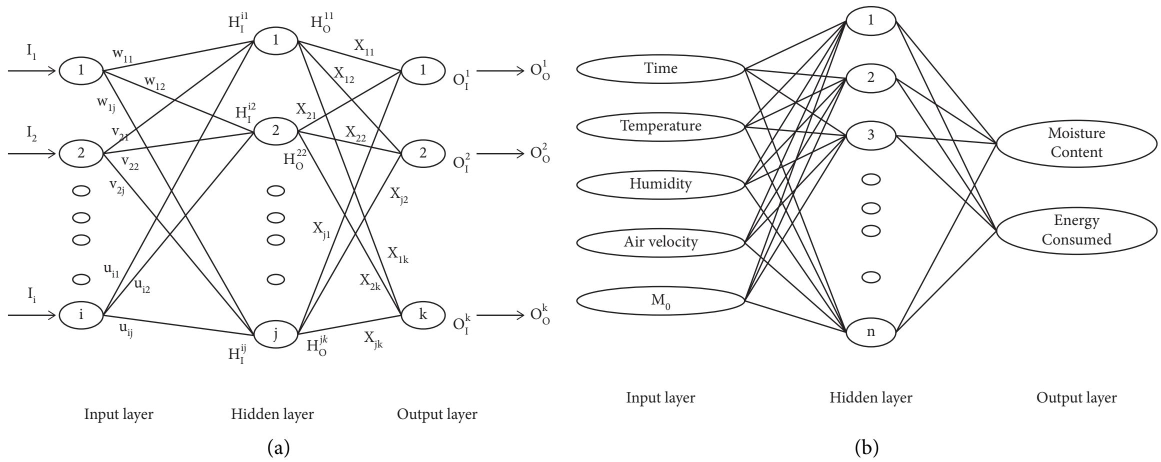


Figure 1: The ANN structure for the single layer network.

$$O_I^k = \left[\left(H_O^{11} \times X_{11}\right) + b_{11}^*\right] + \left[\left(H_O^{22} \times X_{21}\right) + b_{21}^*\right] + \cdots + \left[\left(H_O^{jk} \times X_{j1}\right) + b_{j1}^*\right]. \tag{5}$$

The final output can be expressed as

$$O_O^k = f\left(O_I^k\right). \tag{6}$$

We used the Neural Network Toolbox and MATLAB R2012a to develop our implementation, employing MATLAB's toolbox to write the program, load data files, train and validate the network, and save the model architecture. The model structure is shown in Figure 1(b). The established three-layer ANN had five input variables, including initial moisture content, baking temperature (six levels), baking air velocity (three levels), baking humidity (three levels), and baking time. The final moisture content and energy consumed of the salmon were taken as the two output variables. Before training the network, it is necessary to standardize the input and output data to express the correlation between them accurately. We normalized the general weight value of both input and output data between [0, 1] according to the equation [30, 31].

$$\overline{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \tag{7}$$

where x_i, $\overline{x}_i$, $x_{\min}$, and $x_{\max}$ are the weight values before and after pretreatment of neutral i, and the minimum and maximum weights of each neural network, respectively.

We used only a single layer in our implementation because more layers may cause the local minimum problem [32, 33]. We proposed the feedforward-backpropagation learning algorithm along with a Levenberg–Marquardt (LM) training function in this model [34]. The feedforward neural network is organized in three or more layers, an input layer, an output layer, and one or more hidden layers. From the input layer to the output layer, the network is one-way connection [35]. In this study, we randomly divided the analysis data for the drying process into three parts: the first part was used to train the network and consisted of approximately 70% of the total data points. The second part was used to validate the network and consisted of approximately 15% of the samples. The remaining 15% were used as experimental inputs [36, 37]. We took into account the different numbers of neurons in the hidden layer. The predicted moisture content and energy consumed change computed to evaluate the performance of fitting and predicting by using the least mean square error (MSE) metric and coefficient of determination (R^2). An MSE of 0.01 was deemed to indicate convergence. We allowed a maximum of 1000 iterations to ensure that the network completed the training process. The linear (purelin) transfer function provided better correlation coefficients for the processed hidden layer output data (O_I^1) and was therefore found suitable for the output neuron [38].

3. Results and Discussion

3.1. Effects of Different Baking Conditions of Salmon. LF-MRI can obtain the fault visualization information of the sample and obtain the H^+ proton density and distribution in the sample, so as to reflect the content and distribution of water or oil in the sample. The higher the content of water and oil in the sample, the greater the proton density. H^+ proton density imaging was performed on salmon pieces at different baking temperatures, as shown in Figure 2. At the beginning of baking, the sample water distribution was relatively uniform, the proton density was larger, and the fat was mainly concentrated in the fat grain of the sample. With the extension of baking time, the color of the NMR image of the sample gradually becomes lighter and the moisture gradually decreases. At the same time, the reduction rate of proton density was accelerated as the sample temperature increased. According to the results of LF-MRI, the water loss rate is different with different heating temperatures. The higher the temperature, the faster the water loss.

SEM of baked salmon at different baking temperatures is illustrated in Figure 3. The effect on the microstructure of baked salmon was characterized by thick or thin muscle fibrils. It can be seen that muscle fibrils of samples baked at 100°C were thick and had small interstices. The thickness and interstice of muscle fibrils changed with increase in the

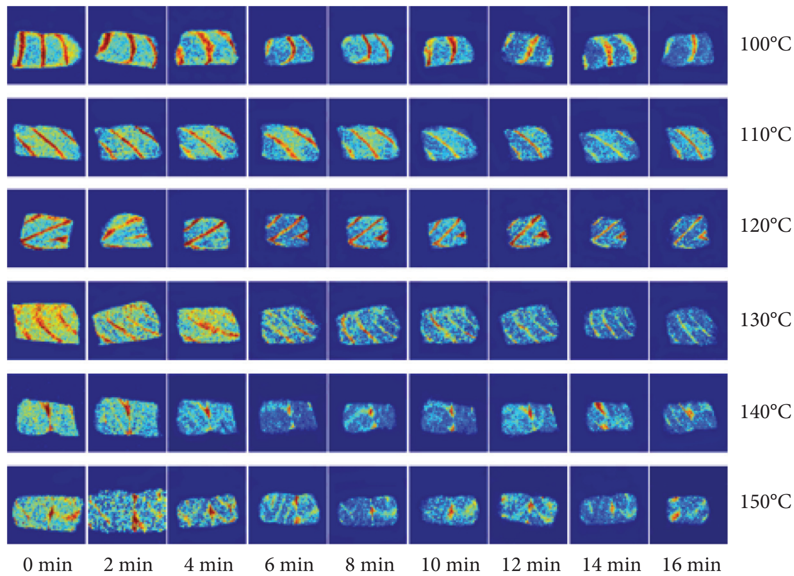


Figure 2: LF-NMR of baked salmon at different baking temperatures.

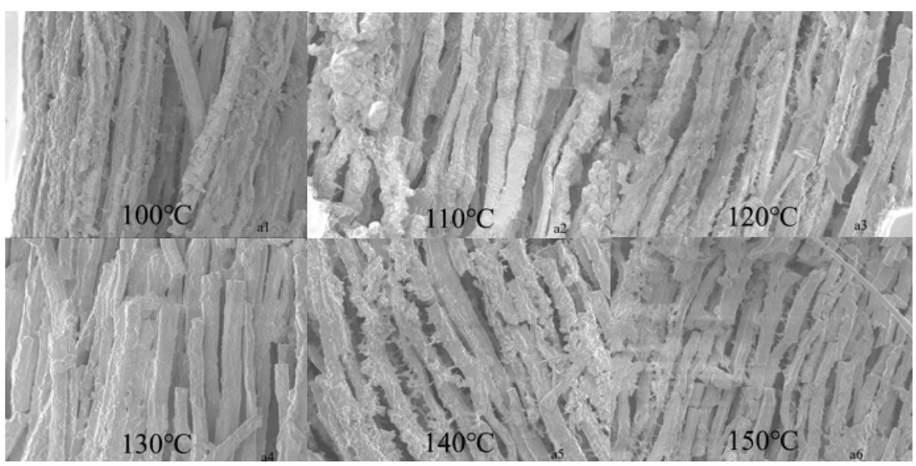


Figure 3: Comparison of internal muscle tissues of baking salmon slices under SEM at different baking temperatures (50×).

drying temperature. When samples were baked at 150°C, a highly interstices final product was obtained with thinner muscle fibrils. These interstices not only affect the textural property but also the transport phenomenon, such as diffusivities of gases and liquids in the sample and resulting higher rate of effective moisture diffusivity at a higher drying temperature [39, 40].

3.2. Effects of Different Baking Conditions on Sensory Evaluation of Salmon. From Tables 1 and 2, the results of sensory evaluation of baking salmon in different temperature ranges can be seen.

When the baking condition was 100/8/0 (temperature/air velocity/humidity) and 150/25/10 (temperature/air velocity/humidity), the color sensory score of baked salmon was the best, reaching the highest score of 7.88, and when the baking condition was 150/16/0 (temperature/air velocity/humidity), the color sensory score was the lowest.

According to the evaluation of the baked salmon from the odour, when the condition was 110/8/0 (temperature/air velocity/humidity), the flavor was rich; basically, no fishy taste, the odour sensory score was the highest, and when the condition was 150/16/0, the fishy taste was heavy, the flavor was slightly light, and the odour sensory score was the lowest. Combined with the LF-NMR image, it is easy to see that the higher the temperature, the more fat was reduced. Fat is an important carrier of flavor substances, so the flavor score decreases with the increase of temperature. Fat is an important carrier of flavor substances, so the odour sensory score decreased with the increase of temperature.

From the hardness and springiness analysis of sensory evaluation, when the baking temperature was low, the fish was too soft, which affected the taste. When the baking condition was 100/25/20 (temperature/air velocity/humidity), the hardness score is the lowest, and when the baking condition was 150/25/10, the hardness and springiness score were the highest. Combined with the scanning electron

Table 2: Sensory evaluation results of baking salmon under different baking conditions (temperature/air velocity/humidity).

Run no.	Baking time (min)	Baking temperature (°C)	Baking humidity (%)	Baking air velocity (m/s)	Color (point)	Odour (point)	Hard (point)	Springiness (point)	Taste (point)	Sensory evaluation (point)
1	55	100	0	8	6.88	6.75	7.00	6.00	7.50	34.13
2	45	100	0	16	6.88	7.00	6.63	6.75	7.50	34.75
3	35	100	0	25	7.88	7.63	7.13	6.38	7.69	36.69
4	40	100	10	8	6.63	6.25	6.75	7.00	7.25	33.88
5	35	100	10	16	6.38	6.13	5.88	5.63	6.25	30.25
6	45	100	10	25	7.00	5.75	5.88	6.13	7.13	31.88
7	45	100	20	8	7.63	7.00	7.25	6.63	6.38	34.88
8	40	100	20	16	6.63	6.94	7.00	6.13	6.44	33.13
9	40	100	20	25	6.63	6.88	5.63	5.88	7.38	32.38
10	45	110	0	8	7.75	8.06	7.44	7.00	7.88	38.13
11	35	110	0	16	6.13	6.88	7.00	6.63	7.50	34.13
12	35	110	0	25	7.00	7.00	6.88	6.50	7.13	34.5
13	40	110	10	8	7.50	7.25	6.50	6.75	8.00	36
14	35	110	10	16	6.50	6.50	7.50	6.75	7.13	34.38
15	40	110	10	25	7.38	7.00	6.50	6.88	7.63	35.38
16	30	110	20	8	6.50	7.88	7.38	6.75	8.00	36.5
17	55	110	20	16	6.75	6.50	6.75	7.00	6.88	33.88
18	30	110	20	25	7.13	7.00	6.88	6.25	6.75	34
19	30	120	0	8	7.00	7.38	6.75	7.00	7.75	35.88
20	28	120	0	16	6.38	6.63	6.13	6.38	7.13	32.63
21	26	120	0	25	6.13	6.25	5.88	5.63	7.13	31
22	35	120	10	8	6.63	7.38	6.50	7.00	7.38	34.88
23	28	120	10	16	6.63	6.38	5.88	6.50	6.88	32.25
24	30	120	10	25	6.00	6.63	6.13	6.00	7.13	31.88
25	22	120	20	8	7.38	6.88	6.88	6.50	7.38	35
26	26	120	20	16	7.00	7.13	7.25	6.88	7.50	35.75
27	28	120	20	25	6.88	7.13	6.63	6.50	7.75	34.88
28	28	130	0	8	6.88	7.50	6.75	6.63	7.63	35.38
29	26	130	0	16	6.88	7.25	6.63	6.50	6.88	34.13
30	28	130	0	25	6.00	6.00	6.88	6.50	6.88	32.25
31	26	130	10	8	6.50	6.13	6.25	5.50	6.75	31.13
32	28	130	10	16	6.25	6.88	6.75	6.88	6.75	33.5
33	24	130	10	25	6.63	7.38	5.63	6.75	6.50	32.88
34	28	130	20	8	6.25	6.50	6.75	7.00	7.38	33.88
35	40	130	20	16	6.63	6.88	5.75	6.13	6.88	32.3
36	26	130	20	25	6.50	7.00	6.25	6.00	6.75	32.5
37	30	140	0	8	7.25	6.75	7.50	6.00	6.75	34.25
38	28	140	0	16	6.75	7.13	6.25	6.13	7.88	34.13
39	22	140	0	25	6.75	7.38	7.00	7.13	8.25	36.5
40	30	140	10	8	7.13	6.63	7.50	6.50	6.38	34.13
41	30	140	10	16	6.38	6.25	6.50	5.75	7.50	32.38
42	20	140	10	25	7.38	7.13	7.63	6.25	7.75	36.13
43	22	140	20	8	6.63	6.88	6.88	6.00	6.75	33.13
44	22	140	20	16	6.63	7.25	7.25	7.00	7.38	35.5
45	22	140	20	25	7.38	7.50	7.13	7.13	7.25	36.38
46	28	150	0	8	7.00	7.63	7.25	6.75	7.25	35.88
47	28	150	0	16	6.75	7.25	6.63	7.00	7.69	35.31
48	18	150	0	25	5.38	6.50	6.38	6.00	7.50	31.75
49	20	150	10	8	6.75	7.38	7.00	6.00	7.00	34.13
50	28	150	10	16	7.00	6.88	7.63	6.63	7.75	35.88
51	18	150	10	25	7.88	6.75	7.63	7.25	7.75	37.25
52	24	150	20	8	6.50	7.38	6.50	6.00	7.00	33.38
53	20	150	20	16	5.50	7.25	6.75	5.50	7.63	32.63
54	18	150	20	25	7.13	7.38	6.88	6.75	7.75	35.88

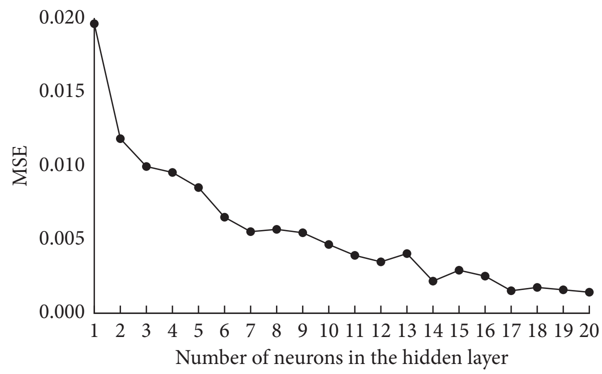


Figure 4: Experimental results used to determine the number of hidden layer neurons.

Table 3: Training error.

No.	MSE	$R_{training}$	$R_{validation}$	R_{test}	R_{all}
1	0.0196	0.96188	0.96272	0.96345	0.96213
2	0.0118	0.97704	0.97621	0.97895	0.97718
3	0.00992	0.98083	0.98552	0.98144	0.98169
4	0.00954	0.98159	0.98218	0.98224	0.98177
5	0.00853	0.983	0.98253	0.9822	0.98277
6	0.0065	0.98716	0.98844	0.98924	0.98764
7	0.00553	0.9893	0.98505	0.98518	0.98802
8	0.00573	0.9888	0.98485	0.98887	0.98817
9	0.00546	0.98934	0.98503	0.98765	0.98842
10	0.00471	0.99088	0.9877	0.98574	0.98959
11	0.00395	0.99244	0.98784	0.98756	0.99097
12	0.0035	0.99371	0.98905	0.99093	0.9927
13	0.00407	0.99207	0.98799	0.9879	0.99087
14	0.00219	0.99589	0.99117	0.9933	0.99487
15	0.00289	0.99425	0.99015	0.98711	0.99265
16	0.00249	0.99528	0.99341	0.99164	0.99447
17	0.00153	0.99718	0.99569	0.99487	0.99661
18	0.00179	0.9966	0.9922	0.99429	0.99569
19	0.00163	0.99688	0.99457	0.99578	0.99636
20	0.00142	0.99713	0.99444	0.99532	0.99645

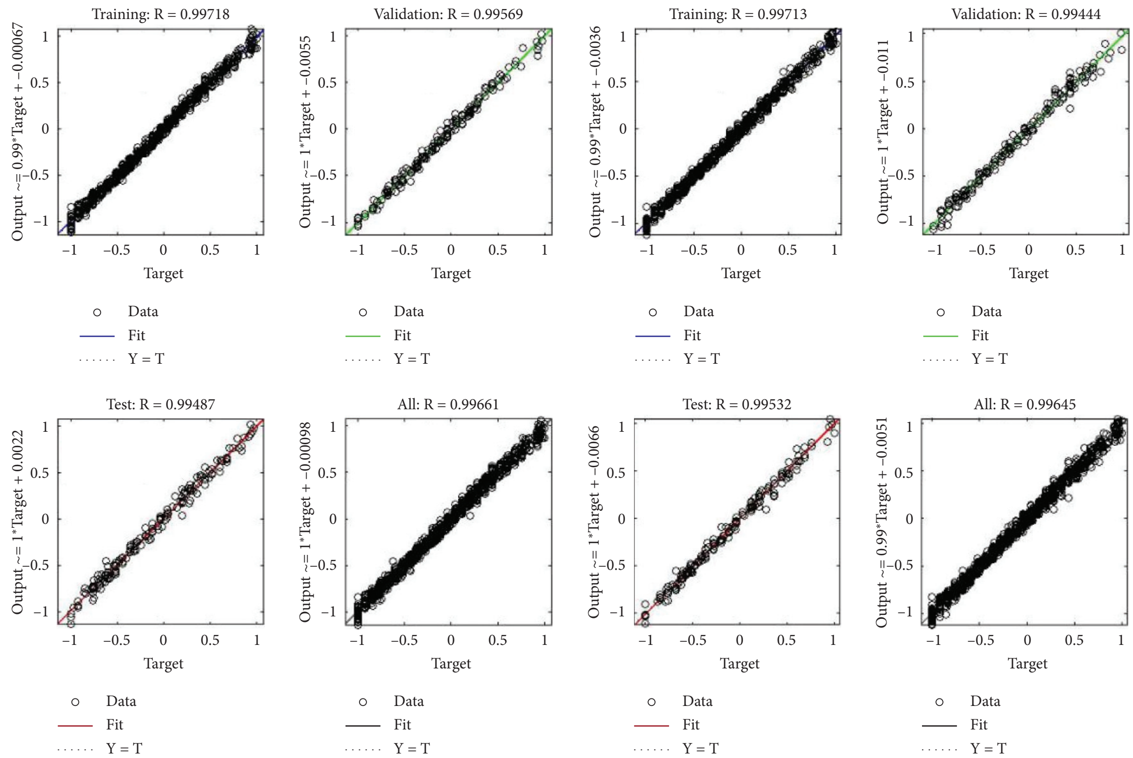
microscope results, it can be seen that with the increase of temperature, the aggregation of fibers increases the hardness of fish correspondingly.

According to the evaluation of the baked salmon from the taste, when the baking condition was 140/25/0 (temperature/air velocity/humidity), the taste was best. When the baked salmon was rated by the total score of the five senses, the baked fish score reached the highest when the baking condition was 110/8/0 (temperature/air velocity/humidity), reaching 38.13. Therefore, the control of baking conditions had a great impact on the quality of baked salmon, and the control of baking conditions provided strong technical support for the production of high-quality baked salmon in the factory.

3.3. ANN Model Performance. The behavior of biological products under processing conditions is highly nonlinear in nature [38]. The moisture content and energy consumed in the case of salmons also show a similar kind of trend. It is therefore justified to apply ANN modeling to such complex data. Due to the adaptable nature of ANN, further addition of data can be performed to a pre-existing data set, and the model can be retrained to cover a wider range of levels for the process variables under study. Data sets generated through 54 experiments amounted to 824 points of which 576 data points were taken for training, 124 for testing, and the remaining 124 for validation. The data set for training, testing, and validation was created randomly using diver and function available in MATLAB, based on the overall correlation coefficient.

Figure 4 and Table 3 illustrate the network performance for varying numbers of neurons in the hidden layer with the testing data. We determined the number of neurons in the hidden layer by predicting the percentage change in the moisture content and energy consumed. After repeated trials, it was found that a network with 20 hidden neurons produced the best performance during model development. However, according to Table 3, a network with 17 hidden neurons, $R_{training}$, $R_{validation}$, and R_{all} were better than a network with 20 hidden neurons, just R_{test} was less.

In addition, Figure 5 depicts the predicted moisture content and energy consumed versus experimental moisture



(a) (b)

Figure 5: Comparison between experimental and predicted drying time values during training, validation, and testing of the ANN model. (a) 5-17-2 ANN model (b) 5-20-2 ANN model.

content and energy consumed of the baked salmon for the training, cross-validation, and testing data sets, respectively. When a network with 17 hidden neurons, the numerical deviation is relatively average. The MSE value was 0.00153. Moreover, the R^2 values of the training, cross-validation, and testing were 0.99718, 0.99569, and 0.99487. When a network with 20 hidden neurons, the numerical deviation trend starts to increase. The MSE value was 0.00142. The R^2 values of the training, cross-validation, and testing were 0.99713, 0.99444, and 0.99532, respectively. Through calculation, it is found that with the increase of neurons, smaller MSE will appear, but the trend of numerical deviation was larger and larger. The best network topology occurred with 5 input layer neurons, 17 hidden layer neurons, and 2 output layer neurons, with the tansig (hyperbolic tangent sigmoid) function and the Levenberg–Marquardt training algorithm.

Table 4 shows the weights and bias estimation model data obtained by the ANN tool MATLAB R2012a. ANN accurately predicted the drying behavior of the sturgeon bone marrow. We chose the BP model suitable for this study not only because its accuracy but also its generality, being able to predict the behavior of the entire experimental range [41]. The model parameters described in this section (Table 1) along with the others defined are almost certainly useful for applying this model to moisture content prediction in other food products [38].

Table 4: ANN model topology for moisture ratio prediction, with values of weights and bias obtained for an optimal network.

Model characteristics	Values
Topology	5-17-2
Initial weight matrix (source: input; destination HL)	$IW^{(1,1)} = \begin{bmatrix} 0.0340 & -0.6069 & 0.1846 & 0.0075 & -0.0045 \\ 6.7763 & 0.1493 & 13.0727 & -11.9573 & -15.1271 \\ 4.2918 & 3.0888 & -4.5059 & -4.1846 & -0.2724 \\ 0.2795 & 0.7744 & -0.1183 & -0.5689 & -0.8343 \\ -0.1182 & -1.0187 & -0.3782 & 0.0346 & -0.0781 \\ -2.5263 & 0.3931 & -6.2039 & 6.3303 & 8.4023 \\ -4.6055 & -1.1384 & 2.8311 & -4.2474 & -1.4673 \\ -0.5345 & -0.0322 & 0.9956 & -0.8186 & -0.3755 \\ -5.7742 & -0.2511 & 1.8793 & -2.4914 & -0.7750 \\ -6.6278 & 0.2228 & 13.6548 & -1.6653 & 12.3485 \\ -0.2446 & -0.1205 & -1.6402 & 0.6623 & 0.5255 \\ -0.9744 & 1.4309 & -1.4061 & -0.3931 & -1.2273 \\ -0.9328 & -0.1929 & -1.2080 & 0.2418 & 1.4552 \\ -0.3836 & -1.1143 & -2.1544 & -0.3124 & 3.6305 \\ 3.3940 & 0.0204 & -1.0750 & -2.4157 & -4.6613 \\ 0.1291 & 2.0827 & -0.4832 & -0.1416 & -0.1289 \\ 1.5412 & 0.2131 & 1.7673 & -0.0981 & -2.2353 \end{bmatrix}$
Bias (destination: Hl)	$b^{(1)} = (-1.2492\ 0.3481 - 2.9091\ -0.8604 - 0.1607\ 1.2039\ 3.7819\ 0.8839\ 0.5489\ 1.9421 - 0.9530\ 2.3238\ 1.7793 - 3.4663\ 7.2344 - 1.0129\ -2.6145)^T$

Table 4: Continued.

Model characteristics	Values
Layer weight matrix (source: HL; destination: Ol)	$\mathrm{LW}^{(2,1)} = \begin{bmatrix} 7.7204 & -3.3330 \\ -0.9045 & -0.4445 \\ -0.1174 & 0.0059 \\ 0.8435 & 0.0052 \\ -0.4356 & -0.7571 \\ -0.8952 & -0.4819 \\ -0.5011 & 0.2040 \\ 2.0063 & -0.9561 \\ -0.3586 & 0.1726 \\ -0.2169 & 0.1401 \\ 1.1846 & -0.4866 \\ 0.3855 & -0.0420 \\ 1.0322 & 1.1438 \\ 0.2626 & -0.1518 \\ 0.3136 & -0.0127 \\ -0.3295 & -0.2015 \\ 0.2248 & 1.1083 \end{bmatrix}^{T}$
Bias (destination: Ol)	$\mathrm{b}^{(2)} = \begin{bmatrix} 4.8355 \\ -2.5197 \end{bmatrix}$

4. Conclusions

According to the experiment, it was demonstrated that ANN is a reliable software-based method; therefore, results of the experiment support conclusions in this part. However, we have no conclusions in this part. Also, we have no connection with the relationship between moisture content, low-field nuclear magnetic resonance (LF-NMR), scanning electron microscope (SEM), and sensory evaluation in the baking process of salmon.

Data Availability

All the data generated or analyzed during this study are included in this article. The data used can be acquired from the first author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

Authors' Contributions

Pengfei Jiang conducted investigation, wrote the original draft, and performed plot analysis. Zhu Kaiyue, Shang Shan, Jin Wengang, Yu Wanying, Li Shuang, and Wang Shen performed partial analysis, visualization, and language check. Xiuping Dong reviewed and edited the manuscript, supervised the work, and acquired funding.

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