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Article

Research on Food Processing Optimization and Nutrition Retention Based on Multivariate Statistical Analysis

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Abstract: This study explores the optimization method of food processing with potato crisps as an example. The experimental data were analyzed by principal component analysis using one-way and response surface tests with crushing force, oil content, L* value, sensory score, composite score and volatile components detected by electronic nose as indexes. The regression effect of the quadratic polynomial regression model established with the normalized composite score obtained from the principal component analysis as the response value was highly significant ($p<0.01$, $R^2=0.9591$). Determine the optimal pretreatment process parameters of potato for the bleaching temperature of 92 ℃, bleaching time of 4min, slice thickness of 4mm and freezing time of 3h, in this condition to get the normalized composite score of 0.9633, close to the predicted value (0.9696), indicating that the combination of the principal component analysis and the response surface analysis method of the potato crisps processing process optimization of the comprehensive evaluation method is accurate and feasible. In order to optimize the food processing process, this paper proposes food nutrition retention measures from two aspects of cooking methods and processes, ingredient selection and procurement, respectively.

Keywords: regression model; response surface; principal component analysis; food processing

1. Introduction

Food processing is a complex process involving multiple stages and numerous variables, including raw material characteristics, processing parameters (such as temperature, time, pressure, etc.), and environmental factors [1]. In many food processing stages, raw material utilization rates are generally low, particularly in processes such as cutting, grinding, and screening, where a significant amount of raw material is wasted and not fully utilized [2-3]. Many processing companies rely heavily on traditional manual operations or imprecise mechanical equipment when handling raw materials, and lack efficient resource recovery systems in stages such as cutting and sorting, resulting in raw material value not being maximized and significant raw material losses during processing [4-5]. Additionally, in traditional processing methods, many devices rely on high-temperature and high-pressure operations, leading to waste of energy and water resources. Heat loss during baking and boiling processes is high, and the generated waste heat is not fully recovered and utilized [6-7]. Furthermore, many traditional processing methods, especially those involving high temperatures, high pressures, and prolonged processing times, may cause degradation of vitamins, minerals, and other functional components in food, resulting in food quality losses. For example, thermal processing may lead to significant losses of heat-sensitive components such as vitamin C and B vitamins [8-10]. This has become a major research focus in food processing technology. It is worth noting that chemical additives such as preservatives, colorants, and flavor enhancers are frequently used in food processing to extend shelf life, improve appearance, or enhance taste [11]. If additives exceed normal usage limits, they can lead to the accumulation of harmful substances in food, posing serious health risks to consumers. Especially in the processing of low-quality raw materials, additives are frequently used to mask the deficiencies of the raw materials. Excessive use of artificial colorants, flavorings, and other substances can also affect the natural flavor of food, increase potential health risks, and exacerbate environmental pollution and waste disposal issues [12-14].

Against the backdrop of growing global food demand, how to utilize scientific methods and technological innovations to optimize processing procedures has become a key research direction in the food industry. Through process optimization across different stages of food processing, raw material waste can be reduced, energy saved, and nutrient loss during processing minimized, thereby enhancing the sensory quality and nutritional value of food [15-17]. Multivariate statistical analysis, based on data mining, applies mathematical, computer science, and statistical principles to explore the interrelationships among multiple variables. It identifies hidden patterns and relationships in data, as well as correlations and causal relationships between variables, through comprehensive analysis of multiple variables. It has important applications in decision support and variable selection, with primary methods including factor analysis, principal component analysis, cluster analysis, regression analysis, and discriminant analysis [18-20]. Multivariate statistical analysis is suitable for complex, multi-variable studies such as food processing technology.

Currently, modern food processing technologies encompass various aspects such as thermal processing, non-thermal processing, fermentation, and packaging. Optimizing each of these stages can significantly enhance food safety and market competitiveness [21]. Thermal processing plays a crucial role in food processing by sterilizing, preserving, and enhancing food stability. However, traditional thermal processing often comes with issues such as high energy consumption, prolonged heating times, and nutrient loss. To address these challenges, optimization efforts in thermal processing primarily focus on reducing heating time, improving heating uniformity, lowering energy consumption, and minimizing nutrient loss. Literature [22] summarizes that various food processing forms under microwave-assisted conditions (such as microwave heating and freezing) achieve higher efficiency and better food quality while reducing operational costs. Infrared heating is also superior to traditional thermal processing technologies. Literature [23] further optimizes the temperature and time parameters of infrared processing using response surface methodology, thereby improving the quality of pre-processed foods.

Non-thermal processing technologies can preserve the integrity of nutritional components without altering the physical properties of food. Literature [24] utilized biocolloid agents for fruit processing, demonstrating that this method not only reduces juice viscosity but also retains the original nutritional components and sensory characteristics of the juice, provided specific concentration and precipitation time conditions are met. Reference [25] introduced high-pressure processing of food under low-temperature conditions, which reduces microbial activity, thereby extending the shelf life and retaining the original nutritional components of the food. Reference [26] combined ultrasonic treatment and enzymatic treatment to effectively retain carotenoids in carrots; when applied separately, ultrasonic treatment was less effective than enzymatic treatment. Literature [27] reviews how pulsed electric fields, through pasteurization of juice, significantly reduce the loss of nutritional and physical-chemical properties such as color and aroma, maintaining the nutrient content in the juice. Additionally, other non-thermal processing technologies include hulling, grinding, polishing, germination, fermentation, radiation, LED, and cold plasma. Literature [28] tested the nutritional components of millet food processing using the aforementioned non-thermal processing technologies. Except for hulling, grinding, and polishing, which reduced nutrient content, the other methods improved nutrient levels. These technologies reduce processing temperatures or shorten processing times, minimizing nutrient degradation and oxidation, thereby ensuring food functionality and health benefits. Optimized fermentation technology can also enhance nutritional value and increase probiotic content.

Additionally, in terms of process optimization, Reference [29] employed a quadratic regression rotatable orthogonal design to optimize the mixing and baking process ratios for machine-made locust flower tea, thereby improving its sensory quality. Reference [30] used principal component analysis and experimental design to rank refining process indicators, optimize those with higher scores, and balance efficiency and environmental sustainability during processing. Literature [31] combined response surface regression analysis and genetic algorithms to predict extrusion parameters such as speed and temperature in screw food extrusion processes, thereby selecting appropriate extrusion conditions to optimize the processing process.

The study was conducted to optimize the food processing process by using potato as the main raw material to make fried potato crisps. First, the effects of each pretreatment condition on the crushing force, sensory evaluation, oil content, brightness L* and overall score of potato crisps were analyzed. Then, the effects of slice thickness, blanching temperature, blanching time, salt concentration, and freezing time on potato crisps were investigated by a one-way experiment. Secondly, based on the results of the one-way experiment, Box-Behnken Design experiment was designed to optimize the processing process of fried potato crisps using response surface method with sense composite score as the response value. Finally, food nutrition retention measures were proposed in terms of cooking methods and processes, ingredient selection and procurement.

2. Research Materials and Methods

2.1. Materials and Instruments

(1) Materials

Potato, variety Holland 17, was provided by Shandong Institute of Biotechnology. Palm oil was purchased from Yihai Kerry Cereals and Oil Industry Co. Salt was purchased from Yonghui Supermarket, Pukou District, Nanjing, Jiangsu Province, China.

(2) Instruments

TMS-Pro mass spectrometer, Beijing Ying Sheng Hengtai Science and Technology Co. Nh310 colorimeter, Shanghai Caroca Super Instrument Co. Nh310 colorimeter, Shanghai Carocacho Instrument Co. Electronic nose, Beijing Ying Sheng Hengtai Technology Co. SOX500 fat meter, Beijing Chenxi Yongchuang Technology Co. VF-80C vacuum fryer, Zhongshan Weijia Vacuum Machinery Factory.

2.2. Test methods

2.2.1. Vacuum Fried Potato Preparation Process

The process flow of low temperature vacuum frying of potato crisps is as follows:

Raw material→screening→cleaning→peeling→slicing→bleaching→dipping→draining→pre-freezing→vacuum deep-frying→de-oiling→packaging→finished product

2.2.2. One-Way Tests

(1) One-way experiment of pretreatment process

The effects of slice thickness, rinsing temperature, rinsing time, salt concentration and freezing time on product quality were investigated using color difference value, crushing power, sensory evaluation, comprehensive evaluation and volatile components as indicators.

The effects of slice thickness of 1, 3, 5 and 7 mm on product quality were investigated by fixing the blanching temperature at 80 °C, blanching time of 3 min, dipping solution (with 0.1% salt concentration and without salt added), dipping time of 40 min and freezing time of 3h (−18 °C).

The effects of fixed slice thickness of 5mm, blanching time of 3min, impregnation solution (with 0.1% added salt concentration and without added salt), impregnation time of 40min and freezing time of 3h (−18 °C) were investigated to examine the effects of blanching temperatures of 70, 80, 90 and 100°C on the quality of the products.

Fixing the slice thickness of 5mm, rinsing time of 3min, impregnation time of 40min and freezing time of 3h (−18 °C), the effect of adding blank, adding 0.1% salt concentration, and 2 different impregnating solutions on the quality of the products were investigated.

The effects of fixing the rinsing temperature at 80°C, rinsing time of 3min, impregnating solution (adding 0.1% salt concentration and no salt) and impregnating time of 40min, and freezing time of 1, 2, 3, and 4h on the quality of the products were investigated.

Vacuum frying and degreasing were carried out under the same conditions after sample pretreatment, and the parameters of both were: vacuum degree 0.098 MPa, frying temperature (88±3) °C, time 32min, and centrifugal degreasing speed 400r/min, time 6min.

(2) Determination of oil content

Referring to the Soxhlet extraction method in GB/T 5009.6-2016 “Determination of fat in food”, it was determined by SOX500 fat tester.

(3) Determination of crushing force

TPA method is used to determine the crushing force, the use of P/36R cylindrical probe, 65% compression ratio, trigger force 0.15N, 30mm/min test rate drop distance of 20 mm. each sample is measured 6 times in parallel to take the average.

(4) Determination of color difference

Determine the brightness L*, red-green value a* and yellow-green value b* of the samples of different experimental groups, and take the average value of each sample for 6 times of parallel measurement.

(5) Determination of electronic nose flavor

3g samples of potato crisps were put into the special headspace bottle for electronic nose, and the volatile substances of potato crisps were determined by manual headspace sampling method. Dry air was used as the carrier gas, the flow rate was 300mL/min, the sample sampling time was 60s, the cleaning time was 60s, the sampling interval time was 5s, and the auto-zeroing time was 10s.

(6) Sensory evaluation of potato crisps After selecting 10 sensory evaluators for certain training, the 100-point sensory evaluation test was carried out on vacuum low-temperature deep-fried crisps.

(7) Comprehensive weighted score

The best sensory quality is set as 100 points, and its weighting factor is set as 30. the smaller the crushing force is, the better, the minimum crushing force is set as 100 points, and its weighting factor is set as 20. the smaller the oil content is, the better, the oil content is set as 100 points, and its weighting factor is set as 30. the larger the brightness value L* is, the better, and it is set as 100 points, and its weighting factor is set as 20. according to the test, the maximum of sensory score is 30 points, and its corresponding score is (N1/sensory score max) × 30. the minimum value of crushing force is 20 points, and its corresponding score is (N1/sensory score max) × 30. According to the test, the maximum value of sensory score is 30 points, and the corresponding score is (N1/sensory score max) × 30, and the minimum value of crushing force is 20 points, and the corresponding score is (crushing force min/N2) × 20, and the minimum value of oil content is 30 points, and the corresponding score is (oil content min/N3) × 30. The maximum value of the luminance value is counted as 20 points, and its corresponding score is (N4/luminance value max) × 20. max: maximum value. min: minimum value.

Composite score (N) = (N1/sensory score max) × 30 + (crushing force min/N2) × 20 + (oil content min/N3) × 30 + (N4/L*max) × 20

where: N1 is the sensory score value, N2 is the crushing force, N3 is the oil content, and N4 is the L* value.

(8) Electron microscope analysis

The dried potato crisps were cut into 3mm × 3mm × 1mm slices, pasted on the sample stage of the scanning electron microscope, and observed after spraying gold.

2.2.3. Response Surface Tests

Based on the one-way test, the Box-Behnken model was used to optimize the process of vacuum fried potato preparation by selecting four factors as independent variables and sensory scores as response values to determine the best formulation. Design Expert 13 software was used to design the response surface test.

2.3. Data Processing

The data of the one-way test were compiled and analyzed for the significance of differences using SPSS 27 software ($p < 0.05$). The tests were repeated three times to take the mean and the results were expressed as mean ± standard deviation. Plotting was performed using Origin 2022 software. Response surface test data were processed using Design Expert 13 software.

The methods of multivariate statistical analysis are shown below:

(1) Multiple linear regression mathematical modeling

Assuming that the dependent variable is Y and there are M independent variables $x_1, x_2, \cdots, x_m$, and that the intrinsic linkage between Y and these M independent variables is linear, the multiple linear regression model is as follows:

$$Y = b + \sum_{i=1}^{m} b_i x_i \tag{1}$$

where $b_0, b_1, \cdots, b_m$, are the M+1 parameters to be estimated.

If we have N sets of observations: $(x_{n1}, x_{i2}, \cdots, x_{tm}; y_t)$, with $t = 1, 2, ..., n$, then this N set of observations has the following structural form:

$$\left.\begin{aligned} y_1 &= b_0 + b_1 x_{11} + b_2 x_{12} + \cdots + b_m x_{1m} \\ y_2 &= b_0 + b_1 x_{21} + b_2 x_{22} + \cdots + b_m x_{2m} \\ &\vdots \\ y_n &= b_0 + b_1 x_{n1} + b_2 x_{n2} + \cdots + b_m x_{nm} \end{aligned}\right\} \tag{2}$$

$$\left.\begin{array}{l} Y=\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_B \end{bmatrix} X=\begin{bmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1,0} \\ 1 & X_{21} & X_{22} & \cdots & X_{2,0} \\ & \vdots & & & \\ 1 & X_{p1} & X_{p2} & \cdots & X_{p,0} \end{bmatrix} \\ b=\begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_a \end{bmatrix} \end{array}\right\} \tag{3}$$

Then the mathematical model (2) of multiple linear regression can be written in the following form:

$$Y = bX \tag{4}$$

(2) Least squares method for multiple linear regression

The regression solution is to solve for b in equation (4), if we have n set of data for the independent variable x and its corresponding y, inside the regression equation, the best way to solve the regression coefficients corresponding to the characteristics is to use the sum of squared minimization errors, which represent the difference between the predicted y value and the actual y value. If the accumulation of errors is simply used, then the positive and negative differences of these errors will cancel each other out, and in order to avoid this, so it is the sum of squared errors that is used (least squares method). The formula for summing squared errors is as follows:

$$Q(b)=\sum_{i=1}^{n}(y_i-b_0-b_l x_{il}-\cdots-b_m x_{im})^2 \tag{5}$$

Then the above formula is transformed into a mathematical problem, that is, to find a set of b so that the above formula reaches the minimum value, and the commonly used methods for solving the problem are gradient descent method [32], ordinary least squares method [33] and so on. The ordinary least squares method is simpler and more convenient to implement than the gradient descent method. The mathematical formula of ordinary least squares is:

$$b=(X^T X)^{-1} X^T Y \tag{6}$$

The solution b is the coefficients of the multiple linear regression model, X, Y is the matrix defined in equation (3), and X^T is the transformation of the X matrix. The method is applicable for the presence of the inverse matrix of $X^T X$.

3. Results and Analysis

3.1 Effect of Pretreatment on Potato Quality

3.1.1. Effect of Pretreatment on Potato Quality

The effects of pretreatment on the quality of potato crisps are shown in Table 1. The effects of each pretreatment condition on the product crushing force, sensory evaluation, oil content, brightness L* and comprehensive score were analyzed. The crushing force was greatly affected by the thickness of the slices, and when the thickness of the slices was greater than 5mm, the crushing force was zero, and the product showed sponge-like soft slices, mainly due to the fact that the water inside the product could not evaporate quickly, and the internal fiber structure was damaged to a small extent, resulting in soft products. There was a significant effect of each pretreatment condition on sensory evaluation ($P<0.05$). Oil content had no significant effect ($P>0.05$) on the other treatment conditions except for the rinsing time and impregnating solution ratio, which showed a significant effect ($P<0.05$). The oil content of potato crisps showed a tendency of decreasing and then increasing with the extension of the bleaching time, which was mainly due to the fact that too much hot blanching time destroyed the tissue composition of raw materials, and the oil was easy to enter into the internal tissues during the subsequent frying process. In the impregnating solution proportioning test, the oil content of the group containing 0.1% salt was relatively low, mainly due to the fact that 0.1% salt molecules can coalesce on the surface of potato crisps, hindering the further penetration of oil and grease, and lowering the oil content. L* value had a significant effect on L* except for the thickness of the slices, which had no significant effect (P<0.05). Rinsing inactivated polyphenol oxidase and peroxidase, which cause browning in potato. The study showed that blanching dissolved soluble sugars in the samples and reduced the occurrence of Meladic reaction when the samples were deep-fried.The L* value reached its maximum at the blanching temperature of 100 °C, which might be greater than the starch pasting temperature at this time, reducing reducing the reducing sugars in the Meladic reaction, and, at the same time, inactivating various enzymes causing browning to improve the brightness of the products. The composite scores were significant ($p < 0.05$) except for the freezing time, which had no significant effect. The composite score was the weighted average of crushing power, sensory evaluation, oil content and L* value, and the highest value of the composite score was used as the final index for factor screening.

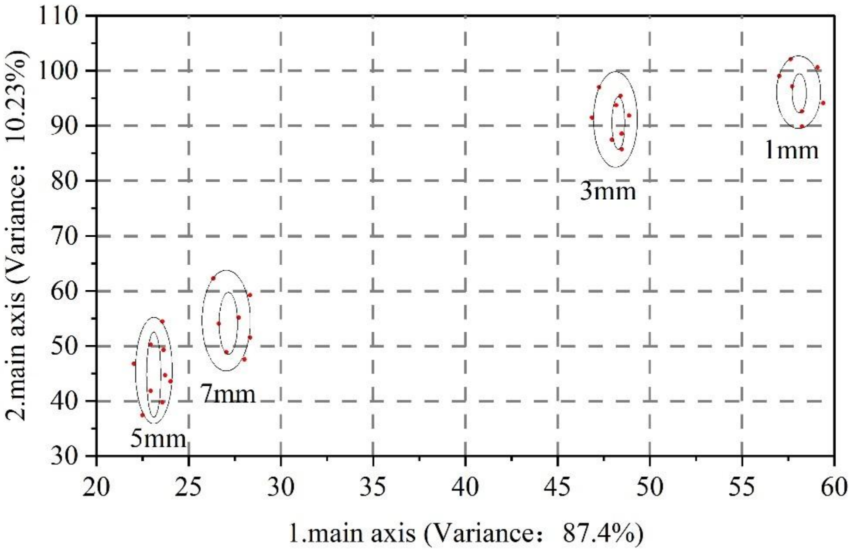
Table 1. Effect of retreatment on the quality of potato.

Pretreatment	Level	Broken force/N	Perception evaluation	Oil content/%	L*	Comprehensive score
Slice thickness/mm	1	5.91±2.32^{d}	70.71±2.31^{a}	28.11±0.91^{a}	63.51±4.71^{b}	86.441±2.61^{a}
	3	18.45±1.11	80.31±4.23^{a}	23.53±1.51^{c}	71.31±0.93^{a}	83.12±2.53^{ab}
	5	154.91±1.43^{b}	85.32±3.85^{a}	22.31±2.22^{c}	70.65±3.13^{a}	80.61±2.72^{b}
	7	315.51±3.21^{a}	74.01±1.02^{b}	26.25±1.46^{b}	63.71±1.46^{b}	69.81±1.23^{c}
Drift temperature/°C	70	206.91±8.95^{a}	71.71±6.86^{b}	23.23±2.22^{b}	60.4±2.33^{b}	79.1±5.01^{c}
	80	100.36±2.16^{b}	80.71±4.02^{a}	28.32±1.02^{a}	64.21±1.06^{b}	85.05±2.43^{b}
	90	66.71±1.25^{b}	81.73±3.51^{a}	23.26±2.15^{b}	70.13±3.11^{a}	99.06±2.61^{a}
	100	96.53±2.75^{b}	75.37±1.12^{b}	22.53±1.22^{b}	62.86±2.11^{b}	89.49±1.94^{b}
Blanking time/min	1	401.24±2.96^{a}	69.61±10.02^{b}	22.01±1.13^{b}	68.6±6.52^{a}	79.51±5.12^{b}
	3	65.25±1.11^{b}	68.63±2.93^{b}	22.21±2.45^{b}	65.91±3.23^{a}	93.81±3.03^{a}
	5	83.26±6.54^{b}	77.33±4.94^{a}	23.45±1.43^{b}	70.65±3.11^{a}	90.03±4.03^{a}
	7	61.36±1.96^{b}	63.33±4.75^{c}	26.01±0.94^{a}	69.91±1.03^{a}	89.71±3.06^{a}
Salt concentration	Blank	192.15±1.03^{a}	75.05±3.43^{b}	21.05±0.63^{a}	68.24±6.55^{a}	85.03±3.13^{b}
	0.1% salt	80.83±6.33^{b}	84.04±3.55^{a}	22.15±1.45^{a}	65.53±3.54^{a}	96.51±4.03^{a}
Freezing time/h	1	86.83±5.23^{b}	62.03±6.61^{b}	22.33±1.31^{a}	68.33±2.23^{a}	69.95±4.63^{c}
	2	173.45±2.35^{a}	69.75±6.13^{a}	21.01±2.13^{a}	66.23±3.54^{a}	72.23±3.14^{bc}
	3	26.34±1.08^{d}	71.74±0.68^{a}	24.96±3.0^{a8}	66.5±4.18^{a}	94.45±2.33^{a}
	4	76.1±7.4^{c8}	74.08±8.54^{a}	23.01±0.98^{a}	70.61±3.15^{a}	80.37±5.05^{b}

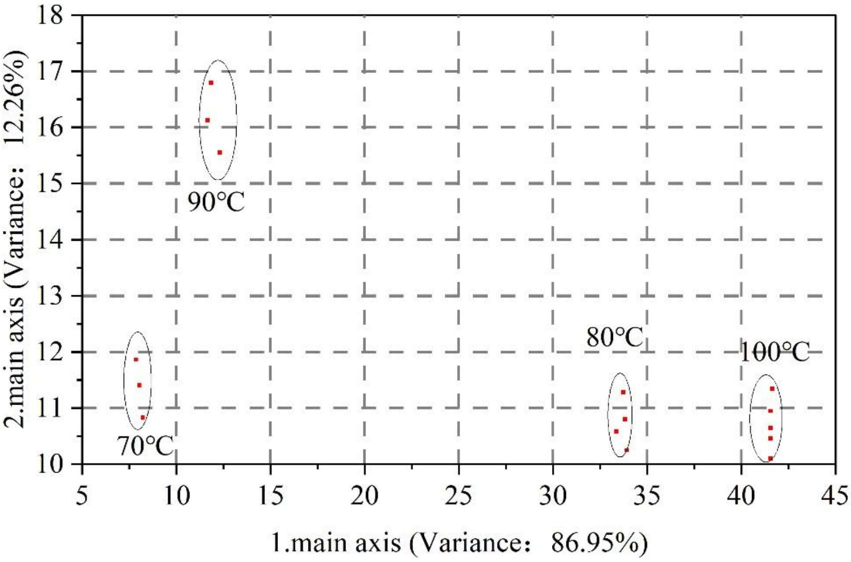
3.1.2. Effect of Pretreatment on Potato Quality

The effects of different pretreatment processes on potato quality are shown in Figure 1. (a)~(e) represent the effects of slice thickness, blanching temperature, blanching time, added salt, and freezing time on potato quality, respectively. Principal Component Analysis (PCA) was performed to analyze the quality substances of potato crisps by different pretreatment processes. In the PCA method of analysis, the larger the total contribution rate, the more comprehensive the overall information of the sample [34]. The difference between the sample quality substances was judged according to the distance of the samples on the horizontal and vertical coordinate axes, and the farther the distance, the greater the difference. The horizontal coordinate indicates the size of the contribution rate of the first principal component, and the contribution rate (or weight) is larger, so if the distance between different samples on the horizontal coordinate is larger, it means that the difference between them is more obvious. And even if the distance of the samples on the vertical coordinate is large, due to the small contribution rate (or weight) of the second principal component, the actual difference between different samples is smaller.

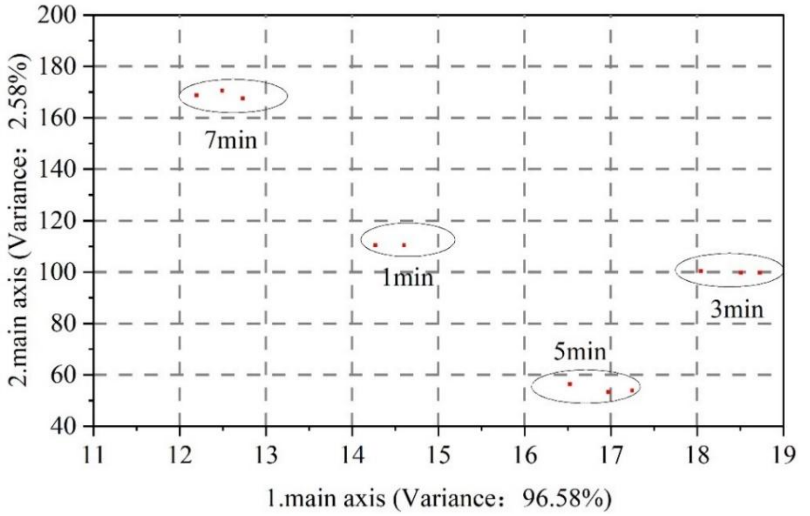
As can be seen from Figure 1, the total contribution rate of slice thickness, bleaching temperature, bleaching time, added salt and freezing time are 97.63%, 99.21%, 99.16%, 99.53% and 98.63%, respectively, which are all greater than 80%, and can counter the overall information of the samples. According to the difference of the samples' distance on the horizontal coordinate in Figure 1, the selection of the distance is relatively far away while combining with the comprehensive score can be seen, the selection of the slice thickness, rinsing temperature, rinsing time, salt concentration, and freezing time were 3mm, 90°C, 3min, 0.1% salt, and 2h for the subsequent test, respectively.



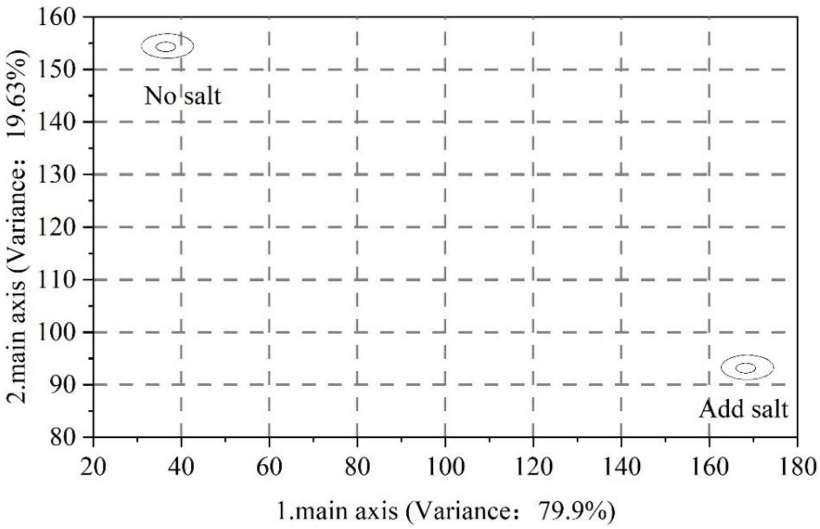
(a) Slice thickness



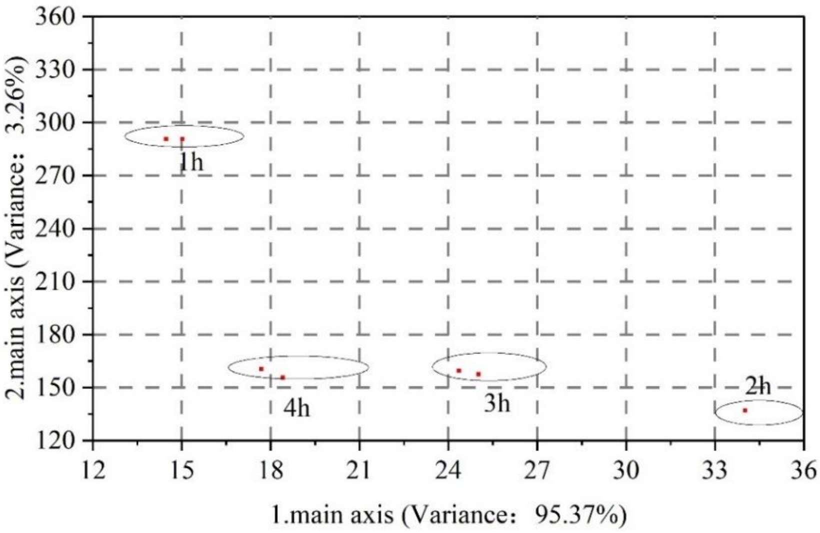
(b) Drift temperature



(c) Blanking time



(d) Add salt



(e) Freezing time

Figure 1. The effect of different pretreatment processes on potato quality.

3.2. Analysis of the Results of the One-Way Test

After the pretreatment of potatoes above, this chapter uses the official evaluation criteria of potato crisps to comprehensively evaluate potato crisps from four dimensions of morphology, color, aroma and taste, respectively. The full score is 100 points, and the specific evaluation criteria for each dimension are shown below.

(1) Morphology (30 points):

Flake shape is complete, no fragments, the score is between 24 and 30.

The shape of the flake is more complete, with a small number of large fragments, and the score is between 17 and 23.

Incomplete flakes with a few fragments, scores between 9 and 16.

Incomplete flake shape, with a large number of fragments, the score between 0 and 8.

(2) Color (20 points):

Pale yellow, uniform color, no frying overcooked color, score between 16~20.

Light yellow, more uniform color, no frying overcooking color, score between 11 and 15.

Yellow, average color, slight frying overcooking color, with a score between 6 and 10.

Yellow, uneven color, heavier frying burnt color, the score between 0 and 5.

(3) Aroma (20 points):

With the unique aroma of processed potato, strong aroma, no odor, the score between 16 and 20.

With the aroma of processed potato, the aroma is strong, no odor, the score is between 11 and 15.

With the aroma of processed potatoes, general aroma, no obvious odor, scores between 6 and 10.

No potato processing aroma, odor is obvious, the score between 0 and 5.

(4) Taste (30 points):

Crispness is good, no greasiness, no burnt bitterness and harpiness, the score value between 24 to 30.

Good crunchiness, no greasiness, no burnt bitterness and harsh flavor, with a score between 17 and 23.

Average crunchiness, greasiness, burnt taste or harsh taste, with a score between 9 and 16.

Poor crispiness, greasy feeling, burnt bitterness and harsh flavor, with scores between 0 and 8.

The comprehensive evaluation results are shown in Table 2. The evaluation results showed the effects of different slice thicknesses, blanching temperatures, blanching times, salt concentrations and freezing times on potato crisps. It can be seen that when the selected slice thickness, rinsing temperature, rinsing time, salt concentration, and freezing time were 3 mm, 90°C, 3 min, 0.1% salt, and 2 h, respectively, the comprehensive evaluation scores of potato crisps were above 90, which were higher than those of other treatments. Therefore, the pretreatment work used above can maximize the product texture and flavor.

Table 2. The results of the comprehensive evaluation of potato chips.

Factor	Handling	Score
Slice thickness/mm	1	71
	3	96
	5	82
	7	75
Drift temperature/°C	70	76
	80	84
	90	91
	100	63
Blanking time/min	1	66
	3	95
	5	78
	7	79
Salt concentration	Blank	61
	0.1% salt	93
Freezing time/h	1	66

	2	95
	3	74
	4	75

3.3 Response Surface Result Analysis

3.3.1 Principal Component Analysis of Test Results

Box-Behnken Design experiments were designed based on the results of the one-way experiments, setting different rinsing temperatures (X1), rinsing time (X2), slice thickness (X3) and freezing time (X4). The experimental factors and levels are shown in Table 3, with different levels of treatment indicated by A, B and C, respectively.

Table 3. Factors and levels table of test.

Factor	X1/°C	X2/min	X3/mm	X4/min
A	80	3	3	2
B	90	4	4	3.5
C	100	5	5	3

The results of the experimental design are shown in Table 4. Principal component analysis was performed based on the experimental results.

Table 4. Box-Behnken experimental design and results.

N	X1/°C	X2/min	X3/mm	X4/min	N1	N2	N3	N4	N
1	B	A	A	B	63.9	32.1	70.5	25.7	61.1
2	B	C	B	C	66.4	35.9	71	59.5	57.5
3	B	B	B	B	90.9	32.7	68.2	20.8	69.9
4	C	B	B	A	56.5	33.3	67.1	29.3	56.7
5	B	B	B	B	89.9	32.9	68.2	10.1	75
6	B	B	B	B	90.5	32.9	68.3	6.1	83.9
7	A	A	B	B	66	27.9	67.2	153.4	59.8
8	B	B	C	A	69.3	30.5	64.3	21.1	63.1
9	B	B	B	B	94.9	32.8	68.2	8	80.2
10	B	C	A	B	53.9	36.4	68.3	11.9	60.67
11	B	B	A	A	69	34.4	67.4	45.9	59.1
12	C	A	B	B	63.5	30.1	68.2	65.3	58.6
13	C	B	A	B	67.5	32.9	70.8	51.4	59.6
14	B	A	B	A	55.5	34.1	67.93	56.8	54.4
15	A	B	A	B	66	18.2	71.5	96.9	71.3
16	B	A	B	C	65	34.5	68.4	26	59.6
17	A	B	C	B	48.5	37	55.2	93.6	46.4
18	B	A	C	B	64.5	35.8	67.6	58.1	56.09
19	A	C	B	B	61.9	33	65.6	83.4	55.6
20	C	B	B	C	70	28	68.3	40	62.9

SPSS17.0 software was used to analyze the data of each index in Table 4 for principal component analysis. The eigenvalues, contribution rates and eigenvectors of potato pretreatment principal components are shown in Table 5. A total of 5 principal components were extracted, and the cumulative contribution rate reached 100%. According to the principle that the contribution rate is greater than 85%, it indicates that the three extracted principal components can comprehensively reflect the quality information of potato crisps. Therefore, the 1st principal component, the 2nd principal component and the 3rd principal component were selected for the subsequent analysis of the composite score and standard score. According to the size of the absolute value of the eigenvectors of the five indexes, it can be seen that the indexes determining the 1st principal component are mainly sensory evaluation and comprehensive score, and those determining the 2nd principal component are crushing power and oil content. What determines the 3rd principal component is L^* value and oil content.

Table 5. Main component analysis results.

Principal component	Eigenvalue	Contribution%	Cumulative contribution%	Eigenvector				
				N1	N2	N3	N4	N
1		44.8	44.8	0.586	-0.052	0.189	-0.242	0.715
2		26.46	71.26	-0.028	-0.739	0.527	0.479	-0.041
3		18.82	90.08	0.071	0.518	0.752	0.168	-0.284
4		5.14	95.22	0.523	0.396	-0.378	0.65	0.137
5		4.78	100	-0.673	0.051	-0.044	0.147	0.608

Composite and standardized scores were calculated for the score values of the 1st principal component, 2nd principal component and 3rd principal component, and the principal component score values with the normalized composite score are shown in Table 6. The normalized score values ranged from 0 to 1, with the highest normalized score in experimental group No. 6 and the lowest in experimental group No. 11.

Table 6. Principal component scores and standardized score.

N	F1	F2	F3	F	Z	N	F1	F2	F3	F	Z
1	1	-0.025	0.03	0.441	0.584	11	11	-0.431	-0.625	0.099	0.466
2	2	-0.573	-0.19	1.29	0.536	12	12	-1.798	0.089	-0.367	0.329
3	3	1.927	0.617	-0.082	0.852	13	13	-0.577	0.26	0.654	0.544
4	4	-0.099	-0.657	-0.098	0.5	14	14	-2.525	-0.266	0.241	0.238
5	5	2.362	0.527	-0.097	0.902	15	15	-3.915	0.048	-1.836	0
6	6	3.083	0.759	-0.363	1	16	16	-0.051	-0.749	0.378	0.519
7	7	-3.164	0.078	-0.941	0.134	17	17	0.018	-1.412	-2.068	0.374
8	8	0.047	-0.744	-1.327	0.46	18	18	-1.023	-0.697	0.478	0.405
9	9	3.038	-0.476	-0.289	0.903	19	19	-1.43	-0.174	-0.453	0.353
10	10	-0.8	-1.142	0.557	0.402	20	20	-0.295	0.482	-0.86	0.53

3.3.2. Response Surface Modeling and ANOVA

The quadratic multinomial regression equation for the standardized composite scores was obtained as the response value in Table 6, using Design-Exper 8.0.6 to fit the data with multiple regressions:

$$\begin{aligned} Y &= 0.963 + 0.15X1 + 0.073X2 + 0.045X4 - 0.135X1X3 + 0.136X2X3 \\ &-0.081X2X4 - 0.384X1^2 - 0.221X2^2 - 0.183X3^2 - 0.189X4^2 \end{aligned} \tag{7}$$

The regression model ANOVA is shown in Table 7. The regression model was highly significant ($p<0.01$). The misfit term p=0.3863 ($p>0.05$), the misfit term is not significant, the test results are less disturbed by unknown factors. And the model coefficient of determination $R^2=0.9591$, indicating that the model fit well, the experimental error is small, the model selection is appropriate, and the model can be used to determine the optimal pretreatment conditions for potato crisps. From the p-value, it can be seen that the effect of factors X1, X2, X1X3, X2X3, X12, X22, X32, X42 on the standardized scores is highly significant ($p < 0.01$), and the effect of X4, X2X4 on the standardized scores is significant ($p<0.05$), which indicates that the effect of the factors on the response values in the design is not a simple linear relationship, and that the interaction term and the quadratic term have a significant effect.

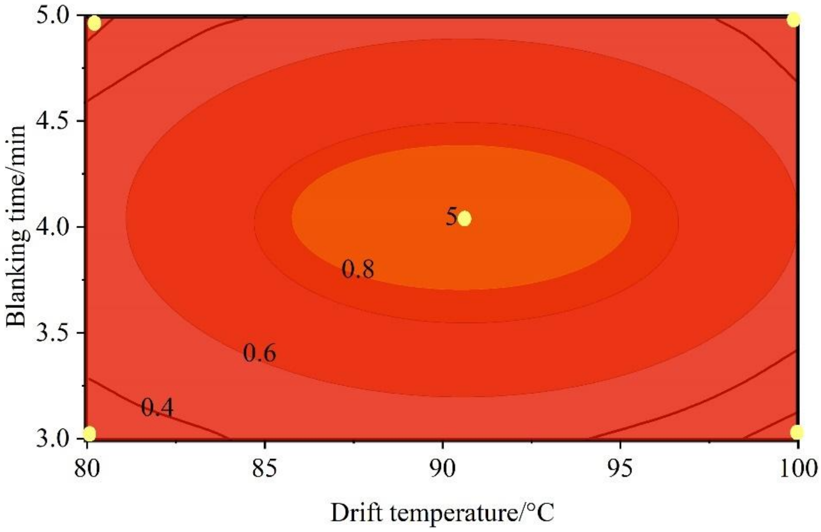
Table 7. Analysis variance of regression model.

Variance source	Sum of squares	Freedom	Mean square	F	*p*	Sig.
Model	1.679	14	0.11	24.259	<0.0001	**
X1	0.182	1	0.165	34.717	<0.0001	**
X2	0.066	1	0.062	13.37	0.0031	**
X3	0.004	1	0.013	2.578	0.1297	-
X4	0.045	1	0.028	5.844	0.0286	*
X1X2	-0.023	1	0.01	0.42	0.5246	-
X1X3	0.081	1	0.0709	13.887	0.0041	**
X1X4	0.0067	1	0.0083	0.152	0.7068	-
X2X3	0.072	1	0.063	14.817	0.0026	**
X2X4	0.019	1	0.004	5.669	0.0311	*
X3X4	-0.012	1	0.004	0.0076	0.984	-
X12	0.954	1	0.957	193.103	<0.0001	**
X22	0.333	1	0.334	68.868	<0.0001	**
X32	0.199	1	0.215	44.486	<0.0001	**
X42	0.246	1	0.235	50.401	<0.0001	**
Residual error	0.0703	13	0.01	-	-	-
Pseudo term	0.0538	8	0.026	1.427	0.3863	-
Net error	0.0137	6	0.0062	-	-	-
Total variation	1.7536	21	-	-	-	-
R^2	0.9591	-	-	-	-	-
R_{adj}^2	0.9217	-	-	-	-	-

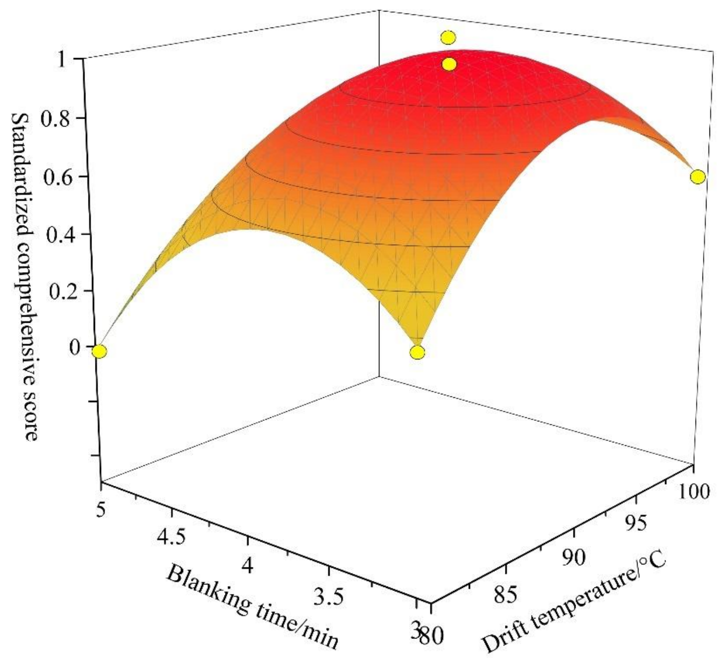
3.2.3. Interaction Term Analysis

Contour plots can reflect the effect of factor interactions on response values. Circles indicate that the interaction between factors is not significant and ellipses indicate that the interaction between factors is significant.

The interaction between rinsing temperature and rinsing time is shown in Fig. 2, (a) and (b) represent the response surface and contour plots, respectively. The interaction between rinsing temperature and rinsing time was more significant, and the standardized score gradually decreased when the rinsing time was greater than 4 min. The longer the bleaching time, the higher the temperature, resulting in serious damage to the tissue structure of the samples and deterioration of the quality, affecting the final standardized score.



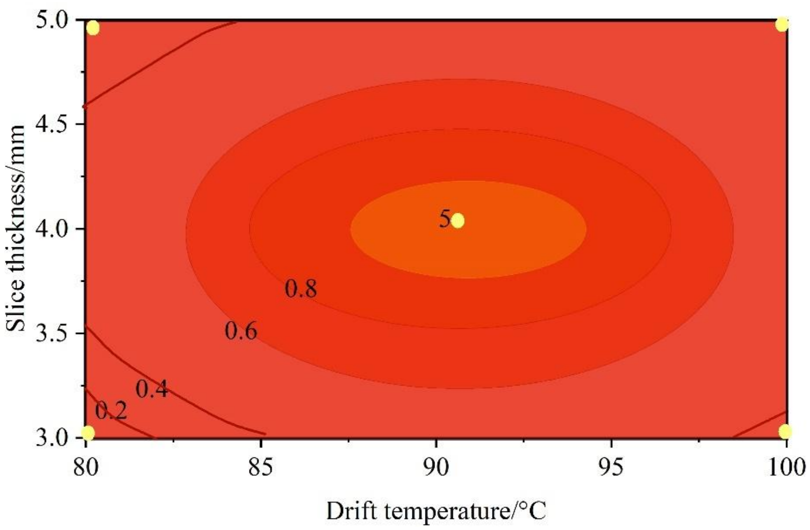
(a) Response diagram



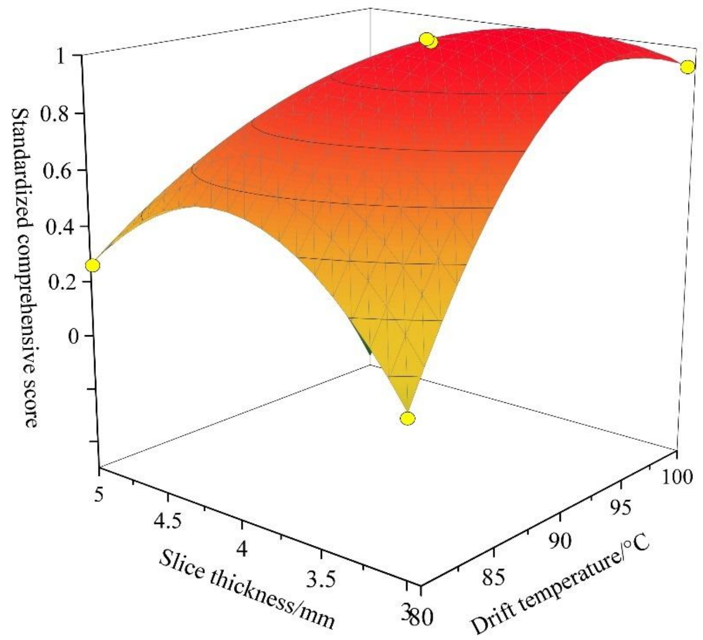
(b) Contour map

Figure 2. The interaction of the hot temperature and the time of the blanking.

The interaction between rinsing temperature and slice thickness is shown in Fig. 3, (a) and (b) represent the response surface and contour plots, respectively. The interaction between rinsing temperature and slice thickness was significant, and the standardized composite score reached the maximum value when the slice thickness and rinsing temperature were 4 mm and 90°C, respectively. When the slice thickness was greater than 4mm the sample thickness was greater, the internal starch granules were pasteurized, making the product crushing force increased and the crispness decreased. Under a certain rinsing temperature and time, the browning caused in the sample for the complete inactivation, which is conducive to the improvement of product color.



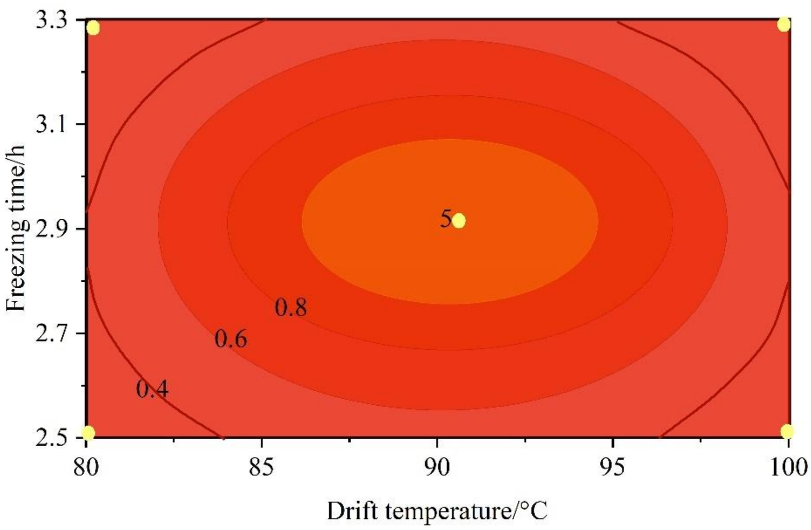
(a) Response diagram



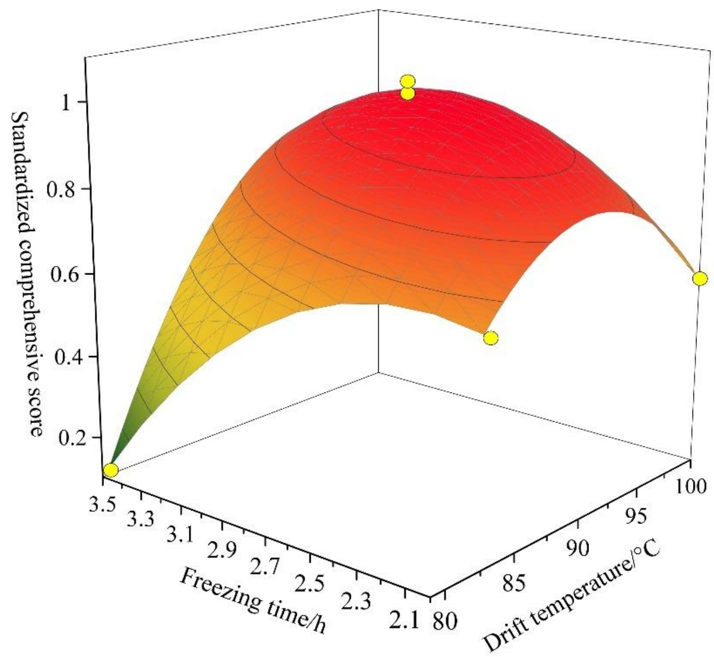
(b) Contour map

Figure 3. The interaction of the temperature and the thickness of the section.

The interaction between rinsing temperature and freezing time is shown in Fig. 4, (a) and (b) represent the response surface and contour plots, respectively. There was no significant relationship between the interaction of rinsing temperature and freezing time, and rinsing temperature and freezing time had a greater effect on crispness and oil content. When the rinsing temperature and freezing time were greater than 90 °C and 3 h, the product standardization composite score decreased.



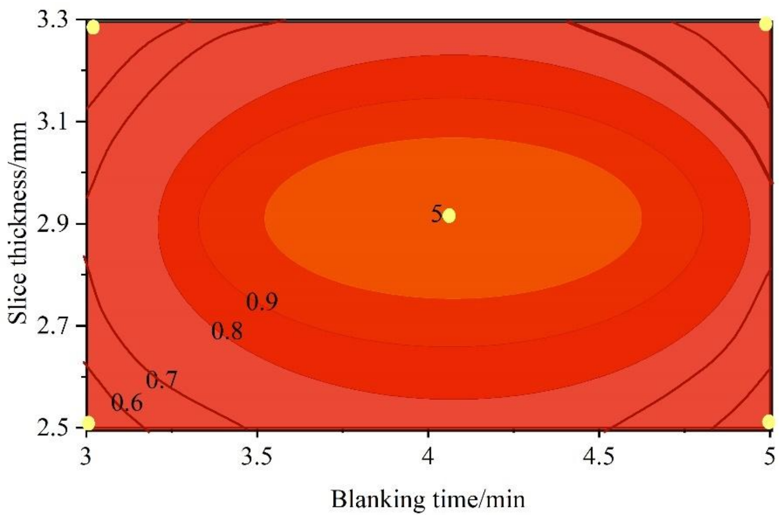
(a) Response diagram



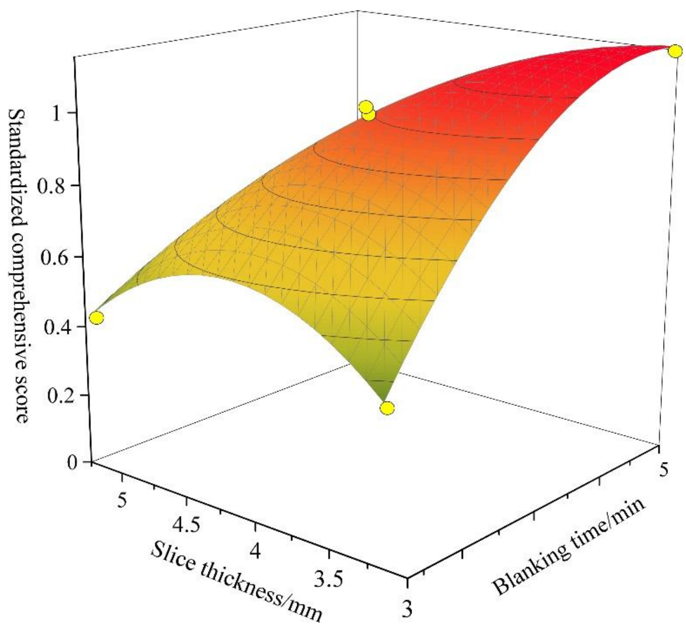
(b) Contour map

Figure 4. The interaction of the temperature and the freezing time.

The interaction between rinsing time and slice thickness is shown in Fig. 5, (a) and (b) represent the response surface and contour plots, respectively. The interaction between rinsing time and slice thickness was significant. With a certain rinsing time and an increase in slice thickness, the contour lines were dense, which was favorable for product presentation and increased the standardized composite score, and when the thickness was more than 4 mm and the rinsing time was more than 4 min, the product quality was poorer and the standardized composite score decreased.



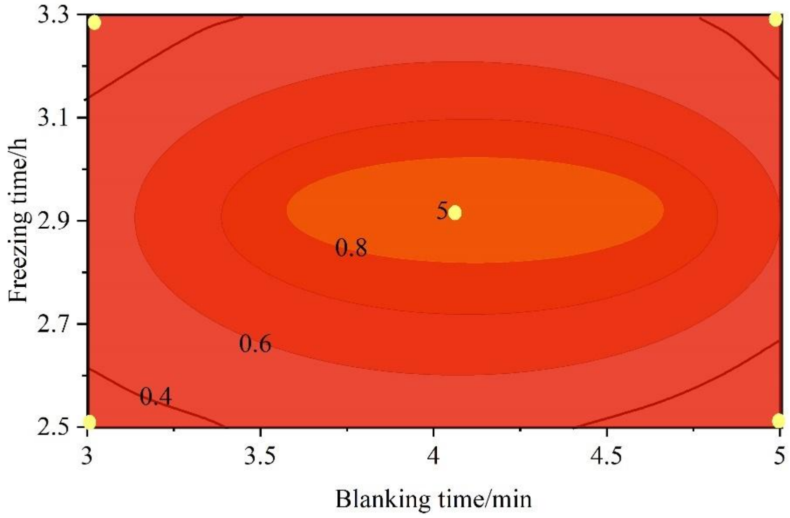
(a) Response diagram



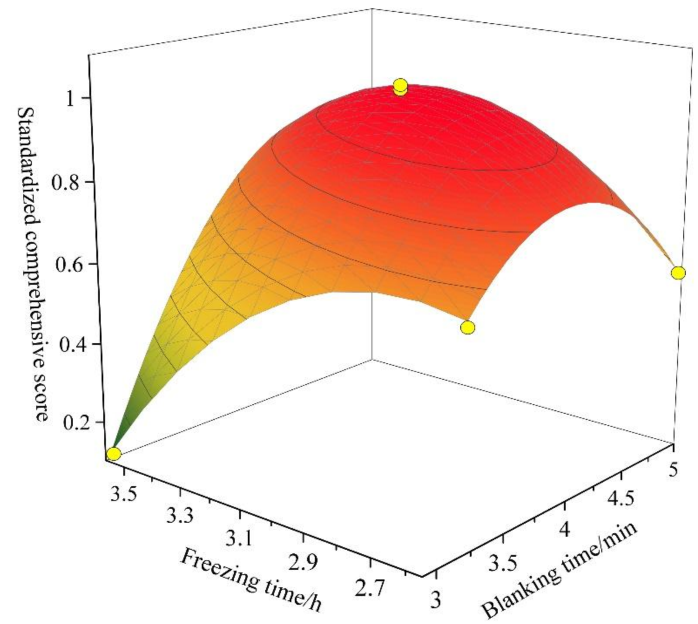
(b) Contour map

Figure 5. The interaction of the drift time and the thickness of the section.

The interaction between rinsing time and freezing time is shown in Fig. 6, with (a) and (b) representing the response surface and contour plots, respectively. When the freezing time was less than 3 h and the rinsing time was less than 4 min, the contour lines were denser, indicating that the two had a greater effect on the standardized composite score of potato crisps in this range. Appropriate freezing time and rinsing time are conducive to the formation of porousness of the samples, improve the product crispiness, color and reduce the oil content, which is favorable to the product quality.



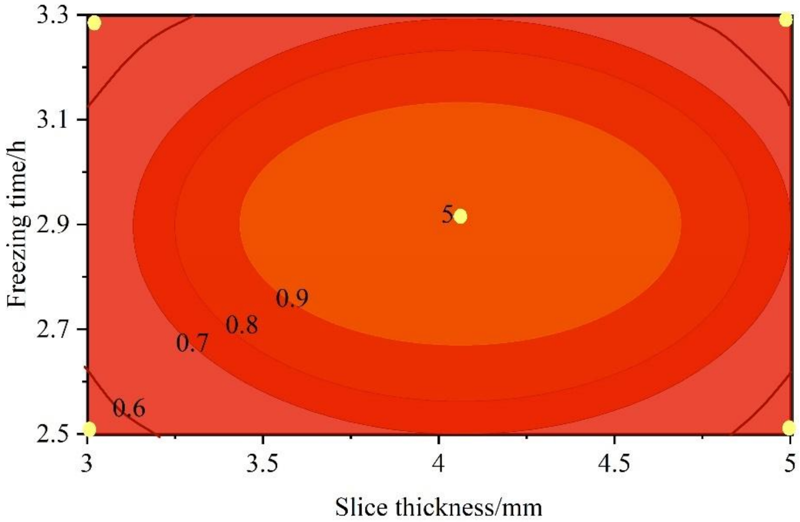
(a) Response diagram



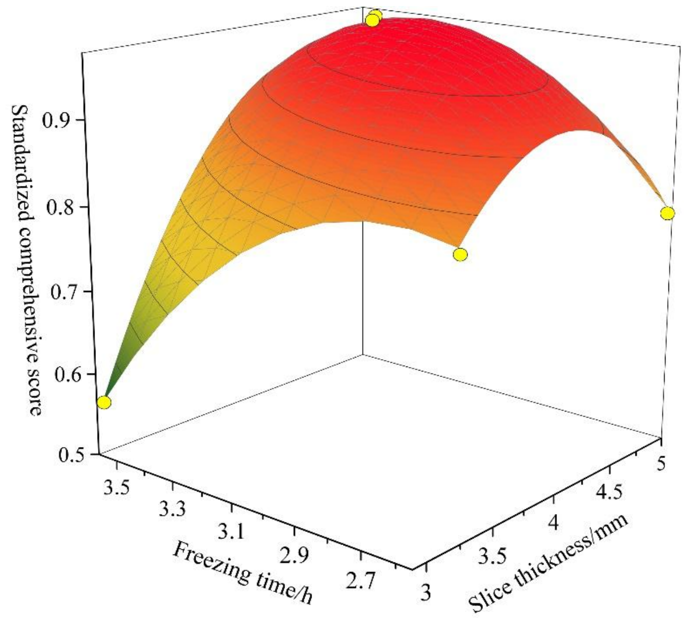
(b) Contour map

Figure 6. The interaction of the time of drift and the freezing time.

The interaction between slice thickness and sensory scores is shown in Figure 7, with (a) and (b) representing the response surface and contour plots, respectively. There was no significant relationship between slice thickness and sensory score. The standardized composite scores of the samples increased when the freezing time and slice thickness were less than 3 h and 4 mm, respectively. This indicates that a certain freezing time and slice thickness are conducive to the formation of product quality, thus indirectly increasing the standardized composite score of the samples.



(a) Response diagram



(b) Contour map

Figure 7. The interaction of slice thickness and sensory score.

3.2.4. Verification Tests

The potato pretreatment process validation experiment was carried out under the optimal process conditions. The obtained response surface model was analyzed by the software Design-Expert 8.0.6, and the optimal pretreatment process parameters for potato were blanching temperature of 92.63℃, blanching time of 4.03min, slicing thickness of 4.13mm and freezing time of 3.06h, and the normalized composite score of potato was 0.9696. Considering the feasibility of the operation, the optimal pretreatment process for potato crisps after modifying the parameters was blanching temperature of 92℃, blanching time of 4min, slicing thickness of 4mm and freezing time of 3.06h. After correcting the parameters, the optimal pretreatment process of potato crisps was 92℃, 4min of rinsing time, 4mm of slice thickness and 3h of freezing time, and the normalized composite score of 0.9633 was obtained, which was basically consistent with the predicted value, indicating that the regression model was accurate, and that the comprehensive evaluation method of the combination of the principal component analysis and the response surface analysis method for optimizing the pretreatment process of potato crisps was accurate and feasible.

4. Nutrient Retention Measures

4.1. Cooking Methods and PROCESS optimization

4.1.1 Rationalization of Meals

Rational mixing and matching is the key to achieving a balanced diet, and the goal of a balanced diet can only be realized if the varieties and quantities of various types of food are reasonably matched. A balanced diet can maximize the body's normal growth and development, immunity and physiological function needs, meet the body's supply of energy and nutrients, and reduce the risk of diet-related chronic diseases. For example, a combination of vegetables and fruits can increase vitamins and minerals and ensure that the organism consumes enough vitamins and antioxidants every day. Increased intake of potatoes may reduce the risk of constipation, but excessive intake of fried chips and French fries may increase the risk of obesity. Whole grain intake, which reduces the risk of all-cause mortality and the onset of cardiovascular disease, helps to maintain a normal body weight and slows weight gain. In addition, some dairy products can be included in the diet in moderation to provide the body with high quality proteins. In conclusion, consuming different types of food together can provide a wide range of nutrients.

4.1.2. Selection of Cooking Methods with Better Nutrient Retention

When choosing a cooking method, there are specific cooking methods that can be used in order to retain as many nutrients as possible in the ingredients. For example, steaming is an effective low-temperature cooking method that retains the minerals in ingredients by isolating them from water or oil, and is particularly suitable for cooking ingredients such as seafood. For meat ingredients, grilling is an ideal choice if you wish to maintain their original flavor and retain the nutrients. Barbecue uses dry heat to form a caramelized layer on the surface of the food, effectively locking in the food nutrients [35]. As another example, stewing is a slow cooking method that takes a long time to fully release the nutrients of the ingredients and retain the original flavor of the food. Meanwhile, poaching is a relatively simple cooking method, in which ingredients are put into boiling water to cook, and for ingredients such as seafood, poaching can make them more flavorful, and the boiled water can be used as soup or seasoning. In addition, chilled is a way of cooking by adding various seasonings and spices, chopping the ingredients and mixing them well, especially popular in the summer. It not only enriches the flavor, but also works with a wide range of ingredients, making it a relatively healthy cooking option.

4.2. Optimization of Food Selection and Procurement

4.2.1. Selection of Fresh Ingredients

When choosing fruits, the exterior should be smooth and free of visible scratches or discoloration. When pressed gently, the fruit should feel firm and elastic, and should not feel limp or loose. Vegetables should look clean, fresh and undamaged. Meat should have a natural color and luster; avoid meats with irritating odors or brown spots, and should be flexible to the touch, not overly slimy or flabby. As a general rule, fresh ingredients usually have a clean, fresh odor with no off-flavors or rancid tastes.

4.2.2. Rationalize Ingredient Storage

To ensure that food maintains its freshness and nutritional value, proper storage is essential. Choosing local and seasonal ingredients can minimize moisture loss and nutrient depletion caused by long distance transportation and storage. At the same time, the taste and flavor of the food should be maintained under appropriate storage conditions to avoid over-storage in the refrigerator, which may result in changes in the texture of the food. When storing ingredients, make sure there is enough space inside the refrigerator for cold air circulation to maintain its cooling effect. In addition, regular cleaning of the refrigerator, including the interior walls and corners, is necessary to ensure a hygienic environment for food storage.

5. Conclusion

In this study, potato was used as the main raw material to optimize its processing. The single-factor results showed that different pretreatment methods had significant effects ($p<0.05$) on the existence of crushing power, sensory evaluation and comprehensive score, and affected the volatile components of this sample. A total of five principal components were extracted by principal component analysis, and the total contribution rate of the first three principal components was greater than 85%; the indexes determining the 1st principal component were mainly sensory evaluation and comprehensive score, and those determining the 2nd principal component were crushing force and oil content; those determining the 3rd principal component were L* value and oil content. The standardized composite score obtained as the response value, the quadratic multinomial regression equation is obtained as:

$$Y = 0.963 + 0.15X1 + 0.073X2 + 0.045X4 - 0.135X1X3 + 0.136X2X3$$
$$-0.081X2X4 - 0.384X1^2 - 0.221X2^2 - 0.183X3^2 - 0.189X4^2$$

The standardized composite score obtained based on this method is basically consistent with the predicted value, indicating that the regression model can be optimized for the food processing process. In order to maximize the retention of food nutrition, this paper proposes cooking methods and processes, ingredient selection and procurement optimization methods.

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