Hindawi
Journal of Food Quality
Volume 2022, Article ID 8858235, 11 pages
https://doi.org/10.1155/2022/8858235

Research Article

Determination of Total Saccharide Content in *Auricularia auricula* Based on Near-Infrared Spectroscopy

Gen Yang,[1] **Shanlei Li**,[1,2] **Shixian Ji**,[1,2] **Yunjie Wang**,[1,2] **Jinmei Wang**,[1,3,4] **Liqiang Ji**,[1,2] **and Changqin Li**[1,3,4]

[1]*National R & D Center for Edible Fungus Processing Technology, Henan University, Kaifeng 475004, China*
[2]*Henan Lon Fon Industrial Co. Ltd., Puyang 457300, China*
[3]*Functional Food Engineering Technology Research Center, Henan Province, Kaifeng 475004, China*
[4]*Joint International Research Laboratory of Food & Medicine Resource Function, Henan Province, Henan University, Kaifeng 475004, China*

Correspondence should be addressed to Changqin Li; xiaoya0204@163.com

Received 10 July 2020; Revised 7 September 2020; Accepted 27 December 2021; Published 24 February 2022

Academic Editor: Yungpeng Cao

In this paper, the content of total saccharide in *Auricularia auricula* from different regions was determined. Then, near-infrared (NIR) technology was used to collect the spectral information of the samples. The sample data were divided into calibration set and validation set. The best quantitative model of the total saccharide content of *A. auricula* was established by selecting the parameters such as spectral range, pretreatment method, and partial least square method (PLS) main factor number of the calibration set data. The validation set data were used to verify the reliability of this model. In this model, the original spectrum was used to preprocess by standard normal variate (SNV) + second derivative (SD) to eliminate the scattering effect caused by uneven particle distribution and the influence of noise on spectral data. The spectrum range was 4000–10000 cm^{-1}, and the final choice of PLS main factor number was 11. Under this condition, the calibration set R_c^2 of the model was 0.9092, the root mean square error of calibration (RMSEC) was 1.405, the root mean square error of prediction (RMSEP) was 1.507, and the residual predictive deviation (RPD) was 3.32. The validation samples were used to test the model, and the result showed that $R_v^2 = 0.9048$ of the validation set. The result proved that the predicted value of the validation samples had a good linear relationship with the measured value. According to the *T*-test of the two sets of data in the validation set, the difference between the predicted value and the chemical value was not significant ($P \geq 0.05$). The results were in line with the expected objectives. The established NIR quantitative model can be used to predict the total saccharide content of the black fungus sample to be tested.

1. Introduction

Auricularia auricula is the fruiting body of edible fungus used as medicine and food [1,2], which contains active ingredients such as cellulose, polysaccharide, and minerals such as calcium, iron, and phosphorus [3]. *A. auricula* polysaccharide (AAP) is one of the main effective components and has biological activities such as antitumor, lowering blood glucose, anticoagulant, antiaging, and enhancing immunity [4–7]. Therefore, *A. auricula* has great potential for medicinal development. At present, the methods of AAP extraction include water extraction, acid-base extraction, ultrasonic-assisted extraction, and enzyme extraction, but these methods usually take a lot of time and manpower and damage the original medicine to a certain extent [8]. Because of the complex composition of polysaccharides, it is difficult to determine them directly. In practice, the content of total saccharide is often used to replace the content of polysaccharide to evaluate the quality of food. So, it is necessary to find a rapid and accurate method to determine the total saccharide content of *A. auricula*.

In recent years, near-infrared (NIR) spectroscopy has attracted more and more attention because of its fast detection speed, environmental protection, and no loss of

samples. Especially since the 1990s, NIR had been widely used in industrial fields, such as applied physics, textile, architecture, history, pharmacy, and food [9–15]. In the near-infrared spectrum analysis, the commonly used modeling methods include multiple linear regression (MLR), principal component regression (PCR), partial least squares (PLS), and other linear correction methods, as well as artificial neural network (ANN) and support vector machine (SVM) and other nonlinear correction methods [16–18].

In this paper, the PLS method was used as the modeling method to establish the near-infrared total saccharide prediction model of *A. auricula*.

2. Materials and Methods

2.1. Materials. 166 batches of *A. auricula* were collected from different regions in China during 2018-2019, and the specific information was shown in Table 1. All samples were sealed and stored in a cool and dry place.

2.2. Instruments and Equipment. Spot light 400 mid/near-infrared spectrometer (PerkinElmer Inc, U.S.); rotary evaporator (EYELA Inc., Japan); AB135-s 100000 level electronic balance (Mettler Toledo Inc, Switzerland); UV-2600 ultraviolet visible spectrophotometer (Shimadzu Inc, Japan); DHG-9053A electric blast drying oven (Yi Heng, Shanghai, China); HH-S4 digital display constant temperature water bath (Xiang Tian, Changzhou, China); and SK-1 fast mixer (Hua Feng, Jintan, China).

2.3. Determination Method of Total Saccharide Content

2.3.1. Preparation of Test Solution. The sample of *A. auricula* was ground, passed through a 20 mesh sieve, and then 0.25 g of A. auricula powder was precisely weighed and placed in a 250 mL conical flask. 50 mL water and 15 mL concentrated hydrochloric acid were added, heated, and refluxed in a 100°C water bath for 3 h. After cooling to room temperature, the filter residue was washed with distilled water, the filtrate and washing solution were combined, and the volume of water was fixed to 250 mL to prepare the test solution.

2.3.2. Drawing of Standard Curve. 0.1, 0.2, 0.4, 0.6, 0.8, and 1.0 mL of 100 mg/*L* glucose standard solution were accurately taken to 10 mL test tube with plug, and then distilled water was added to make up to 10 mL. 1.0 mL of 5% phenol solution was added into the test solution, and then 5.0 mL of concentrated sulfuric acid was added. The reaction solution was mixed by using a rapid mixer. Then, the test tube was placed in a water bath at 30°C for 20 min, and an appropriate amount of reaction solution was taken to measure the absorbance at 490 nm. The standard curve was drawn, and the standard curve equation was calculated with the absorbance value as the ordinate and the glucose concentration (mg/mL) as the abscissa.

2.3.3. Determination of Sugar Content in Samples. 0.2 ml of the test solution was accurately piped into a 10 mL tube with plug, and distilled water was added to make up to 1.0 mL. The absorbance was measured according to the above steps. The total saccharide content w was calculated by the standard curve, and the value was expressed in percentage (%). The calculation formula is as follows:

$$w = \frac{m_1 \times v_1 \times 10^{-6}}{m_2 \times v_2 \times (1-\omega)} \times 100, \quad (1)$$

where v_1 is the constant volume of sample, V_2 is the volume of the sample solution taken during colorimetric determination, m_1 is the sugar content in the sample solution which can be obtained from the standard curve, m_2 is the sample quality, and ω is the water content of the sample.

2.3.4. The Method of Near-Infrared Spectrum Collection. 166 batches of *A. auricula* powder samples (80 mesh) were spread separately on the integrating sphere of the NIR spectrometer, and the samples should be completely covered with the integrating sphere. The scanning spectrum range was 4000–10000 cm^{-1}, the scanning times were 64, and the resolution was 8 cm^{-1}. The original spectral data of sample were shown in Figure 1.

2.4. Method and Verification of Establishing Quantitative Model. The spectral data of samples were analyzed by Spectrum Quant software, and partial least square (PLS) method was selected as the modeling method. Four indexes, RMSEC (root mean square error of calibration), RMSEP (root mean square error of prediction), R^2 (coefficient of determination), and RPD (residual predictive deviation), were used to evaluate the performance of the model. Generally, the larger the R^2, the smaller the RMSEC and RMSEP, and the better the model prediction effect. And, the smaller the difference between RMSEC and RMSEP, the better the generalization ability of the prediction model. Generally, the ratio of RMSEC/RMSEP needs to be controlled between 0.8 and 1.2. RPD is the final evaluation index of the model, and its evaluation standard adopts the threshold segmentation method [19–21]. When RPD <2.0, it indicates that the model is very poor and cannot be applied; when RPD is 2.0–2.5, it indicates that the model can make a rough prediction and correlation evaluation of the samples; when RPD is 2.5–3.0, it indicates that the model is better and can be used for quantitative analysis of samples; when RPD> 3.0, it indicates that the model has excellent predictive ability and can be used for model analysis [22]. The calculation formula of RPD is as follows:

$$RP\ D = \frac{1}{\sqrt{1-R^2}}. \quad (2)$$

3. Results

3.1. Determination Results of Total Saccharide Content of A. auricula. According to formula (1), the measurement

Table 1: Sample information of *A. auricula*.

Number	Name	Province	Number	Name	Province
1	*A. auricula*	Yunnan	33	*A. auricula*	Heilongjiang
2	*A. auricula*	Guangdong	34	*A. auricula*	Heilongjiang
3	*A. auricula*	Guangdong	35	*A. auricula*	Zhejiang
4	*A. auricula*	Heilongjiang	36	*A. auricula*	Sichuan
5	*A. auricula*	Yunnan	37	*A. auricula*	Jilin
6	*A. auricula*	Sichuan	38	*A. auricula*	Jilin
7	*A. auricula*	Jilin	39	*A. auricula*	Heilongjiang
8	*A. auricula*	Heilongjiang	40	*A. auricula*	Zhejiang
9	*A. auricula*	Henan	41	*A. auricula*	Hubei
10	*A. auricula*	Henan	42	*A. auricula*	Shandong
11	*A. auricula*	Fujian	43	*A. auricula*	Zhejiang
12	*A. auricula*	Hebei	44	*A. auricula*	Heilongjiang
13	*A. auricula*	Yunnan	45	*A. auricula*	Heilongjiang
14	*A. auricula*	Hebei	46	*A. auricula*	Guizhou
15	*A. auricula*	Ningxia	47	*A. auricula*	Sichuan
16	*A. auricula*	Fujian	48	*A. auricula*	Sichuan
17	*A. auricula*	Shanxi	49	*A. auricula*	Sichuan
18	*A. auricula*	Jilin	50	*A. auricula*	Sichuan
19	*A. auricula*	Shandong	51	*A. auricula*	Chongqing
20	*A. auricula*	Anhui	52	*A. auricula*	Heilongjiang
21	*A. auricula*	Henan	53	*A. auricula*	Heilongjiang
22	*A. auricula*	Fujian	54	*A. auricula*	Heilongjiang
23	*A. auricula*	Jilin	55	*A. auricula*	Anhui
24	*A. auricula*	Heilongjiang	56	*A. auricula*	Heilongjiang
25	*A. auricula*	Heilongjiang	57	*A. auricula*	Jilin
26	*A. auricula*	Heilongjiang	58	*A. auricula*	Anhui
27	*A. auricula*	Heilongjiang	59	*A. auricula*	Jilin
28	*A. auricula*	Heilongjiang	60	*A. auricula*	Jilin
29	*A. auricula*	Heilongjiang	61	*A. auricula*	Sichuan
30	*A. auricula*	Heilongjiang	62–69	*A. auricula*	Shanghai
31	*A. auricula*	Heilongjiang	70–166	*A. auricula*	Jilin
32	*A. auricula*	Heilongjiang			

results of the total saccharide content in 166 batches were shown in Table 2.

3.2. Removal of Model Abnormal Samples. In this study, software was used to identify the abnormal samples automatically. The PCA score map was used to cluster analyse the spectral data of *A. auricula* samples, and the differences among the samples were counted. Diagnosis of abnormal data by test of studentized residual and leverage values method [23]. Finally, 47 batches of abnormal samples were removed from the model. The modeling process was shown in Figures 2 and 3.

3.3. Division of Calibration Set and Verification Set. The calibration set and verification set were selected from all samples randomly. The following two conditions must be met during the selection process: ① ensure that the total saccharide content of the verification set samples covers the content gradient of all samples. ② Ensure that the content range of the selected verification set samples does not exceed the calibration set.

In Table 3, the samples of the verification set were completely distributed within the range of the calibration set, indicating that the division of the sample set meets the modeling requirements.

3.4. Selection of Spectral Range for Modeling. The calibration model is established by choosing appropriate spectral range which has strong prediction ability, and good robustness can often be obtained [24]. In Figure 1, the sample had obvious characteristic peak absorption at 5100 cm^{-1} and 7000 cm^{-1}. Meanwhile, R^2, RMSEC, RMSEP, and RPD were used as model evaluation indicators to establish the model in four spectral intervals. The appropriate spectral range was selected by comparing the modeling results of different spectral intervals. The results are shown in Table 4.

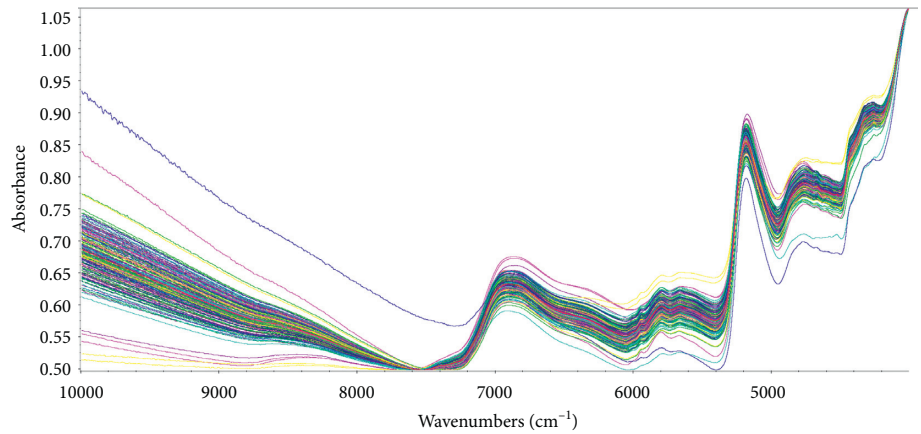

Figure 1: NIRS spectrum of (A) auricula.

In Table 4, when the spectral range was 4000–10000 cm^{-1}, the values of RMSEC and RMSEP were the smallest, and the model effect was the best.

3.5. Selection of Spectral Pretreatment Methods. It is necessary to preprocess the original spectrogram. The robustness and accuracy of the model can be improved by preprocessing the spectrogram. Common preprocessing methods include S-G convolution smoothing, FD (first derivative), SD (second derivative), SNV (standard normal variable transformation), and MSC (multivariate scattering correction). In this study, R^2, RMSEC, and RMSEP were used as model evaluation indicators to compare the modeling results of different pretreatment methods and selected the appropriate spectral pretreatment method.

In Table 5, the best pretreatment method of total saccharide model of *A. auricula* was "SNV + SD." The spectrum of *A. auricula* after pretreatment was shown in Figure 4.

3.6. Determination of the Main Factor of PLS. When the method of partial least squares was used to establish the model, the appropriate number of PLS main factors was related to the quality of the model directly. If the number of PLS main factors was too small, it would cause the loss of useful information in the original spectrum, which would often reduce the predictive ability of the model. If the number of PLS main factors was too much, some information that was not related to the sample would be included. This situation would lead to a larger prediction error of the model [25]. According to the comprehensive evaluation index R^2 and RMSEP, the number of main factors used in PLS modeling was 11.

4. Verification and Evaluation of the Model

4.1. External Verification. The near-infrared quantitative model was used to predict the total saccharide content of the validation set samples, and the predicted value of the quantitative model and the measured chemical value were shown in Table 6 and Figure 5. In Figure 5, $R^2 = 0.9048$ was higher than 0.9 of the verification set, which indicated that there was a good linear relationship between the predicted value and the measured value of the model. Then, the statistical software of SPSS was used to test the predicted results with paired *T*-test. The set confidence was 95%. The results showed that there was no significant difference between the predicted value and the measured chemical value of the quantitative model ($P = 0.182 \geq 0.05$).

4.2. Evaluation of the Model. The parameters of the quantitative model were shown in Table 7, and the linear scatter diagram of the chemical value and the predicted value of the model was shown in Figure 6. The best near-infrared model of total saccharide content of *A. auricula* was obtained by the screening of modeling parameters.

5. Discussion

The quantitative analysis of edible mushroom mainly focused on the determination of water, protein, polysaccharides, triterpene, and other components. Although the chemical standard analysis method can detect the total saccharide content, its operation steps are tedious and the efficiency is low; there are some limitations in the practical application process. In the research on the detection of effective components in *Cordyceps militaris*, Wang Di [26] proved that it was feasible to use near-infrared technology combined with PLS algorithm to achieve rapid prediction of effective components in edible mushroom. Li Junshan [27] directly measured the water content in *Poria cocos* by near-infrared technology combined with PLS method and established a prediction model. The optimal number of the latent variables for the model was 8. The coefficient of determination (R^2) for the model was 0.998. The RMSECV was 0.453, and RMSEP was 0.366. The results of the model showed that the method of determining the water content of *Poria cocos* by near-infrared technology was faster and simpler than other methods. Wu Lun [28] determined the saponins content of *the Honey-Fried Processing of Rhizoma Cimicifugae* by near-infrared technology. Through the study of the band range, the spectrum used for modeling was finally determined, and the intervals are 5200–6700 cm^{-1}

Table 2: The results of total saccharide content of *A. auricula*.

Number	Total saccharide content (%) ($x \pm s$, $n = 3$)
1	14.54 ± 0.37
2	15.28 ± 0.12
3	12.03 ± 1.45
4	12.60 ± 1.20
5	18.37 ± 3.31
6	13.60 ± 2.86
7	10.79 ± 1.25
8	11.07 ± 0.97
9	15.42 ± 3.02
10	18.60 ± 1.16
11	13.14 ± 2.07
12	9.26 ± 0.62
13	11.82 ± 1.36
14	11.37 ± 0.66
15	11.92 ± 1.28
16	12.23 ± 3.56
17	19.78 ± 0.98
18	12.47 ± 2.20
19	18.22 ± 2.03
20	19.36 ± 0.80
21	14.43 ± 0.26
22	17.86 ± 2.13
23	17.82 ± 3.90
24	13.25 ± 1.54
25	14.04 ± 0.27
26	4.52 ± 0.57
27	7.91 ± 3.66
28	6.08 ± 1.00
29	4.01 ± 0.08
30	5.94 ± 1.99
31	9.56 ± 0.44
32	6.31 ± 3.79
33	9.62 ± 1.31
34	11.49 ± 2.60
35	12.33 ± 1.34
36	15.61 ± 0.97
37	12.86 ± 3.31
38	11.91 ± 1.39
39	12.77 ± 2.11
40	6.99 ± 0.01
41	14.91 ± 1.00
42	3.83 ± 1.57
43	9.02 ± 0.47
44	5.41 ± 0.06
45	5.54 ± 0.25
46	4.98 ± 1.04
47	3.33 ± 2.28
48	10.07 ± 1.89
49	4.62 ± 0.13
50	10.67 ± 0.64
51	11.57 ± 2.88
52	5.75 ± 1.31
53	4.63 ± 0.14
54	10.01 ± 2.13
55	2.85 ± 1.50
56	3.59 ± 1.36
57	2.99 ± 1.13
58	11.85 ± 0.41
59	5.25 ± 1.53
60	11.60 ± 1.12

Table 2: Continued.

Number	Total saccharide content (%) ($x \pm s$, $n = 3$)
61	20.93 ± 0.41
62	19.19 ± 3.29
63	19.47 ± 3.69
64	14.07 ± 2.52
65	8.33 ± 0.66
66	3.48 ± 1.02
67	7.09 ± 0.76
68	4.78 ± 1.80
69	6.27 ± 0.26
70	14.66 ± 2.93
71	25.24 ± 0.32
72	8.51 ± 1.53
73	5.16 ± 0.19
74	14.52 ± 2.93
75	12.22 ± 0.18
76	5.11 ± 1.91
77	13.56 ± 0.7
78	10.54 ± 0.27
79	7.35 ± 0.06
80	9.38 ± 1.2
81	6.51 ± 0.05
82	8.90 ± 0.46
83	21.48 ± 0.6
84	14.83 ± 1.1
85	4.05 ± 1.48
86	14.43 ± 0.5
87	15.68 ± 0.75
88	9.98 ± 2.36
89	6.65 ± 1.93
90	5.85 ± 1.47
91	5.16 ± 0.04
92	12.29 ± 0.96
93	7.59 ± 0.97
94	8.41 ± 0.22
95	6.69 ± 0.36
96	14.54 ± 1.07
97	9.51 ± 0.73
98	1.30 ± 0.05
99	5.55 ± 0.34
100	7.88 ± 0.52
101	5.73 ± 1.3
102	17.33 ± 1.48
103	11.61 ± 0.08
104	4.09 ± 0.95
105	10.52 ± 0.19
106	12.61 ± 3.13
107	8.88 ± 0.37
108	18.72 ± 0.04
109	11.02 ± 1.64
110	9.66 ± 1.73
111	12.62 ± 0.58
112	2.61 ± 0.64
113	10.24 ± 0.31
114	3.27 ± 0.23
115	7.62 ± 0.15
116	12.23 ± 1.70
117	2.67 ± 0.17
118	8.75 ± 3.07
119	14.86 ± 0.48
120	6.10 ± 0.29

Table 2: Continued.

Number	Total saccharide content (%) ($x \pm s$, $n = 3$)
121	11.01 ± 1.73
122	13.83 ± 3.31
123	11.26 ± 2.65
124	5.97 ± 2.53
125	11.53 ± 2.20
126	17.25 ± 3.11
127	6.89 ± 0.15
128	4.11 ± 1.28
129	8.19 ± 2.31
130	9.59 ± 2.02
131	15.18 ± 1.32
132	3.81 ± 2.51
133	14.84 ± 0.80
134	14.39 ± 0.46
135	14.51 ± 1.45
136	3.66 ± 0.17
137	12.90 ± 0.79
138	2.56 ± 0.15
139	6.38 ± 0.27
140	4.86 ± 0.11
141	10.27 ± 0.34
142	9.79 ± 0.67
143	15.98 ± 1.86
144	14.39 ± 0.81
145	2.11 ± 1.53
146	14.10 ± 0.2
147	10.61 ± 0.32
148	6.68 ± 1.68
149	12.00 ± 1.56
150	16.17 ± 1.29
151	6.48 ± 0.16
152	14.46 ± 0.64
153	11.69 ± 1.71
154	9.96 ± 3.03
155	12.10 ± 0.43
156	13.69 ± 0.74
157	10.38 ± 3.23
158	13.77 ± 0.78
159	12.01 ± 0.41
160	11.95 ± 0.50
161	13.14 ± 0.18
162	13.85 ± 0.70
163	8.44 ± 2.14
164	4.61 ± 0.36
165	7.04 ± 0.64
166	15.71 ± 0.09

and 7700–8800 cm^{-1}. This study showed that the selection of spectral range played an important role in the prediction effect of the model. Li Xiaowen [29] determined the total saccharide content of *Coprinus comatus* by near-infrared technology. 80 samples of *C. comatus* with different maturity in the same growth cycle were collected, and the PLS model was established after pretreatment such as normalization, second derivative, and smoothing. The results showed that the correlation coefficients of calibration set and prediction set were 0.9989 and 0.9823, respectively. The total saccharide content of *C. comatus* was detected quickly and accurately.

According to the documentation, the combination of near-infrared spectroscopy and chemometrics to establish a prediction model can quickly and accurately predict the content of the tested substance, and it is suitable for the rapid detection of nutrients in edible mushroom.

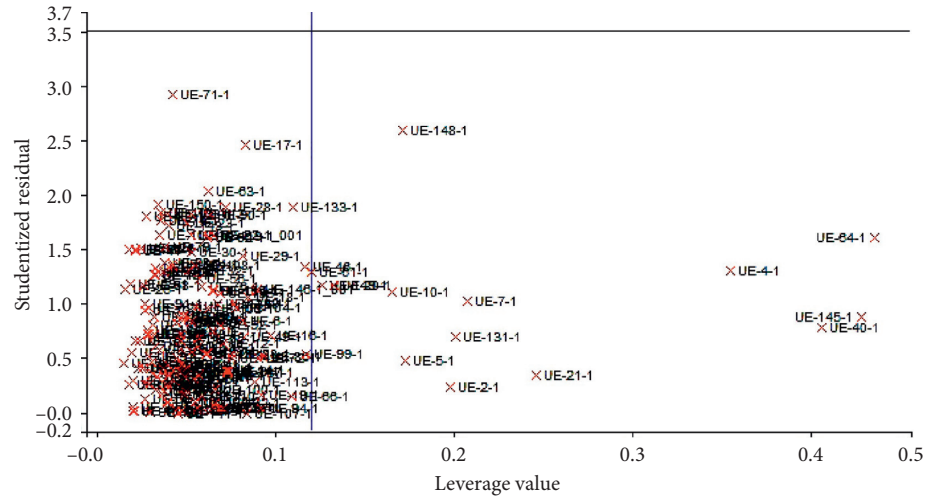

Figure 2: Test of studentized residual.

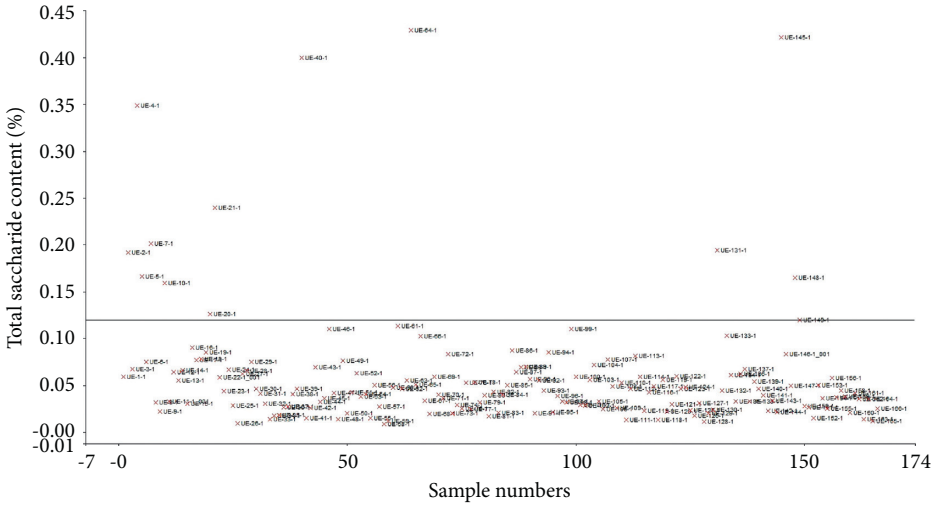

Figure 3: Leverage values of samples.

Table 3: Range of total saccharide content in calibration samples and validation samples.

Sample set	Number of samples	Maximum (%)	Minimum (%)
Correction set	104	19.1896	2.5641
Validation set	15	17.3300	3.5860

Table 4: Experimental results of spectral range screening.

Spectral range	R^2	RMSEC	RMSEP	RPD
4200–5380 cm^{-1}	0.5384	3.168	3.488	1.47
5390–6060 cm^{-1}	0.4732	3.384	3.714	1.38
6070–7500 cm^{-1}	0.8255	1.948	2.081	2.39
4000–10000 cm^{-1}	0.9092	1.405	1.507	3.32

Table 5: Experimental results of spectral pretreatment.

Pretreatment method	R^2	RMSEC	RMSEP	RPD
MSC + FD	0.7410	2.373	2.602	1.96
MSC + SD	0.9083	1.412	1.514	3.30
SNV + FD	0.7788	2.193	2.415	2.12
SNV + SD	0.9092	1.405	1.507	3.32

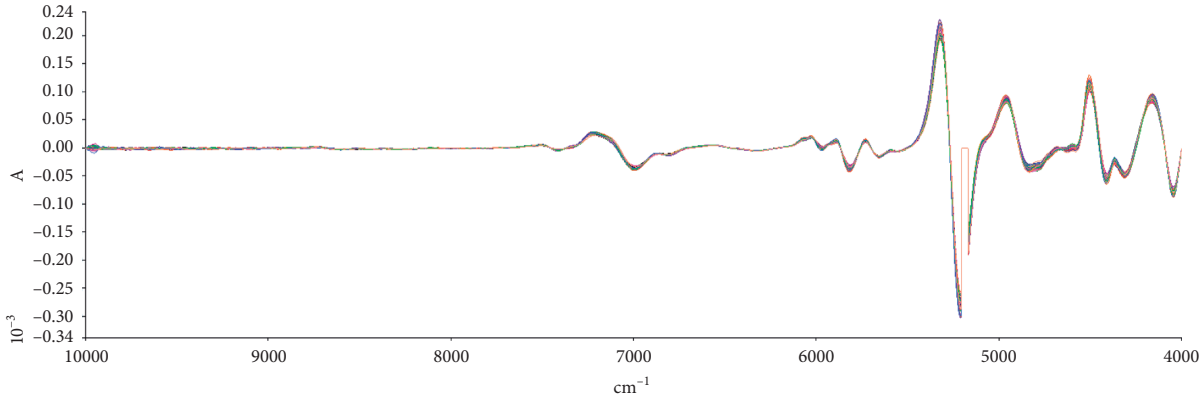

Figure 4: Spectrum of *A. auricula* after pretreatment.

Table 6: Prediction results of total saccharide content of validation samples.

Number	Chemical value (%)	Predicted value (%)
35	12.33	11.86
56	3.59	4.28
60	11.60	12.35
67	7.09	6.79
72	8.51	6.61
77	13.56	13.29
94	8.41	5.88
102	17.33	18.27
130	9.59	8.20
142	9.79	11.34
152	14.46	13.23
157	10.38	10.97
164	4.61	4.95
166	15.71	13.45
87	15.68	14.27

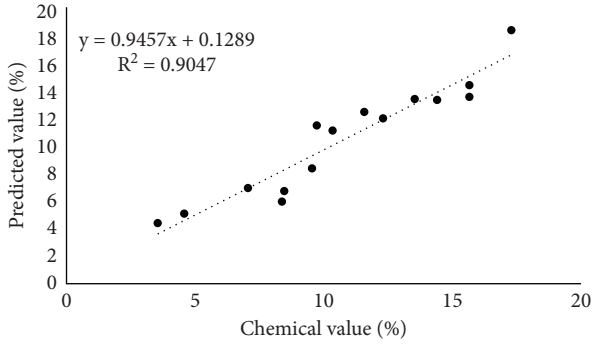

Figure 5: The predicted vs. chemical value of validation samples.

Table 7: Parameters of the optimal NIR models for total saccharide.

Projects	NIR model parameters
Pretreatment method	SNV + SD
Spectral range (cm^{-1})	4000–10000
PLS main factor number	11
R^2	0.9092
RMSEC	1.405
RMSEP	1.507
RPD	3.32

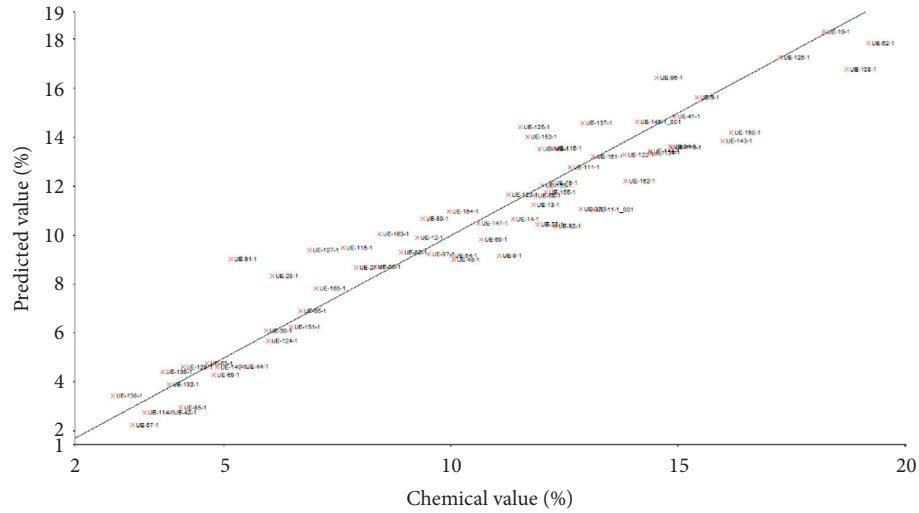

Figure 6: The predicted vs. measured value of the optimal model for total saccharide.

6. Conclusion

In this study, the near-infrared model of the total saccharide of *A. auricula* established had 104 calibration sets and 15 validation sets, the best pretreatment method was SNV +SD, the best spectral range was 4000–10000 cm^{-1}, and the best PLS main factor number was 11. R^2, RMSEC, RMSEP, and RPD of the quantitative model were 0.9092, 1.405, 1.507, and 3.32, respectively. The predicted value of the model had a good linear relationship with the measured value. According to the *T*-test of the validation set, the difference between the predicted value and the measured chemical value was not significant ($P \geq 0.05$).

The results showed that the quantitative model had good fitting ability, and it is feasible to determine the total saccharide content of *A. auricula* by near-infrared spectroscopy. This method is simple and accurate, which can effectively determine the total saccharide content of *A. auricula*. It can provide technical reference for further expanding the application of near-infrared spectroscopy in the determination of total saccharide content, and it is expected to be used in the detection and analysis of the quality of traditional Chinese medicine.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

All authors declare that there are no conflicts of interest regarding this study.

Acknowledgments

This work was funded by the National Key R&D Program of China (2018YFD0400200).

References

[1] C. Li and W. Wang, "New research advances in mushroom based dietary fiber," *China Food Additives*, vol. 10, pp. 159–164, 2015.

[2] X.-M. Wang, J. Zhang, L.-H. Wu et al., "A mini-review of chemical composition and nutritional value of edible wild-grown mushroom from China," *Food Chemistry*, vol. 151, pp. 279–285, 2014.

[3] S. A. Heleno, R. C. Ferreira, A. L. Antonio, M.-J. R. P. Queiroz, L. Barros, and I. C. F. R. Ferreira, "Nutritional value, bioactive compounds and antioxidant properties of three edible mushrooms from Poland," *Food Bioscience*, vol. 11, pp. 48–55, 2015.

[4] J. Zhang, Q. Chen, and C. Huang, "History, current situation and trend of edible mushroom industry development," *Mycosystema*, vol. 34, no. 4, pp. 21–37, 2015.

[5] T. Hu, L. Li, and G. Hui, "Selenium biofortification and its effect on multi-element change in *Auricularia auricular*," *Food Chemistry*, vol. 295, 2019.

[6] L. Zhu, *Study on Isolation, Purification, Physicochemical Properties and Anti-fatigue Function of Polysaccharides from Auricularia Auricula*, Northeast Forestry University, Harbin, China, 2008.

[7] Z. Yin, Z. Liang, C. Li, J. Wang, C. Ma, and W. Kang, "Immunomodulatory effects of polysaccharides from edible fungus: a review," *Food Science and Human Wellness*, vol. 10, no. 4, pp. 393–400, 2021.

[8] T. Ye, L. Qian, and J. Cui, "*Auricularia auricular* polysaccharide protects myocardium against ischemia/reperfusion injury," *Chinese Journal of Applied Physiology*, vol. 26, no. 2, pp. 154–158, 2010.

[9] Y. Xiong and Z. Chen, "Review of research progress in *Auricularia auricular* polysaccharide [J]," *Food Research and Development*, vol. 1, pp. 181–183, 2007.

[10] X. Fan, C. Yin, and L. Ye, "In vitro antioxidant activity of total flavonoids from solid fermented fungal substance of *Auricula auricular*," *Journal of Nuclear Agricultural Sciences*, vol. 33, no. 2, pp. 313–321, 2019.

[11] Y. Mu, *Composition Analysis and Quality Evaluation of Tibetan Black Fungus*, Heilongjiang University, Harbin, China, 2013.

[12] G. Reich, "Near-infrared spectroscopy and imaging: basic principles and pharmaceutical applications," *Advanced Drug Delivery Reviews*, vol. 57, no. 8, pp. 1109–1143, 2005.

[13] C. Wang, *Application of Near Infrared Spectroscopy Technique in Quantification and Qualitation Analysis of Anoectochilus Roxburghii*, Fujian University of Traditional Chinese Medicine, Fuzhou, China, 2017.

[14] I. W. Budiastra, S. Sutrisno, S. Widyotomo, and P. C. Ayu, "Prediction of caffeine content in java preanger coffee beans by NIR spectroscopy using PLS and MLR method," *IOP Conference Series: Earth and Environmental Science*, vol. 147, no. 1, Article ID 012004, 2018.

[15] L. Gao, C. Pan, and J. Chen, "Rapid determination of moisture and reducing sugar in sweet potato by near-infrared spectroscopy coupled with chemometrics," *Food Science*, vol. 38, no. 22, pp. 205–210, 2017.

[16] L. Sun, X. Zhang, and R. He, "Near-infrared scanning polysaccharide content classification of Auricularia auricular based on SVM [J/OL]," *Electronic Science and Technology*, vol. 8, pp. 1–7, 2019.

[17] Y. Hao, *The Quantitative Analysis Method on Active Pharmaceutical Ingredient and Excipients of Five Oral Solid Preparation by NIR spectroscopy*, Jiamusi University, Jiamusi, China, 2018.

[18] H. Zhan, *Study on the Quantitative Analysis of Paeoniae Radix Rubra and Other Chinese Herbal Medicine by Near Infrared spectroscopy*, China Academy of Chinese Medical Sciences, Beijing, China, 2017.

[19] C.-W. Chang, D. A. Laird, and C. R. Hurburgh, "Influence of soil moisture on near-infrared reflectance spectroscopic measurement of soil properties," *Soil Science*, vol. 170, no. 4, pp. 244–255, 2005.

[20] V. Bellon, J. L. Vigneau, and F. Sévila, "Infrared and near-infrared technology for the food industry and agricultural uses: on-line applications," *Food Control*, vol. 5, no. 1, pp. 21–27, 1994.

[21] H. Yan, B. Chen, and W. Zhu, "Rapid determination of milk powder quality by near-infrared spectroscopy analysis," *China Dairy Industry*, vol. 3, pp. 49–52, 2009.

[22] F. Yang, H. Hou, and Z. Sun, "Quantitative model optimizing of milk powder protein and fat by near infrared spectroscopy," *Food Science and Technology*, vol. 41, no. 11, pp. 253–258, 2016.

[23] L. Chen, H. Zhang, and M. Hao, "Rapid detection of moisture and ash content in *Epimedii Herba* using near-infrared spectroscopy," *Chinese Traditional and Herbal Drugs*, vol. 46, no. 9, pp. 1368–1373, 2015.

[24] X. Lü, J. Jiang, and J. Yang, "Detection of capsaicin content by near-infrared spectroscopy combined with optimal wavelengths," *Journal of Zhejiang University*, vol. 45, no. 6, pp. 760–766, 2019.

[25] W. Zhang, W. He, and Y. Wu, "Determination of the content of compound aspirin/dicyanidone by near-infrared spectroscopy combined with partial least square method," *Yunnan Chemical Technology*, vol. 46, no. 8, pp. 84–86, 2019.

[26] 王. Wang Di, 张. Zhang Aili, 孟. Meng Qingfan, 逯. Lu Jiahui, 金. Jin Lu, and 滕. Teng Lirong, "Application of near infrared spectroscopy on rapid determination of essential components for Cordyceps militaris," *Acta Optica Sinica*, vol. 29, no. 10, pp. 2795–2799, 2009.

[27] J. Li, X. Peng, and B. Zhang, "Studies on rapid quantitative analysis of the water in *Poria Cocos* by near infrared diffuse reflectance spectroscopy," *Asia-Pacific Traditional Medicine*, vol. 7, no. 8, pp. 36–38, 2011.

[28] L. Wu, Y. Su, H. Yu et al., "Rapid determination of saponins in the honey-fried processing of rhizoma Cimicifugae by near infrared diffuse reflectance spectroscopy," *Molecules*, vol. 23, no. 7, p. 1617, 2018.

[29] X. Li, P. Li, and J. Yuan, "Determination of total saccharide content in *Coprinus comatus* based on visible/near infrared spectroscopy," *Jiangsu Agricultural Sciences*, vol. 41, no. 9, pp. 279–281, 2013.