

Classification of Rice Producing Area in Heilongjiang Province Based on Cross-Media Feature Fusion

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Abstract. In order to realize the rapid and accurate real estate traceability of rice in Heilongjiang Province, this paper combines computer vision technology and near-infrared spectral data mining technology to the five major production areas of Heilongjiang Province, the five major production areas, Chahayang production area and Jiansanjiang production. A total of 150 grains of rice were analyzed and studied. In this study, based on the fusion of generalized Cartesian product feature, the feature of rice shape based on rice image and the characteristics of rice near-infrared spectral data were merged, and the classification of rice origin was carried out by using support vector machine algorithm. Finally, the accuracy of the model is 90.7%. The experimental results show that the method can be used as a preliminary application to reach the classification of rice.

1. Introduction

As a large province of rice cultivation, Heilongjiang Province has an annual output of rice in the forefront of the country. The real Heilongjiang rice has a short grain shape with an aspect ratio of about 1.6:1, less white belly, high gelatinity, and clear and transparent beige [1]. In recent years, the phenomenon of inferior rice with false and substandard fillings has appeared in the market. The traditional rice safety traceability technology mainly includes chemical traceability technology such as stable isotope fingerprint technology and mineral element fingerprint technology [2], and also includes physical traceability technologies such as near-infrared spectroscopy technology and computer vision detection technology. Because the chemical traceability technology has a long detection period, it is difficult to realize real-time online detection. However, although the physical traceability technology has a faster detection speed but lower accuracy, which reduces the reliability of practical applications, this paper proposes a fusion based on cross-media features [3]. The traceability method of near-infrared spectroscopy and computer vision combined detection aims to solve the problem of accuracy and reliability of rice real-time online origin traceability [4].

2. Search Content

2.1. Spectral Feature Extraction of Single Grain Rice Based on Near Infrared Spectroscopy

The establishment of a model for the content of various components of rice by near-infrared spectroscopy has been relatively mature [5]. Using near-infrared spectroscopy to detect rice, the near-



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infrared spectrum of rice can be obtained, and the near-infrared spectrum of rice can be taken at intervals on the same interval. The value taken should be a set of vectors, that is, the nearness of rice. Infrared spectral data features. In this study, since the difference in rice is small, it is necessary to analyze in a large interval and a small interval, so the selection of n is set to 100, that is, the near-infrared spectral wave number interval is 100. Using the extracted near-infrared spectral data characteristics of rice, combined with the machine learning model, the rice production area can be identified, and at the same time, it can be integrated with other spatial features of rice. This part of the study mainly uses near-infrared spectroscopy combined with support vector machine model to identify the origin of rice in Heilongjiang Province, thus providing a rapid detection method for rice identification.

2.2. Feature extraction of single grain rice pictures

The original image acquired usually contains large noise for various reasons, so the original image needs to be preprocessed. Median filtering is better than other filtering methods to remove noise and smooth the image to make the image clearer. The original image is filtered to remove noise and then its grayscale image and brightness are enhanced. The image with the enhanced brightness is subjected to image segmentation. The image is converted to a binary image to facilitate the extraction of the contour features of the image in the next step. Therefore, in this study, by extracting the contour features of the rice image, the five shape features of the rice are obtained, and the features are area, perimeter, aspect ratio, length and width, respectively.

2.3. Rice origin classification based on cross-media feature fusion

The combination of near-infrared spectroscopy and computer vision technology is the combination of the composition and appearance characteristics of the sample. By mathematically pre-processing and transforming to analyze the near-infrared spectrum of single-grain rice, the internal component data characteristics of single-grain rice can be obtained. Similarly, appearance-based contours and color features are extracted for single grain rice. By trans-media multi-modal multi-dimensional fusion of internal component data features and appearance image features of rice in different producing areas, the characteristics of rice in different dimensions are mapped to the same latitude to form new features. Reconstructing the reconstructed features using the current popular machine learning model, and using the feature-fused model can significantly improve the generalization ability on the classification problem. Previous studies have only used a single method to identify products. This study is based on the way of feature layer fusion across media to explore ways to improve the accuracy of rice origin.

3. Research methods and experimental methods

3.1. Feature fusion method based on Cartesian product

The rice image is characterized by a series of shape features such as the circumference, area, length, width and aspect ratio of rice. The characteristics of rice near-infrared spectral data reflect the absorption of near-infrared light by rice, because the shape of rice will be rice. The absorption of near-infrared light has an effect, so there must be a coupling relationship between the characteristics of rice image and the characteristics of rice near-infrared spectral data. However, due to the lack of a priori condition of this coupling relationship, the two features cannot be decoupled accurately and efficiently. The traditional features are connected in parallel only to the first-order fit of the rice features and do not take into account the coupling between the features of the different views. The application of the foregoing method is more accurate in the case where each feature is a near-independent Gaussian distribution, and there is a significant deviation in the case where there is coupling of each feature. Therefore, in this study, a generalized Cartesian product fusion method is adopted. The near-infrared spectral data characteristics of rice and the rice image features were mapped from low-dimensional to high-dimensional shared space, and the second-order fitting method was used to fit the coupling relationship between the features.

The characteristic $U(u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8, u_9, u_{10})$ of the near-infrared spectral data of rice and the characteristic $V(v_1, v_2, v_3, v_4, v_5)$ of the rice image are fused by a generalized Cartesian product, $X_{rong} = U \times V = (u_1 v_1, u_1 v_2, u_1 v_3, \dots, u_2 v_3, \dots, u_{10} v_5)$ and X_{rong} is a feature of fusion.

3.2. Support vector machine algorithm

Support Vector Machines (SVM) is a binary classifier whose main idea is to establish a hyperplane as the decision surface, so that the isolated edge between the positive and negative examples is maximized, that is, the optimal classification is super flat. This not only reduces the likelihood of prediction errors, but also reduces the risk of overfitting.

Kernel functions can be used to solve nonlinear classification problems in support vector machines, which is equivalent to mapping data to high-dimensional spaces and defining segmentation hyperplanes. Commonly used kernel functions are: Polynomial Kernel Function, Radial Basis Function (RBF), Sigmoid Kernel Function, etc.

Support vector machine parameters ω, b , The update algorithm process is:

Construct constrained optimization problems:

$$\begin{aligned} \min_{\alpha} & \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j (x_i^* x_j) - \sum_{i=1}^m \alpha_i \\ \text{s.t.} & \sum_{i=1}^m \alpha_i y_i = 0 \\ & \alpha_i \geq 0, i = 1, 2, \dots, m \end{aligned}$$

Using SMO algorithm to find the corresponding α vector minimum α^* vector when the minimum is the upper formula.

$$\text{Calculate } \omega^* = \sum_{i=1}^m \alpha_i^* y_i x_i$$

Find all the s support vectors, that is, satisfy the sample (x_s, y_s) corresponding to $\alpha_s > 0$, calculate the corresponding b_s^* for each (x_s, y_s) support vector by $y_s (\sum_{i=1}^m \alpha_i y_i x_i^T x_s + b) = 1$, calculate these

$$b_s^* = y_s - \sum_{i=1}^s \alpha_i y_i x_i^T x_s, \text{ and the average of all } b_s^* \text{ corresponding is the final } b^* = \frac{1}{S} \sum_{i=1}^S b_s^*.$$

3.3. Classification based on support vector machine

First, construct three support vector machine classification models, named SVM_1, SVM_2, SVM_3 , classification model SVM_1 for the rice production combination one (Wuchang, Jiansanjiang) for two classification, SVM_2 for rice production combination two (jiansanjiang, Chahayang) for the second classification, SVM_3 classifies the rice combination (Chahayang, Wuchang).

Then, using the existing rice near-infrared spectrum and the rice image data set to train SVM_1, SVM_2 , and SVM_3 respectively, the model accuracy rates acc_1, acc_2, acc_3 and weight parameters $\omega_1^*, \omega_2^*, \omega_3^*, b_1^*, b_2^*, b_3^*$. The support vector machine classification decision function is $f(x) = \text{sign}(\omega^* x + b^*)$. In this study, x is the fusion feature of rice near-infrared spectral data and rice image feature based on generalized Cartesian product X_{rong} , and X_{rong} is input into three support vector machine models respectively classification. Therefore, the final decision formula of SVM is

$f_1(X_{rong}) = \text{sign}(\omega_1^* X_{rong} + b_1^*)$. If $f_1(X_{rong}) = 1$, the classification result of rice origin is Wuchang. If $f_1(X_{rong}) = -1$, the classification result of rice origin is Jiansanjiang; the final decision formula of support vector machine is $f_2(X_{rong}) = \text{sign}(\omega_2^* X_{rong} + b_2^*)$, if $f_2(X_{rong}) = 1$, the classification result of rice production is Jiansanjiang. If $f_2(X_{rong}) = -1$, the classification result of rice production is Chahayang; the final decision formula of support vector machine is $f_3(X_{rong}) = \text{sign}(\omega_3^* X_{rong} + b_3^*)$. If $f_3(X_{rong}) = 1$, the classification result of rice origin is Wuchang. If $f_3(X_{rong}) = -1$, the result of classification of rice origin is Chahayang.

Finally, the three supports vector machine classification results y_1, y_2, y_3 are statistically analyzed. If two or more repetitions occur in y_1, y_2, y_3 , the mode in y_1, y_2, y_3 is used as the rice prediction. The place of origin, that is, the rice producing area is $\text{Mo}(y_1, y_2, y_3)$. For example, the predicted result of SVM_1 is Wuchang, the predicted result of SVM_2 is Jiansanjiang, and the predicted result of SVM_3 is Wuchang. The final rice yield prediction result is Wuchang; if y_1, y_2, y_3 are different, then compare $\text{acc}_1, \text{acc}_2, \text{acc}_3$, take the results of the model corresponding to the maximum value of $\text{acc}_1, \text{acc}_2, \text{acc}_3$ as the rice origin, for example: SVM_1 prediction result is Wuchang, SVM_2 prediction result is Jiansanjiang, SVM_3 prediction result is Chahayang, $\text{acc}_1 > \text{acc}_2 > \text{acc}_3$, take the SVM_1 prediction result as the final rice production area, that is, the final prediction result is Wuchang.

4. Results and analysis

4.1. Experimental data preparation

In this experiment, 50 grains of 50 grains of Wuchang, Jiansanjiang and Chahayang were selected respectively, and a total of 150 grains of rice were used as experimental samples, and each of the 150 rice grains was photographed and nearly simultaneously. Infrared light detection, corresponding to the rice image and near-infrared spectrum. The shape characteristics of the obtained rice image and the characteristics of the rice near-infrared spectral data are extracted separately and saved in the table. The obtained rice image shape features are five in total, namely area, perimeter, outer rectangle aspect ratio, width sum. There are ten characteristics of long-infrared near-infrared spectral data, which are the absorption degree of near-infrared light by rice on different wave numbers. Some experimental sample data are shown in Figure 1 and Figure 2.

1	Wave number 1000	Wave number 1100	Wave number 1200	Wave number 1300	Wave number 1400	Wave number 1500	Wave number 1600	Wave number 1700	Wave number 1800
2	0.543773678	0.252828731	0.01419203	0.016143875	0.041075252	0.012643137	0.016090364	-0.041536239	1.389470055
3	0.57065724	0.213727989	0.01543884	0.011177918	0.013707795	0.009727136	0.003723814	-0.003779448	0
4	0.57671893	0.282253758	0.008658572	0.007074807	0.01220364	0.004694985	0.00257089	-0.009450531	0
5	0.59374302	0.252242475	0.007908293	0.005940868	0.010568364	0.0033034	0.003416659	-0.005273416	0
6	0.592093047	0.253594899	0.007448469	0.006494667	0.012151602	0.000496116	-0.002235644	-0.005095575	0.265182456

Figure 1. Part of the rice image shape characteristics

1	obj_area	perimeter	aspect_ratio	width	height
2	178289	6737.966175	0.787383178	897.0308	620.9152
3	303224	6165.054492	1.045555556	1063.758	709.6458
4	127329.5	4040.446068	2.474468085	308.4709	1183.575
5	310333.5	7330.850513	0.954444444	553.8859	1163.856
6	135407	9693.21926	1.322496749	1067.814	722.7787
7	95136	3422.404436	1.239208633	728.4968	356.6957
8	172000	3653.492752	0.866752911	918.3578	441.8818
9	137923.5	4239.347653	2.13814433	1021.727	480.6222
10	271669.5	4979.435087	1.101675978	594.2103	1077.286

Figure 2. Characteristics of some rice near-infrared spectral data

Based on the shape feature of the obtained rice image and the characteristics of rice near-infrared spectral data based on the generalized Cartesian product, the fused rice features are obtained. The total number of fused rice features is 50, which will be saved to the table for experiment. The characteristics of the fused rice are shown in Figure 3.

1	obj_area×Wave Number 900	obj_area×Wave Number 1000	obj_area×Wave Number 1100	obj_area×Wave Number 1200
2	0.509528158	0.763439453	-0.367535846	0.767362054
3	1.45979756	0.669648971	-0.15979475	1.219605234
4	0.182840978	0.033891107	1.124606173	-0.449865214
5	1.388608118	0.934955784	-0.226267794	0.067540624
6	0.232561751	1.58617615	0.094744749	1.131897988
7	-0.034192864	-0.136052357	0.021890879	0.42751458
8	0.472988465	-0.072801591	-0.302076035	0.818794971
9	0.260635725	0.091844604	0.844242321	1.083855349
10	1.188210015	0.304632177	-0.102718387	0.158199749

Figure 3. New features after partial rice fusion

After the feature extraction and feature fusion are completed, the sample size of rice is divided, and all experimental samples are divided into training samples and test samples. Select 80% of the sample size as the training set of the model, and select 20% of the sample size as the test set, that is, the number of samples in the training set is 120 grains, and the number of samples in the test set is 30.

4.2. Experimental results and performance analysis

According to the experimental method, the support vector machine model is trained by using the extracted rice image features, the rice near-infrared spectral data features, and the fusion characteristics of the rice image and the near-infrared spectral data respectively, and the parameters of the support vector machine are optimized. The predicted test sets are predicted separately and compared with the real results. Finally, three model accuracy rates and their confusion matrix based on the same training set, the same test set and different features are obtained. The confusion matrix is shown in Figure 4. Shown. Using the confusion matrix, the recall rate and accuracy of the three models can be obtained, and the F1-Score used to evaluate the performance of the model is obtained. The accuracy, recall rate, accuracy and F1-Score scores of the three models are shown in Table 1. A comparison chart of accuracy, recall and accuracy, and a comparison of F1-Score scores are shown in Figure 5.

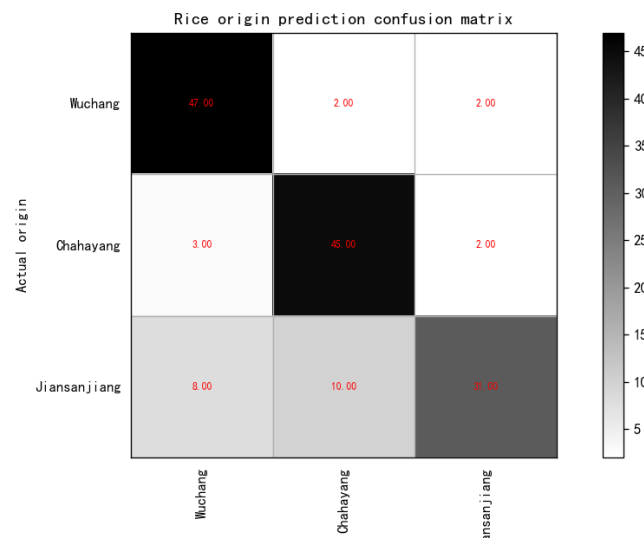


Figure 4. Confusion matrix between rice production forecast and actual rice production area

Table 1. Performance Analysis of Support Vector Machine Model Based on Different Features

	Performance Analysis of SVM Model Based on Rice Image Features	Performance Analysis of SVM Based on Data Characteristics of Rice Near Infrared Spectroscopy	Performance Analysis of Support Vector Machine Model Based on Feature Fusion
Accuracy	0.820	0.740	0.907
Recall	0.829	0.750	0.907
Precision	0.818	0.737	0.906
F1-Score	0.823	0.743	0.906

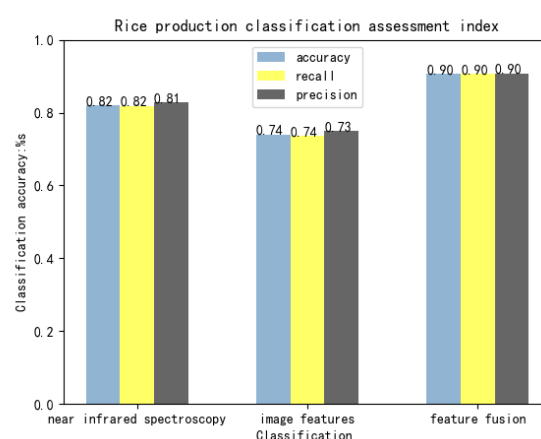


Figure 5. Comparison of accuracy, recall and precision of different classification methods

According to the above chart, in terms of accuracy, the classification method based on feature fusion has an accuracy of 0.90, which is significantly larger than the classification accuracy of 0.74 based on a single feature of rice image and 0.82 based on the characteristics of rice near-infrared spectral data. The classification model of feature fusion can more accurately identify the origin of rice. In terms of F1-

Socre score, the classification method based on feature fusion has a score of 0.906, which is significantly higher than the F1-Score score of 0.823 based on the near-infrared spectral classification method and the F1-Score score of 0.743 based on the image feature method, indicating that the feature fusion is based on The classification model is more robust. Because the classification accuracy and F1-Score scores of classification based on feature fusion are higher than the single classification method, it is more effective to select the traceability based on cross-media feature fusion.

5. Conclusion

The results show that the method of using the cross-media feature fusion method to fuse the rice near-infrared data features with the rice image features, and then using the machine learning method to establish the model of rice origin classification is compared with the traditional, single, whether The method of classifying rice origin by using rice near-infrared spectroscopy is still a method of classifying rice origin by computer vision technology, and it is possible to quickly, stably and accurately identify the origin of rice.

References

- [1] Manos B, Manikas I. Traceability in the Greek fresh produce sector: drivers and constraints[J]. British food journal, 2010, 112(6): 640-652.
- [2] McEntire J C, Arens S, Bernstein M, et al. Traceability (product tracing) in food systems: an IFT(Institute of Food Technology) report submitted to the FDA (Food and Drug Administration), volume 1:technical aspects and recommendations[J]. Comprehensive Reviews in Food Science and Food Safety, 2010,9: 92-158.
- [3] Salampasis M, Tektonidis D, Kalogianni E P. TraceALL: a semantic web framework for food traceability systems[J]. Journal of Systems and Information Technology, 2012, 14(4): 302-317.
- [4] Azuara G, Luis Tornos J, Luis Salazar J. Improving RFID traceability systems with verifiable quality [J].Industrial Management&Data Systems, 2012, 112(3): 340-359.
- [5] Wang R, Prives S, Fischer R, et al. Data analysis and simulation of Auto-ID enabled food supply chains based on EPCIS standard [C]//Automation and Logistics (ICAL), 2011 IEEE International Conference on.IEEE, 2011:5 8-63.