Gaussian Mass Function Based Multiple Model Fusion for Apple Classification

Shuhui Bi, Lisha Chen, Xue Li, Xinhua Qu, and Liyao Ma(✉)

School of Electrical Engineering, University of Jinan, Jinan 250022, Shandong, China
cse_Maly@ujn.edu.cn

Abstract. Near-infrared spectra can be used to predict the internal quality of apple non-destructively, such as Soluble Solids Content (SSC), acidity and so on. However, it needs to establish a prediction model. And for improving the predictive accuracy, some pre-processing methods should be adopted. In this paper, Apples' SSC is considered as a representative index, the Probabilistic Neural Network (PNN) and Extreme Learning Machine (ELM) models are established. After carrying out the Multiple Scattering Correction (MSC), which is to reduce the baseline drift, the classification accuracies of both models are 81.8182% and 77.2727% respectively. For avoiding the limitation of single classification model, and dealing with the uncertainty introduced by hard partition of the instance space, an evidence theory based multiple model fusion is proposed. Especially, the mass function generation is considered. A Gaussian mass function is proposed so as to realize the fusion of PNN and ELM models by combining the mass function based on Dempster's combination rules of evidence theory. The experimental results show that the accuracy of fusion model is 86.3636%, which demonstrate that Gaussian mass function is suitable for apples' multi-model fusion.

Keywords: Apple classification · Gaussian mass function · multi-model fusion

1 Introduction

Agricultural products and food closely related to People's Daily life are in great demand and variety, which brings a huge workload to the quality inspection. Near-infrared spectroscopy (NIR) has technical advantages such as fast, pollution-free, low cost and non-destructive, and has attracted more and more attention in the field of agricultural products and food quality detection [1]. Hu Jing et al. summarized the latest research progress of near infrared spectroscopy technology in recent years at home and abroad in kiwifruit hardness, soluble solids content (SSC), acidity, damage and microbial detection, and prospected the research and application of near infrared spectroscopy analysis technology in kiwifruit quality detection [2]. Cao Niannian et al. took multiple batches of yellow peach chips as the analysis object, collected the raw information of short-wave near-infrared spectroscopy and long-wave near-infrared spectroscopy, and

B. Wang et al. (Eds.): ICMTEL 2023, LNICST 535, pp. 257–269, 2024.
https://doi.org/10.1007/978-3-031-50580-5_22

established the prediction model of all-band linear partial least square method and nonlinear support vector machine after pre-processing [3]. Yu Zhihai et al. established a fast and non-destructive dynamic moisture detection model for red Jujube in southern Xinjiang during processing in order to conduct rapid and non-destructive dynamic moisture measurement for red Junjube in southern Xinjiang during processing [4]. Zhu Jinyan et al. adopted near infrared spectroscopy and extreme learning machine (ELM) method to establish a quantitative detection model for storage quality of blueberry, and realized rapid nondestructive detection of SSC, vitamin C and anthocyanin contents of blueberry fruit [5]. Jie Deng Fei et al. took Qilin watermelon as the research object and used near infrared diffuse transmission spectroscopy to detect the SSC of Qilin watermelon, and studied the influence of variable screening method on the accuracy of watermelon sugar degree prediction model [6].

However, the near infrared technology is an indirect technology, so it is necessary to establish a prediction model. In view of the poor applicability of a single prediction model and the classification uncertainty caused by modeling errors during hard segmentation according to classification indexes, the advantages and effectiveness of each model can be integrated on the basis of the current spectral data preprocessing, so as to make predictions more accurately and improve the reliability of classification models. Has become one of the problems that research must solve.

The quality function describes the degree of evidence's trust in the proposition, and the evidence theory can provide an effective method for the expression and synthesis of uncertain information. When the evidence theory is used to integrate, then the quality function and combination rule play a very important role, but the application of the quality function and combination rule in fruit classification is rare [7]. Xu Xuefang et al. used core mass function (CMF) of molecular clours to study the origin of stellar initial mass function (IMF) [8]. Di Peng et al. introduced D-S evidence theory based on cloud model evaluation to solve the problem of fuzziness and uncertainty of linguistic value evaluation in multi-attribute decision making [9]. Wang Yan et al. built a safety evaluation model based on D-S evidence theory and multi-source information in order to evaluate the safety of dam combined with the properties of surrounding goaf, and verified the feasibility and effectiveness of the evaluation method of multi-source evidence index system [10]. Liao Ruijin et al. combined the chromatographic data and electrical test data, made use of the data fusion principle, organically combined neural network and evidence theory, and proposed a synthetic transformer fault diagnosis method based on the fusion of multi-neural network and evidence theory [11].

Therefore, this paper studies the prediction accuracy of Apples' SSC based on Gaussian mass function and fusion model of multiple classification models.

2 Data Acquisition and Preprocessing

2.1 Data Acquisition

In this paper, 439 red Fuji apple samples were selected, their Near-infrared spectra were acquired by using WY-6100 type fruit online nondestructive testing system within the range of 4000–10000 cm^{-1}, and soluble solid content (SSC) was also collected [11]. The original spectrum of the samples are shown in Fig. 1.

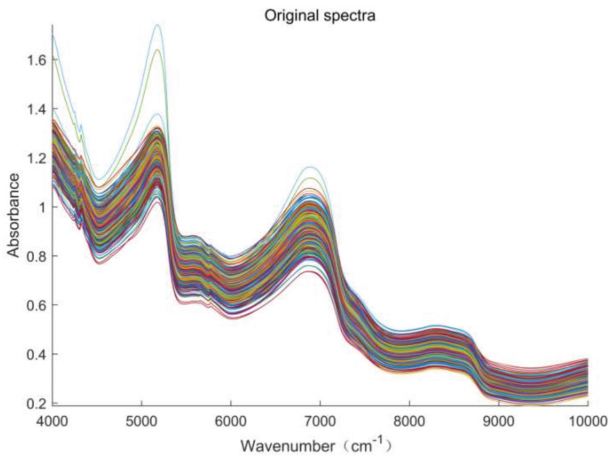

Fig. 1. Original spectra

According to the national standard GB/T12295-90 "Fruit and vegetable products − Determination of soluble solids − Refractometric method", the SSC of each apple sample was measured three times and the average value was taken as the apples' SSC.

In order to reduce the impact of data sets on the accuracy of the prediction model, the data sets should be divided before modeling to make each category more uniform. And 70% of the fruits of each category were randomly selected as the training set and the remaining 30% as the test set.

2.2 Multiple Scattering Correction

In the spectral data acquisition process, spectral information shifts to a certain extent with the change of external environment, which could affect the accuracy of predictive model. In order to reduce the degree of baseline offset, Multiple Scattering Correction (MSC) is selected to preprocess the original spectra [14]. It includes 3 steps: searching for a reasonable "ideal spectrum", unary linear regression, and multiple scattering correction. After that, the spectral information shifts can be reduced, which is demonstrated in Fig. 2.

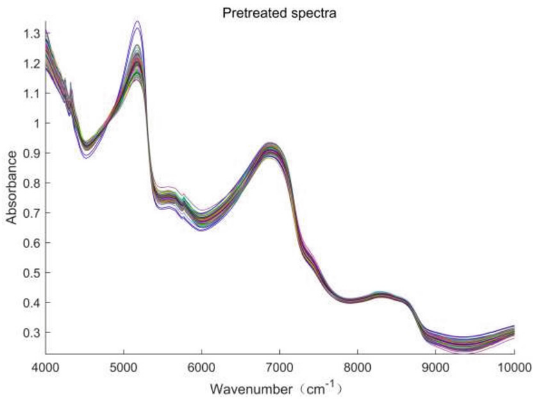

Fig. 2. Spectra after MSC.

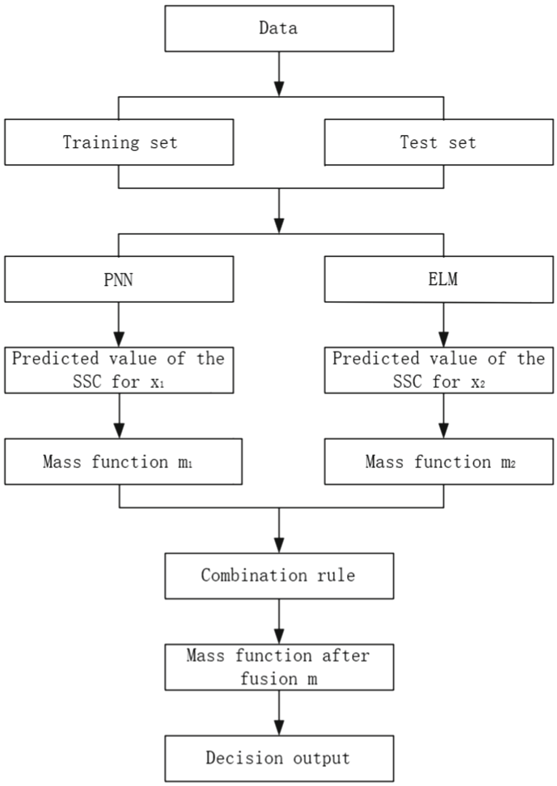

Fig. 3. The fusion process of PNN and ELM model.

3 Gaussian Mass Function Based Multi-model Fusion

In [14], PNN and ELM methods were verified suitable for apples' classification prediction. Therefore, in this study, PNN and ELM methods are used respectively to establish prediction models, wherein, the model input is the characteristic spectra pre-processed by MSC, and the model output is the predicted value of SSC. For improving the prediction accuracy, avoiding the limitation of single classification model, and dealing with the uncertainty introduced by hard partition of the instance space, an evidence theory-based multi-model fusion is proposed. The whole process is shown in Fig. 3. That is, the mass functions of the two prediction models should be obtained, and then, the combination rules are integrated.

3.1 Gaussian Mass Function

The degree to which the evidence trusts the proposition is described by a mass function [15]. In this paper, a Gaussian mass function is generated based on the distance between the predicted value of Apples' SSC and the classification boundary. The reason for the unclear classification is that the predicted value of SSC is close to the boundary of the two kinds of apples, this paper assigns the uncertain quality function of a certain class to the set composed of adjacent classes. According to SSC range and corresponding apple category, the relationship between the level of SSC predicted value x and apple category C can be obtained, as shown below.

$$C = \begin{cases} \mathrm{I}, 13 \leq x < 16 \\ \mathrm{II}, 11 \leq x < 13 \\ \mathrm{III}, 8 \leq x < 11 \end{cases} \tag{1}$$

where, x is SSC. When x is 11, the apple may be Class III or Class II, but the trust degree of the apple in Class III is greater than that in class II. When x is 9.5, the average value of 8 and 11, the trust degree of this apple is the highest. Within the range [8, 9.5], the trust degree of this apple is increasing with the increase of x. Within the range (9.5,11), the trust degree of this fruit is decreasing with the increase of x. Therefore, according the trust degree, this paper constructs the Gaussian mass function diagram as shown in Fig. 4, which is generated based on the distance between SSC and classification boundary.

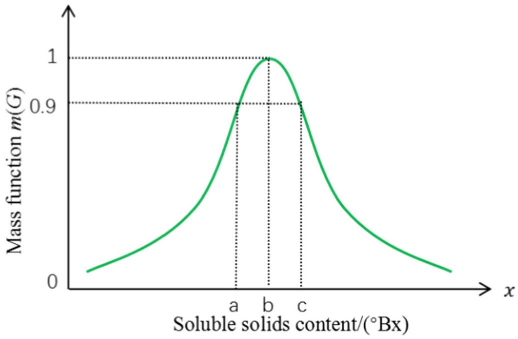

Fig. 4. Gaussian mass function

Where, a and c are the SSC values of the left and right boundary of the classification label respectively, and the mass function value of the corresponding class label is set to 0.9, $b = \frac{(a+c)}{2}$, that is, when the SSC middle value of the class apple is set to 1. Taking Class II fruit as an example, the range of SSC is [11,13], then a is 11, c is 13, and b is 12.

According to Fig. 4, the Gaussian mass function formula of apple can be constructed, as shown below.

$$m(x) = fe^{-\frac{(x-b)^2}{2\sigma^2}}, 8 \leq x < 16 \tag{2}$$

When x is in the range of [8,11) and is close to boundary 8, that is, x is in the range of [8, 9.5), the apple may be classified as class III or it may be uncertain as several kinds of fruit. Based on Eq. (1), C = III is known, and m(III) is obtained according to Eq. (2). Then, the remaining degree of trust can be assigned to {I, II, III} class fruit, that is, $m(\{\text{I, II, III}\}) = 1 - m(\text{III})$.

When x is in the range of [8,11) and close to boundary 11, that is, x is in the range of (9.5, 11), the apple may be classified as Class III or Class II. Based on Eq. (1), C=III is known, and m(III) is obtained according to Eq. (2). Then, the remaining degree of trust can be assigned to {II, III} class fruit, that is, $m\left(\{\text{II}, \text{III}\}\right) = 1 - m(\text{III})$.

When x is in the range of [11,13) and close to boundary 11, that is, x is in the range of [11, 12), the fruit may be classified as Class III or Class II. Based on Eq. (1), C = II is known, and m(II) is obtained according to Eq. (2). Then, the remaining degree of trust can be assigned to {II, III} class fruit, that is, $m\left(\{\text{II}, \text{III}\}\right) = 1 - m(\text{II})$.

When x is in the range of [11,13) and close to boundary 13, that is, x is in the range of (12, 13), the fruit may be classified as Class I or Class II. Based on Eq. (1), C = II is known, and m(II) is obtained according to Eq. (2). Then, the remaining degree of trust can be assigned to {I, II} class fruit, that is, $m\left(\{\text{I}, \text{II}\}\right) = 1 - m(\text{II})$.

When x is in the range of [13,16) and close to boundary 13, that is, x is in the range of [13, 14.5), the fruit may be classified as Class I or Class II.

Based on Eq. (1), $C = \text{I}$ is known, and $m(\text{I})$ is obtained according to Eq. (2). Then, the remaining degree of trust can be assigned to {I, II} class fruit, that is, $m\big(\{\text{I}, \text{II}\}\big) = 1 - m(\text{I})$.

When x is in the range of [13,16) and close to boundary 16, that is, x is in the range of (14.5, 16), the fruit may be classified as Class I or other. Based on Eq. (1), $C = \text{I}$ is known, and $m(\text{I})$ is obtained according to Eq. (2). Then, the remaining degree of trust can be assigned to {I, II, III} class fruit, that is, $m\big(\{\text{I}, \text{II}, \text{III}\}\big) = 1 - m(\text{I})$.

Based on the above analysis, the Gaussian value graph of the class-scale mass function of the three types of Red Fuji apples can be obtained as shown in Fig. 5. Gaussian mass function formula is established in the following.

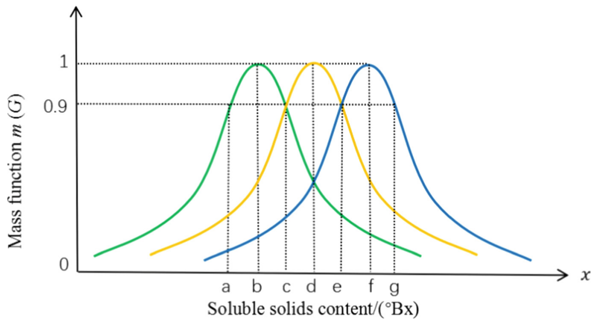

Fig. 5. Gaussian value of the label mass function of three grades of Red Fuji apples

$$m(\text{I}) = \begin{cases} 1, & x = 13 \\ e^{4*(x-14.5)^2*log(0.9/9)}, & x > 13 \end{cases} \tag{3}$$

$$m(\text{II}) = \begin{cases} 1, & x = 11 \\ e^{(x-12)^2*log(0.9)}, & 11 < x < 13 \end{cases} \tag{4}$$

$$m(\text{III}) = e^{4*(x-9.5)^2*log(0.9/9)}, x < 11 \tag{5}$$

$$m\big(\{\text{I}, \text{II}\}\big) = \begin{cases} 1 - m(\text{II}), & 12 \leq x < 13 \\ 1 - m(\text{I}), & 13 \leq x < 14.5 \end{cases} \tag{6}$$

$$m\big(\{\text{II}, \text{III}\}\big) = \begin{cases} 1 - m(\text{III}), & 9.5 \leq x < 11 \\ 1 - m(\text{II}), & 11 \leq x < 12 \end{cases} \tag{7}$$

$$m\big(\{\text{I}, \text{II}, \text{III}\}\big) = \begin{cases} 1 - m(\text{III}), & x < 9.5 \\ 1 - m(\text{II}), & x \geq 14.5 \end{cases} \tag{8}$$

3.2 DS Evidence Theory

In Dempster-Shafer (DS) evidence theory, for decision problems, the set of all decision results is represented by U, which is called the recognition framework.

If the function m:$2^U \to$ [1,2], and meet $\sum\limits_{A\epsilon 2^U} m(A) = 1, m(\phi) = 0$, is called A focal element, $m(X)$ for the quality of the letter X, said the proposition X's trust.

Suppose that two pieces of evidence from different sources, m_1 and m_2, have the same identification frame, U={A_1,A_2,A_3,...,A_n}, $\bigoplus$ is fusion symbol, and Dempster's combination rule of DS evidential theory is

$$m(D) = m_1 \bigoplus m_2(D) = K^{-1} \sum_{A_i \bigcap A_j = D} m_1(A_i)m_2(A_j) \tag{9}$$

In type $1 \le i \le n$, $1 \le j \le n$, $A_i \bigcap A_j = D$ can be obtained by an A_i and A_j intersect.

$A_i \bigcap A_j = D = \phi$ means that event A_i has no intersection with A_j, then

$$K = 1 - \sum_{A_i \bigcap A_j = \phi} m_1(A_i)m_2(A_j) \tag{10}$$

In the formula, K is the normalization factor, which is an indicator to measure the size of contradictions among various evidences.

According to Eqs. (9) and (10), as long as the quality functions of multiple prediction models are obtained, the fusion model can be obtained through the combination rules.

3.3 Gaussian Mass Function Based Multi-model Fusion

Aiming at Apple classification problem, the recognition frames of two prediction models, PNN and ELM, are set as $U = \{\mathrm{I}, \mathrm{II}, \mathrm{III}\}$. When the predicted value of SSC is 13.3537, it can be judged as Class I fruit, according to the accurate value of 13.3537 within the range [13,16]. However, due to the error of a single prediction model and the influence of classification equipment and other factors, the value may be inaccurate and close to the boundary 13 of class I and Class II. Therefore, this sample may also be identified as Class II. In view of this situation, which cannot accurately indicate how many kinds of fruit apples are, uncertainty analysis is introduced in this study, and it is listed as {I,II}, which indicates that it may be Class I or Class II. By taking the spectral data x with the actual SSC value of 13 as input of PNN and ELM, the predicted SSC values of the two models can be obtained as 12.0557 and 13.3537, respectively.

(1) Mass function of PNN prediction model

The output result of the PNN model is taken as the first evidence. The predicted value of PNN is $x_1 = 12.0557$, within the range of $11 \le x < 13$, and then $x = x_1$ is substituted into Eq. (4), $m_1(\mathrm{II}) = 0.9999$. Since $x_1 = 12.0557$ is close to the boundary 13 of Class I and Class II, this apple may also be class II. Substituting into Eq. (6), it can be obtained that $m_1(\{\mathrm{I}, \mathrm{II}\}) = 1 - \mathrm{m}_1(II) = 0.0001$, and the mass function of PNN can be obtained as follows:

$$\begin{cases} m_1(\mathrm{II}) = 0.9999 \\ m_1(\{\mathrm{I}, \mathrm{II}\}) = 1 - m_1(\mathrm{II}) = 0.0001 \end{cases} \tag{11}$$

(2) Mass function of ELM prediction model

The output result of the ELM model is taken as the second evidence. The predicted value of ELM is $x_2 = 13.3537$, within the range of $13 \leq x < 16$, and then $x = x_2$ is substituted into Eq. (3), $m_2(\mathrm{I}) = 0.0052$. Since $x_2 = 13.3537$ is close to the boundary 13 of Class I and Class II, this fruit may also be Class I. Substituting into Eq. (6), it can be obtained that $m_2(\{\mathrm{I}, \mathrm{II}\}) = 1 - \mathrm{m}_2(\mathrm{I}) = 0.9948$, and the mass function of ELM can be obtained as follows:

$$\begin{cases} m_2(\mathrm{I}) = 0.0052 \\ m_2(\{\mathrm{I}, \mathrm{II}\}) = 1 - m_2(\mathrm{I}) = 0.9948 \end{cases} \tag{12}$$

(3) DS evidence theory based Fusion and decision making

Mass function m_1 and m_2 are fused according to Eqs. (9) and (10), and the fused mass function is expressed by m as:

$$K = 0.9948, m(\mathrm{I}) = 0, \mathrm{m}(\{\mathrm{I}, \mathrm{II}\}) = 0.0001, \mathrm{m}(\mathrm{II}) = 0.9999 \tag{13}$$

Then, decision is made according to the size of the mass function. It can be seen from the fusion results that, $m(\mathrm{II}) > \mathrm{m}(\{\mathrm{I}, \mathrm{II}\}) > \mathrm{m}(\mathrm{I})$. It can be concluded that this paper is belong to Class II, which is the same as the actual classification result.

4 Simulation

4.1 Prediction by PNN and ELM

In this paper, the confusion matrix is used to evaluate the predictive models' performance. The confusion matrix is a data table for understanding the performance of the categorical model, and it indicates that how to separate test data into different classes. It is a two-dimensional table with row labels as the actual categories and column labels as the categories predicted by the model.

The original spectral data and SSC of the training set are taken as the input of the PNN and ELM training model to train the PNN and ELM. Then the original spectral data of the test set is taken as the input of the prediction model to predict the Apples' SSC. The predicted SSC values of the PNN and ELM prediction models were converted into class markers, and compared with the original class markers, the confusion matrices of PNN and ELM were obtained, as shown in Tables 1 and 2, respectively.

Table 1. Confusion matrix of PNN prediction model.

Real class mark	Classification Results of PNN			
	Class I	Class II	Class III	Subtotal
Class I	33	3	0	36
Class II	18	75	3	96
Class III	0	0	0	0
Subtotal	51	78	3	132

Table 2. Confusion matrix of ELM prediction model.

Real class mark	Classification Results of ELM			
	Class I	Class II	Class III	Subtotal
Class I	20	16	0	36
Class II	13	82	1	96
Class III	0	0	0	0
Subtotal	33	98	1	132

According to Tables 1 and 2, 108 samples of PNN are accurately classified, among which 33 and 75 apple samples of class I and Class II are correct respectively. 3 class I fruits were improperly divided into class II, 18 II fruits were divided into class I, 3 class II fruits were divided into class III. In summary, with a total of 132 samples, the prediction accuracy was 81.8182%, as shown in Fig. 6. While 102 samples of ELM are accurately classified, among which 20 and 82 samples of Class I and Class II fruits are respectively, 16 class I fruits were divided into class II, 13 II fruits were divided into class I, 1 class II fruits were divided into class III, with a total of 132 samples, and the prediction accuracy was 77.2727%, as shown in Fig. 7.

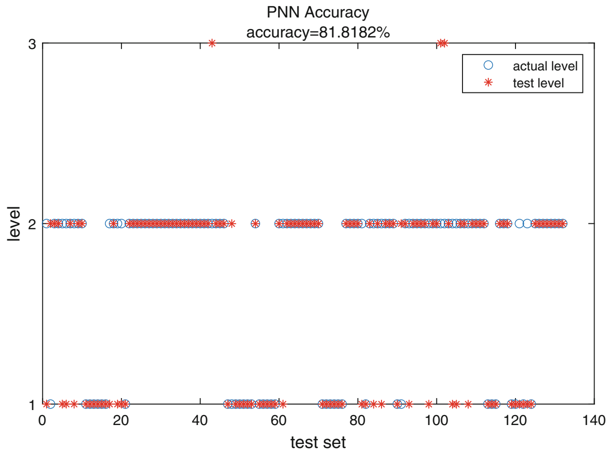

Fig. 6. Classification accuracy of PNN test set

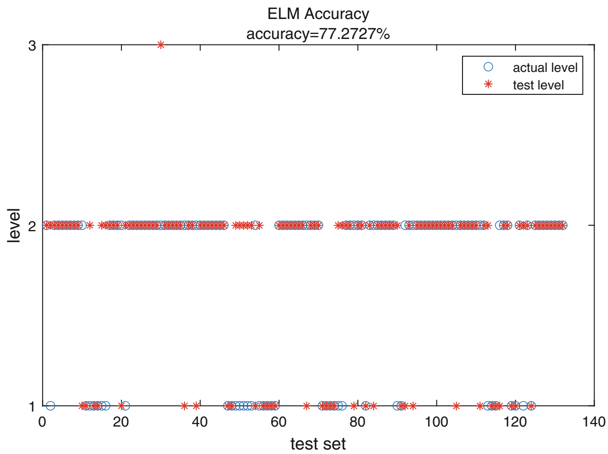

Fig. 7. Classification accuracy of ELM test set

4.2 Simulation Experiment on Fusion Model

The confusion matrix of fusion model by combing PNN model and ELM model is shown in Table 3. As can be seen from Table 3, among the 132 samples, a total of 114 samples were accurately classified after DS fusion, among which 34 samples of class I and 80 samples of class II were right. And 2 samples of class I were wrongly divided into class II, and 16 samples of class II were incorrectly divided into class I.

Table 3. Confusion matrix of DS fusion prediction model.

Real class mark	Classification Results of DS			
	Class I	Class II	Class III	Subtotal
Class I	34	2	0	36
Class II	16	80	0	96
Class III	0	0	0	0
Subtotal	50	82	0	132

The obtained classification accuracy of the fusion model is shown in Fig. 8, the prediction accuracy is 86.3636%. Through the example analysis and simulation experiment, it is proved that the Gaussian mass function proposed in this paper can not only solve the uncertainty caused by discount factor in the classification process and the poor adaptability of a single prediction model, but also improve the prediction accuracy by combining it with Dempster's combination rule.

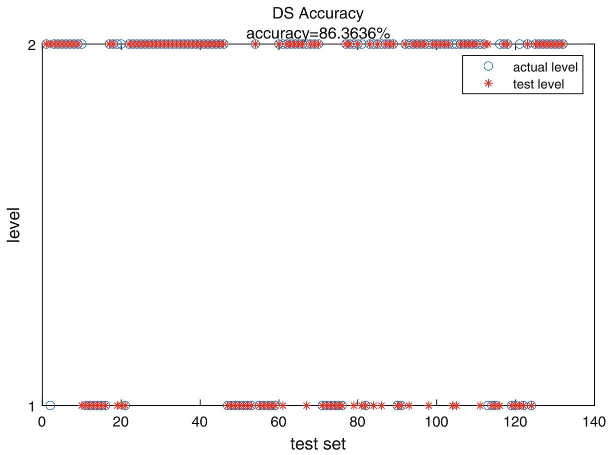

Fig. 8. Classification accuracy after DS fusion

5 Conclusion

Aiming at the limitation of single classification model in the near-infrared spectra technology and the uncertainties caused from the hard partition of the instance space in apples' classification application, an evidence theory-based multi-model fusion was proposed to deal with this issue. A Gaussian mass function was proposed so as to realize the fusion of PNN and ELM models by combining their mass function based on Dempster's combination rules. The maximum mass value of the combined mass function was selected as the final decision of apple grades.

And, the experimental results showed that the proposed mass function in apples classification could improve the prediction accuracy and is reasonable than that using the hard partition.

Acknowledgment. This paper is supported by the Natural Science Foundation of Shandong Province ZR2021MF074, ZR2020KF027 and ZR2020MF067.

References

1. Li, M., Han, D., Lu, D., et al.: Research progress of universal model of near infrared spectroscopy in agricultural products and foods detection. Spectro. Spectral Anal. **42**(11), 3355–3360 (2022)
2. Hu, J., Huang, J., Liu, X., et al.: Research progress of kiwi fruit quality detection based on near infrared spectroscopy. Res. Dev. **43**(2), 196–201 (2022)
3. Cao, N., Liu, Q., Peng, J., et al.: Quantitative determination method of soluble solid and hardness of yellow peach crisp chips based on near infrared spectroscopy. Food Mach. **37**(3), 51–57 (2021)
4. Yu, Z., Luo, H., Kong, D., et al.: Study on dynamic moisture model of Junzao in southern Xinjiang based on near infrared spectroscopy. Xinjiang Agric. Mechanization **2**(1), 35–38 (2022)
5. Zhu, J., Zhu, Y., Feng, G., et al.: Establishment of quantitative models for blueberry storage quality based on near infrared spectroscopy combined with extreme learning machine. Food Ferment. Ind. **48**(16), 270–276 (2022)
6. Jie, D., Xie, L., Rao, X., et al.: Near infrared spectrum variable screening improved the accuracy of watermelon sugar degree prediction model. Trans. Chin. Soc. Agric. Eng. **29**(12), 264–270 (2013)
7. Bi, S., Li, X., Shen, T., et al.: Apple classification method based on multi-model evidence fusion. Trans. Chin. Soc. Agric. Eng. **38**(13), 141–149 (2022)
8. Xu, X., Li, D., Ren, Z.: Cloud core mass function. Adv. Astron. **32**(3), 299–312 (2014)
9. Di, P., Ni, Z., Yin, D., et al.: A multi-attribute decision making optimization algorithm based on cloud model and evidence theory. Syst. Eng. Theory Pract. **41**(4), 1061–1070 (2021)
10. Yan, W., Wei, Y., Fuheng, Ma.: Dam safety evaluation based on D-S evidence theory and multi-source information of GOAF. Water Conservancy Hydropower Technol. **51**(4), 175–183 (2020)
11. Liao, R., Liao, Y., Yang, L., et al.: Research on transformer fault comprehensive diagnosis based on the fusion of multi-neural network and evidence theory. Chin. J. Electr. Eng. **26**(3), 119–124 (2006)
12. Specht, D.F.: Probabilistic neural networks. Neural Netw. **3**(1), 109–118 (1990)
13. Zhou, S., Liang, J.: Partial discharge pattern Recognition based on moment feature and probabilistic neural network. Prot. Control Power Syst. **44**(3), 98–102 (2016)
14. Chen, Li, X., L., Ma, L., Bi, S.: Probabilistic neural network based apple classification prediction. In: Proceedings of 2022 International Conference on Advanced Mechatronic Systems, Japan, pp. 71–75 (2022)
15. Guo, W., Shang, L., Zhu, X., et al.: Nondestructive detection of soluble solids content of apples from dielectric spectra with ANN and chemometric methods. Food Bioprocess Technol. **8**(5), 1126–1138 (2015)