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Shuhui Bi

University of Jinan

Xue Li

University of Jinan

Lisha Chen

University of Jinan

Xinhua Qu

University of Jinan

Tao Shen

University of Jinan

Liyao Ma

`cse_maly@ujn.edu.cn`

University of Jinan

Research Article

Keywords: Gaussian-based mass function, Combination rule, Multi-model fusion, Classification of apples

Posted Date: July 25th, 2023

DOI: <https://doi.org/10.21203/rs.3.rs-3185045/v1>

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Additional Declarations: No competing interests reported.

Evidential apple classification model based on combination of Gaussian mass functions

Shuhui Bi, Xue Li, Lisha Chen, Xinhua Qu, Tao Shen, Liyao Ma[✉]

School of Electrical Engineering, University of Jinan, Jinan 250022, China

Corresponding Author's E-mail: cse_maly@ujn.edu.cn

Abstract: The establishment of stable and highly precise prediction models is of great theoretical and practical significance for the research of the nondestructive testing of the internal quality of fruits with NIR technology. In this paper, focused on Yantai red Fuji apples, probabilistic neural networks (PNN) and partial least squares (PLS) prediction models are developed based on sample data of apple NIR spectra and soluble solid content (SSC). In order to solve the problems of poor adaptability, model instability and uncertainty caused by the hard partitioning of classification in the current research, the two models established in this paper are fused using DS evidence theory. To improve the prediction accuracy of the fusion models, within the framework of DS evidence theory, mass function generation and combination rule selection are discussed. According to the distance between the SSC prediction value and the classification boundary, a Gaussian-based mass function generation approach is designed. Besides, considering Dempster's rule of combination, Yager's rule, Sun Quan's rule and Li-Bicheng's rule, the effects of combination rules on the apple classification results are investigated. The results show that the classification accuracies of the PLS model and PNN model are 93.9394% and 90.1515% respectively, while the classification accuracy of the fusion model reaches 96.2121%. Compared with our previously proposed linear triangular mass function generation method, the Gaussian-based mass function can better represent the SSC value's support degree of class prediction. In addition, compared with Dempster's rule, Dempster's rule achieves fusion results that are more consistent with the actual situation of apple classification. The proposed combination of Gaussian-based mass function and Li-Bicheng's rule of combination can not only improve the mass function and make the classification process closer to the practical application, but also increase the prediction accuracy of the fusion model based on DS evidence theory.

Key Words: Gaussian-based mass function; Combination rule; Multi-model fusion; Classification of apples

0 Introduction

China is the largest producer and consumer of Apple. According to the data of the National Bureau of Statistics, the output of apples in China will reach 4.1833 million tons in 2022, accounting for 41.7% of the total output of fruits in China. But with the increasing market demand for apple's pre-sale quality, the demand for internal quality classification of apples is also increasing. Especially, the soluble solids (SSC) content, as an important evaluating factor, has become the main basis for quality classification [1].

Near infrared spectroscopy (NIRS) has a strong penetrating ability on agricultural products, and can obtain physical and chemical information inside agricultural products. Therefore, as long as a prediction model is established between near-infrared spectroscopy and the physical and chemical characteristics of apples, effective detection of apple internal quality can be achieved [2]. In recent years, domestic and foreign scholars have conducted a series of studies on near-infrared technology in fruit detection [3]. Gu Jingfeng et al. used the near-infrared transmittance detection method to detect the internal sugar content of Yangshan honey peaches. The results showed that the standard error between the detected data and the measured data was ± 0.5 degrees, which realized the high quality and good price of honey peaches [4]. Cao Niannan et al. established partial least squares and support vector machine prediction models for soluble solids and hardness indicators of Huangtao crispy slices using shortwave near-infrared and longwave near-infrared spectroscopy techniques, respectively. The results showed that after multiple scattering correction, the prediction of soluble solids content based on the shortwave near-infrared spectroscopy support vector machine model was the best. The prediction accuracy of the support vector machine model based on long wave near-infrared spectroscopy is optimal in predicting hardness [5].

Peirs et al. used near-infrared diffuse reflectance to detect SSC in apples and found a nonlinear

relationship between the temperature change of the sample and near-infrared spectroscopy^[6]. Shuxian Fan et al. studied the effect of different fruit orientations on spectral measurement quality based on near-infrared spectroscopy, and designed an online detection and calibration model for apple SSC^[7]. McGlone et al. compared the advantages and disadvantages of the models built after apple harvesting and 6 weeks of refrigeration in the wavelength range of 500-1100nm. The results showed that the SSC model established after 6 weeks of storage had better results^[8]. Li Xiaoxu studied the modeling of apple SSC, the selection of instrument parameters and measurement positions based on NIRS technology. The results showed that model based on the NIRS collected at apple's equator were more stable, and partial least squares (PLS) and BP neural network were more effective methods^[9]. Moghimi et al. studied the impact of different preprocessing methods on the prediction results of kiwifruit SSC, and the results showed that the combination of standard normal transformation, median filtering, and first-order differentiation can achieve good prediction results^[10]. Zhang Shujuan et al. used principal component analysis to obtain various principal component data and established a model for identifying fresh jujube varieties and detecting soluble solids. The results showed that the combination of principal component analysis and BP neural network prediction was feasible, providing a new method for rapid non-destructive detection of fresh jujube varieties and soluble solids content^[11]. He Yong et al. proposed the principal component combined with artificial neural network method. The experimental results showed that the feature bands closely related to apple varieties obtained through principal component analysis were 550-565nm and 650-690nm, and the recognition rate of the artificial neural network variety identification model established using the feature bands was greatly improved^[12].

As a matter of fact, in the practical application process of NIRS, when the application object changes, it is necessary to establish a new prediction model. Also, when the sample data is updated, the model needs to be retrained. Moreover, the preprocessing method can affect the accuracy of the prediction model. Therefore, most prediction modeling methods based on NIRS have such problems as limited application range and poor stability. In addition, in the research of non-destructive classification process, the hard segmentation of the category boundary of apple sample space will lead to the decline of classification accuracy. The current modeling research cannot solve the above problems fundamentally. Therefore, how to integrate the advantages and effectiveness of various modeling methods, to improve the reliability of data and classification models, and to better express the uncertainty of class prediction based on current research needs further research. Based on that, evidence theory is an effective method that can be introduced into apple classification to achieve model fusion and to perform uncertainty processing^[13-17].

Liu Peng et al. conducted research on the maturity of apples based on multi-sensor fusion technology, and the results showed that multi-sensor fusion technology can fully utilize the adaptive and generalization capabilities of neural networks, as well as the ability of evidence theory to express fuzzy information and to perform imprecise reasoning, thereby it improves the recognition rate and reliability of apple maturity, and effectively solves the problem of single detection methods having blank recognition intervals or poor stability^[14]. Steinmetz et al. fused the characteristic values of melon color, sugar content and hardness, classified four melons with different maturity, and conducted regression analysis on single feature and multi feature fusion using principal component analysis combined with multi-layer neural network fusion method. The experimental results show that the classification accuracy of multi feature fusion model is higher than that of single model^[15]. Yan et al. introduced uncertainty in apple classification and fused the Extreme learning machine prediction model and partial least squares prediction model with evidence theory. The research found that the classification accuracy rate after using discount based evidence theory fusion was improved compared with the single classification method^[16].

The mass function, as an important component of evidence theory, directly affects the final fusion result. Many scholars have conducted a series of studies on how to reasonably obtain the mass function. Luo Xiaoyan et al.^[18] proposed a rock mass instability prediction method based on weighted evidence theory and fusion of multi domain features. The results indicate that the introduction of similarity measures using weighted thinking to improve the basic probability allocation function can effectively eliminate the problem of high conflicting evidence leading to the failure of traditional evidence fusion algorithms. Zhou Hao et al.^[19] proposed a method of using Support Vector Machine (SVM) output error to weight the Platt probability output to obtain the mass function output of SVM, achieving the combination of SVM and evidence theory in information fusion. Kang Bingyi et al.^[20] used the distance of interval numbers to represent the differences between sample attributes, and then proposed similarity, which was normalized to obtain a mass function. Yu Zhifu et al.^[21] used grey correlation analysis to calculate the grey correlation degree to construct a mass function. The experimental results showed that the multi-sensor radar radiation source recognition method based on grey correlation analysis and evidence theory can correctly identify samples that cannot be recognized or mistakenly recognized by a single sensor. Bi et al. proposed a triangle

mass function generation method based on the distance between the SSC prediction value and the classification boundary. Compared with the mass function generated by hard segmentation, the proposed method is more practical. It can be seen from the confusion matrix that the fusion model achieves accurate classification when the apples' SSC is at the classification boundary value, and the number of three types of apples that are wrongly classified is reduced [17]. It can be seen that the mass function plays a crucial role in the fusion of multiple models in evidence theory.

As one of the cores of DS evidence theory, evidence combination rules combine independent evidence information from different sources to achieve uncertainty reasoning. The Dempster combination rule in evidence theory can fuse different mass functions to produce more reliable evidence information. However, for highly conflicting and completely conflicting data, the Dempster combination rule fails [22], which limits the practical application of DS evidence theory to varying degrees. Therefore, many researchers have proposed many improvement measures from different perspectives. Xing et al. adopted the evidence combination rule of proportional distribution conflict. The results of numerical example verification show that the new combination rule of inference can effectively handle the conflict information in evidence, effectively overcome the difficulties of evidence theory, and improve the credibility of combined evidence [23]. Lang et al. synthesized a new mass function using the principle of balanced complementary reliability allocation. This method not only maintains the advantages of understanding and convergence of relevant information uncertainty in the Dempster combination rules, but also compensates for the shortcomings of the Zadeh paradox and one vote veto [24]. In 1989, Yager raised the issue of the invalidity of evidence theory and improved the combination rules [25]. He believes that the recognition framework is complete, and the conflicting parts represent unreliable and useless information, so he treats the conflicting parts as unknown. Sun Quan believes that there is a conflict between calculated evidence, and some of them are also available, and the degree of their availability mainly depends on the credibility of the evidence. Based on this, he proposed a new composite formula [26]. Li Bincheng believes that the probability of evidence conflict should be weighted according to the average level of support of each evidence [27]. It can be seen that when evidence conflicts occur in different applications, the selection of combination rules can greatly affect the results of evidence fusion.

Therefore, this study focuses on the generation of mass functions and the selection of combination rules in the multi model evidence fusion model for apple classification. Based on the established PLS and Probabilistic Neural Networks (PNN) prediction models, a Gaussian type mass function generation method will be proposed. Based on that, the impact of Dempster, Yager, Sun Quan, and Li Bicheng combination rules on multi model fusion will be explored, and the suitable mass function and combination rules for apple classification will be ultimately selected.

The rest of this paper is organized as follows. In Section 1, evidence theory based multiple model fusion method will be introduced. A Gauss mass function for apples' multiple model fusion will be proposed in Section 2. Several combination rules will be introduced, and Gauss mass function based multiple model fusion will be achieved respectively in Section 3. Simulation is done in Section 4 and conclusion is drawn in Section 5.

1 Multiple Model Fusion Method for DS Evidence Theory

Due to the fact that the raw spectral data of apples collected during the data collection process is prone to baseline drift [16]. In order to retain the effective information in the original data to the greatest extent, this study preprocessed 439 sets of apple original spectral data for multiple scattering correction (MSC), integrated their scattering information into one frequency, and corrected the optical path difference. At the same time, genetic algorithm (GA) processing is used to extract characteristic wavelengths, and to improve the prediction accuracy of a single model [17]. In modeling, 70% of each type of apple samples is randomly selected as the training set, and the remaining 30% is used as the test set. There are a total of 307 training set samples and 132 test set samples. The process of multi model fusion based on DS evidence theory is shown in Fig. 1.

1.1 Introduction to DS Evidence Theory

As an uncertain reasoning method, DS evidence theory meets weaker conditions than Bayesian Probability theory, and has the ability to directly express "uncertainty" and "ignorance", mainly including three parts: mass function, combination rules and decision-making.

In evidence theory, a complete set composed of incompatible basic evidence is represented as a recognition framework U , representing all possible answers to the apple classification problem, but only one answer is correct.

The subset of this framework is called evidence, and if the function $m:2^U \rightarrow [0,1]$ satisfies

$\sum_{A \in 2^U} m(A) = 1, m(\Phi) = 0$, then A is called evidence, $m(A)$ is the mass function of A ^[28], representing the trust in evidence A and 2^U is the power set of U, that is, the set composed of all subsets of U.

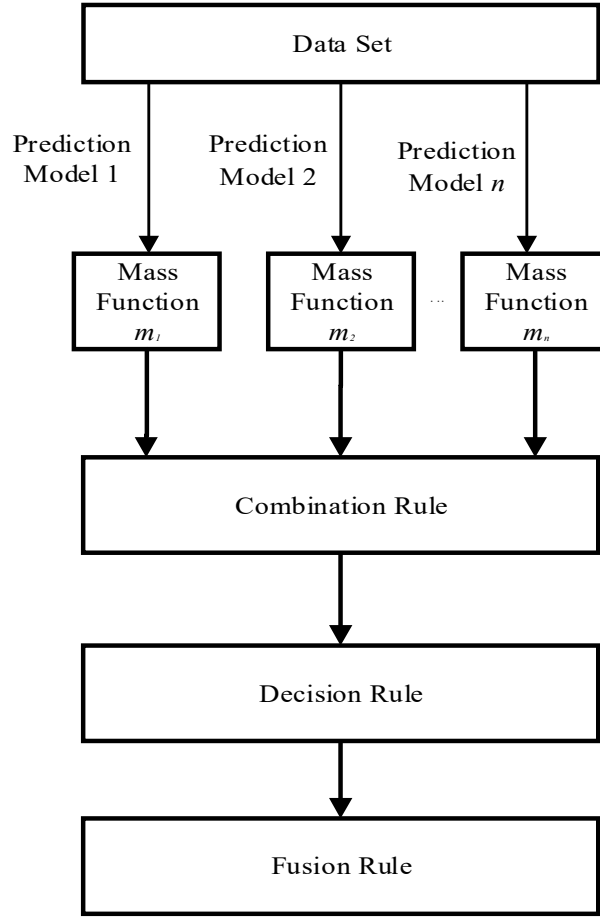


Fig. 1 Process diagram of multiple model fusion in DS evidence theory

1.2 Evaluation Parameters

The prediction performance of the model is evaluated by the Confusion Matrix (CM), also called error matrix, which is mainly used to compare the classification results with the actual measured values. Each column of CM represents the class of the predicted sample, the total number of each column represents the number of predicted data for that class, each row represents the actual class of data, and the total number of data instances for each row represents the number of data instances for that class.

Given a set of class labels $C = (c_1, c_2, \dots, c_k)$, the Confusion matrix of the classifier is:

$$CM = \begin{bmatrix} n_{11} & \cdots & n_{1j} & \cdots & n_{1k} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ n_{i1} & \cdots & n_{ij} & \cdots & n_{ik} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ n_{k1} & \cdots & n_{kj} & \cdots & n_{kk} \end{bmatrix}$$

Among them, n_{ij} represents the number of samples in the class label c_i that the classifier recognizes as class labels c_j . If $i = j$, n_{ii} indicates that the classifier correctly recognizes the number of samples in the class label c_i . If $i \neq j$, n_{ij} indicates that the classifier mistakenly identifies the samples in the class label c_i as the number of class labels c_j .

2 Gaussian mass function

The generation method of mass functions does not have a fixed pattern, and most of them are based on the evidence obtained by experts ^[29]. Based on personal experience, the digital representation of different levels of evidence support in the recognition framework is highly subjective. Therefore, this article

proposes a Gaussian mass function generation method for apple classification. Let m_1 and m_2 are mass function derived from two prediction models, with the same recognition framework $U = \{I, II, III\}$. Where, I, II, III is the classification label set based on the apples' SSC. The relationship between the SSC predicted value x and the apple class C standard is shown in formula (1):

$$C = \begin{cases} I, & 13 \leq x < 16 \\ II, & 11 \leq x < 13 \\ III, & 8 \leq x < 11 \end{cases} \quad (1)$$

Based on the basic principle of Gaussian distribution and the level of trust in apple prediction model classification, this study constructed a Gaussian mass function diagram based on the distance between SSC and classification boundary, as shown in Fig. 2. In which, a , c , e , and g are the left and right boundary values of the classification label, respectively. The corresponding mass function value of the class label is 0.9, $b = (a + c)/2$, $d = (c + e)/2$, and $f = (e + g)/2$, thier corresponding mass function value is set to 1. Taking the class II apple for example, the SSC range is $[11, 13)$, then, $c = 11$, $d = 12$, $e = 13$.

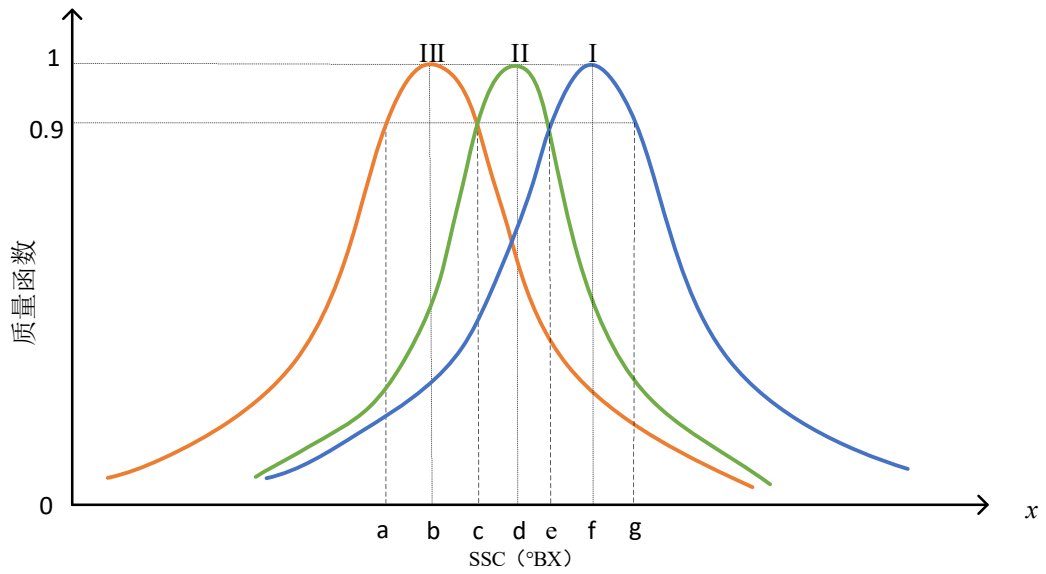


Fig.2 Schematic diagram of Gaussian type mass function

Based on the above analysis, a Gaussian mass function for apple classification can be constructed according to Fig. 2, as shown in (2).

$$m^x(C) = me^{-(x-A)^2/2\sigma^2}, \quad 8 \leq x < 16 \quad (2)$$

In the formula, A is the average value of the left and right classification boundaries of the class, m and σ are constants, and C is class label. Therefore, we can predict the SSC of apples based on near-infrared spectroscopy and actual SSC values.

When the SSC predicted value $x \in [13, 16)$, the closer the SSC predicted value x is to the left classification boundary 13, the more it can be defined as Class II. The closer it is to the average value of the left and right classification boundary 14.5, the more it can be defined in Class I. At this point, $A = 14.5$. By bringing points $(13, 0.9)$, $(14.5, 1)$ and $(16, 0.9)$ into (2), we can obtain:

$$\begin{aligned} me^{-(13-14.5)^2/2\sigma^2} &= 0.9 \\ me^{-(14.5-14.5)^2/2\sigma^2} &= 1 \\ me^{-(16-14.5)^2/2\sigma^2} &= 0.9 \end{aligned}$$

Solution can be obtained by solving above equation: $m = 1$, $\sigma = \sqrt{(-1.125/\ln(0.9))}$. Then, when $x \in [13, 16)$, the mass function in Class I can be summarized as (3) - (5).

$$m^x(I) = e^{-4/9*(x-14.5)^2*\ln(0.9)}, \quad x \geq 13 \quad (3)$$

$$m^x(\{I, II\}) = \begin{cases} 1 - m^x(I), & 13 \leq x < 14.5 \\ 0, & 14.5 \leq x \end{cases} \quad (4)$$

$$m^x(\{I, II, III\}) = \begin{cases} 1 - m^x(I), & x \geq 14.5 \\ 0, & 13 \leq x < 14.5 \end{cases} \quad (5)$$

When the SSC predicted value x is $[13, 16)$, indicating that the closer the predicted value x is to the left classification boundary 11, the more it can be defined as Class III. The closer it is to the average value of the left and right classification boundary 12, the more it can be defined as Class II. The closer it is to the right classification boundary 13, it can be classified as Class II or Class I, denoted by $\{I, II\}$. At this point, $A=12$, bring $(11, 0.9)$, $(12, 1)$ and $(13, 0.9)$ into the (2), that is

$$me^{-(11-12)^2/2\sigma^2} = 0.9$$

$$me^{-(12-12)^2/2\sigma^2} = 1$$

$$me^{-(13-12)^2/2\sigma^2} = 0.9.$$

Solution can be obtained by solving above equation: $m = 1$, $\sigma = \sqrt{(-0.5/\ln(0.9))}$, Then, when $x \in [11, 13)$, the mass function in Class II can be summarized as (6) - (8).

$$m^x(II) = e^{(x-12)^2 * \ln(0.9)}, \quad 11 \leq x < 13 \quad (6)$$

$$m^x(\{I, II\}) = \begin{cases} 1 - m^x(II), & 12 \leq x < 13 \\ 0, & 11 \leq x < 12 \end{cases} \quad (7)$$

$$m^x(\{II, III\}) = \begin{cases} 1 - m^x(III), & 11 \leq x < 12 \\ 0, & 12 \leq x < 13 \end{cases} \quad (8)$$

When the SSC predicted value $8 \leq x < 11$, the closer the SSC predicted value x is to the average value of the left and right classification boundaries 9.5, the more it can be defined as Class III. The closer it is to the right classification boundary 11, the more it can be defined as Class $\{II, III\}$. In this case, $A = 9.5$, bring $(8, 0.9)$, $(9.5, 1)$ and $(11, 0.9)$ into (2), yields:

$$me^{-(8-9.5)^2/2\sigma^2} = 0.9$$

$$me^{-(9.5-9.5)^2/2\sigma^2} = 1$$

$$me^{-(11-9.5)^2/2\sigma^2} = 0.9.$$

Solution can be obtained by solving above equation: $m = 1$, $\sigma = \sqrt{(-1.125/\ln(0.9))}$, Then, when $x \in [8, 11)$, the mass function in Class III can be summarized as (9) - (11).

$$m^x(III) = e^{4/9 * (x-9.5)^2 * \ln(0.9)}, \quad x < 11 \quad (9)$$

$$m^x(\{II, III\}) = \begin{cases} 1 - m^x(III), & 9.5 \leq x < 11 \\ 0, & x < 9.5 \end{cases} \quad (10)$$

$$m^x(\{I, II, III\}) = \begin{cases} 1 - m^x(III), & x < 9.5 \\ 0, & 9.5 \leq x < 11 \end{cases} \quad (11)$$

3. Multiple Model Evidence Fusion Based on Gaussian Mass Function

To achieve apples classification multi model evidence fusion based on Gaussian mass function, this study firstly uses PNN and PLS methods to predict apples' SSC, the overall process of multi model fusion based on evidence theory is shown in Fig. 3.

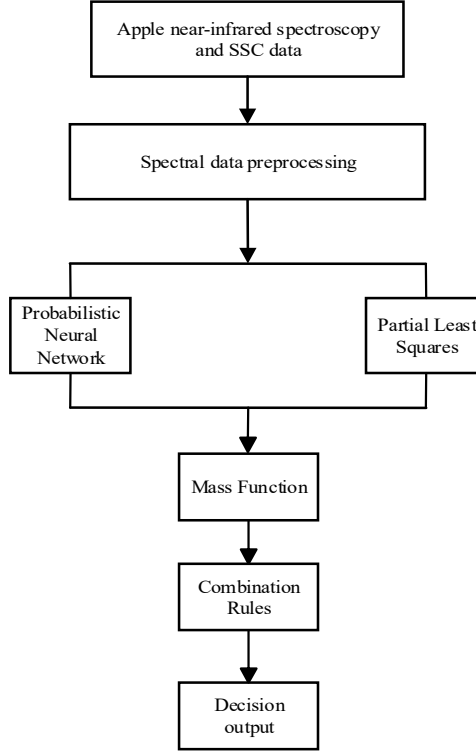


Fig.3 Apple classification process based on evidence theory

3.1 Modeling process by PLS and PNN

Using the processed spectral data and SSC true values as inputs, SSC prediction model can be established by using PNN and PLS methods respectively. The modeling process of PLS is same as [17]. PNN is a feedforward neural network developed from radial basis function neural networks, its theoretical basis is the Bayesian minimum risk criterion [31]. The PNN model consists of four layers: input layer, pattern layer (hidden layer), summation layer, and output layer. Designing a PNN prediction model for Apple SSC mainly involves the following steps:

- ◆ Normalize the sample data in the training and testing sets to form the training and testing sample sets.
- ◆ Set the value of Spread to train the network and obtain the corresponding SSC prediction model.
- ◆ Using the obtained SSC prediction model, predict the test set samples and obtain the prediction results.

The prediction process is shown in Fig. 4.

3.2 Combination Rules

Combination rules is an important step after Gaussian mass function in the fusion process. This study will discuss the combination rules of Dempster, Yager, Sun Quan, and Li Bicheng, and study the multi model evidence fusion under various combination rules, ultimately obtain the most suitable combination rule for apple classification.

(1) Dempster combination rule

Assuming that m_1 and m_2 are mass functions derived from two independent evidence sources with the same recognition framework $U = \{A_1, A_2, \dots, A_n\}$, the Dempster combination rule is:

$$m(A) = K^{-1} \sum_{A_1 \cap A_2 \cap \dots \cap A_n = A} m_1(A_1) m_2(A_2) \dots m_n(A_n), A \neq \phi, U \quad (12)$$

In the equation, $A_1 \cap A_2 \cap \dots \cap A_n = A$ indicates that evidence A can be obtained from evidence intersection of $A_1, A_2, \dots, A_n$, $m(A)$ is the mass function corresponding to the evidence A , and K is the normalization factor, which is an indicator to measure the magnitude of contradictions between various evidence, which is defined as (13).

$$K = 1 - \sum_{A_1 \cap A_2 \cap \dots \cap A_n = \phi} m_1(A_1) m_2(A_2) \dots m_n(A_n) \quad (13)$$

In that, $A_1 \cap A_2 \cap \dots \cap A_n = \phi$ represents evidence $A_1, A_2, \dots, A_n$ have no intersection.

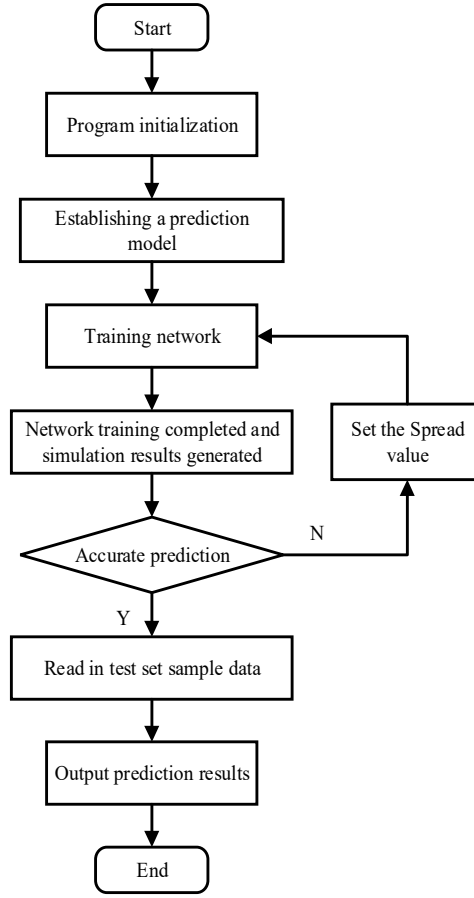


Fig.4 Flow Chart of Apple SSC Prediction Based on PNN

(2) Yager combination rules

Yager combination rule believes that the recognition framework is complete, and the conflicting parts represent unreliable and useless information^[25]. Therefore, the conflicting parts are treated as unknown and all their mass functions are assigned to the corresponding mass functions of the recognition framework U . The detailed definition is given as (14).

$$\begin{cases} m(A) = \sum_{A_1 \cap A_2 \cap \dots \cap A_n = A} m_1(A_1)m_2(A_2) \dots m_n(A_n), A \neq \phi, U \\ m(U) = \sum_{A_1 \cap A_2 \cap \dots \cap A_n = U} m_1(A_1)m_2(A_2) \dots m_n(A_n) + k \\ m(\phi) = 0 \end{cases} \quad (14)$$

Among them, $k = \sum_{A_1 \cap A_2 \cap \dots \cap A_n = \phi} m_1(A_1)m_2(A_2) \dots m_n(A_n)$ is the conflict coefficient.

(3) Sun Quan Combination Rules

Sun Quan^[26] believes that even if there are conflicts between evidence, they are still partially available, and the degree of availability depends on the credibility of the evidence. On this basis, a new synthesis formula was proposed:

$$\left\{ \begin{array}{l} m(A) = p(A) + \hat{k} \times \varepsilon \times q(A) \quad A \neq \phi, U \\ m(U) = p(U) + \hat{k} \times \varepsilon \times q(U) + \hat{k} \times (1 - \varepsilon) \\ m(\phi) = 0 \\ p(A) = \sum_{A_1 \cap A_2 \cap \dots \cap A_n = A} m_1(A_1) m_2(A_2) \dots m_n(A_n) \\ q(A) = \frac{1}{n} \sum_{i=1}^n m_i(A) \end{array} \right. \quad (15)$$

Among them, the mass function corresponding to n evidence sources are $m_1, m_2, \dots, m_n$, and if the conflict coefficient between the evidence sources i and j is k_{ij} , ε is the credibility of the evidence, then:

$$k_{ij} = \sum_{A_1 \cap A_2 = \phi} m_i(A_1) \times m_j(A_2) = 1 - \sum_{A_1 \cap A_2 \neq \phi} m_i(A_1) \times m_j(A_2)$$

$$\varepsilon = e^{-\hat{k}}, \quad \hat{k} = \frac{1}{n(n-1)/2} \sum_{i < j} k_{ij}$$

(4) Rules for the synthesis of Li Bincheng

Li Bincheng^[27] believes that the probability of evidence conflict should be weighted based on the average support level of each evidence, and the synthesis formula is as follows:

$$\left\{ \begin{array}{l} m(A) = \sum_{A_1 \cap A_2 \cap \dots \cap A_n = A} m_1(A_1) m_2(A_2) \dots m_n(A_n) + K \cdot q(A) \quad A \neq \phi, U \\ m(\phi) = 0 \end{array} \right. \quad (16)$$

In the formula, $q(A) = \frac{1}{n} \sum_{i=1}^n m_i(A_i)$, K is the normalization factor and is the same as formula (13).

In this study, $U = \{I, II, III\}$ is the recognition framework, the prediction results of PLS and PNN model are taken as data source 1 and 2 respectively, and their corresponding mass function are m_1 and m_2 . The analysis is carried out based on the above four combination rules and Gaussian mass function.

3.3 Multiple Model Fusion Based on Gaussian Mass Function for Results

For demonstrating the application of various combination rules in apple classification, we randomly selected a set of predicted SSC values at the boundary for analysis and comparison. We selected one actual measured SSC 11 as example, its actual class label is II. The SSC prediction value of PNN method is 11.19 with a prediction class label II, while the SSC prediction value of PLS method is 10.99 with a prediction class label III.

Based on the SSC prediction values of the PLS model, the Gaussian mass function of the PLS prediction model is obtained by incorporating equations (9) and (10).

$$m_1^{10.99}(III) = 0.901$$

$$m_1^{10.99}(\{II, III\}) = 1 - m_1^{10.99}(III) = 0.099$$

Based on the SSC prediction values of the PNN model, the Gaussian mass function of the PNN prediction model is calculated by incorporating equations (6) and (8).

$$m_2^{11.19}(II) = 0.933$$

$$m_2^{11.19}(\{II, III\}) = 1 - m_2^{11.19}(II) = 0.067$$

Then, based on the mass functions of the obtained PNN and PLS models, we discuss the Gaussian mass function generated by fusion under each combination rule.

(1) Gaussian mass function based on Dempster combination rule

Using formulas (12) and (13), we calculate the parameters as

$$K = 1 - m_1^{10.99}(III) \times m_2^{11.19}(II) = 0.159$$

$$m(\text{II}) = \frac{m_1^{11.19}(\text{II}) \times m_2^{10.99}(\{\text{II}, \text{III}\})}{K} = 0.580$$

$$m(\{\text{II}, \text{III}\}) = \frac{m_1^{10.99}(\{\text{II}, \text{III}\}) \times m_2^{11.99}(\{\text{II}, \text{III}\})}{K} = 0.042$$

$$m(\text{III}) = \frac{m_1^{10.99}(\{\text{II}, \text{III}\}) \times m_2^{11.19}(\text{III})}{K} = 0.379$$

(2) Gaussian mass function based on Yager combination rule

Using formula (14), obtain

$$k = m_1^{10.99}(\text{III}) \times m_2^{11.19}(\text{II}) = 0.841$$

$$m(\text{II}) = m_1^{11.19}(\text{II}) \times m_2^{10.99}(\{\text{II}, \text{III}\}) = 0.092$$

$$m(\{\text{II}, \text{III}\}) = m_1^{11.19}(\{\text{II}, \text{III}\}) \times m_2^{10.99}(\{\text{II}, \text{III}\}) = 0.007$$

$$m(\text{III}) = m_1^{11.19}(\{\text{II}, \text{III}\}) \times m_2^{10.99}(\text{III}) = 0.060$$

$$m(\{\text{I}, \text{II}, \text{III}\}) = m_1(\{\text{I}, \text{II}, \text{III}\}) \times m_2(\{\text{I}, \text{II}, \text{III}\}) + k = 0.841$$

(3) Gaussian mass function based on Sun Quan combination rule

Using formula (15), we obtain

$$\hat{k} = \frac{1}{2 \times (2-1)/2} k_{12} = k_{12} = m_1^{11.19}(\text{II}) \times m_2^{10.99}(\text{III}) = 0.841 \quad \varepsilon = e^{-\hat{k}} = 0.4313$$

$$q(\text{II}) = \frac{1}{2} \times [m_1^{11.19}(\text{II}) + m_2^{10.99}(\text{II})] = 0.467$$

$$q(\text{III}) = \frac{1}{2} \times [m_1^{11.19}(\text{III}) + m_2^{10.99}(\text{III})] = 0.451$$

$$q(\{\text{II}, \text{III}\}) = \frac{1}{2} \times [m_1^{11.19}(\{\text{II}, \text{III}\}) + m_2^{10.99}(\{\text{II}, \text{III}\})] = 0.083$$

$$p(\text{III}) = m_1^{11.19}(\{\text{II}, \text{III}\}) \times m_2^{10.99}(\text{III}) = 0.060$$

$$p(\text{II}) = m_1^{11.9}(\text{II}) \times m_2^{10.99}(\{\text{II}, \text{III}\}) = 0.092$$

$$p(\{\text{II}, \text{III}\}) = m_1^{11.9}(\{\text{II}, \text{III}\}) \times m_2^{10.99}(\{\text{II}, \text{III}\}) = 0.007$$

$$m(\text{II}) = p(\text{II}) + \hat{k} \times \varepsilon \times q(\text{II}) = 0.261$$

$$m(\text{III}) = p(\text{III}) + \hat{k} \times \varepsilon \times q(\text{III}) = 0.224$$

$$m(\{\text{II}, \text{III}\}) = p(\{\text{II}, \text{III}\}) + \hat{k} \times \varepsilon \times q(\{\text{II}, \text{III}\}) = 0.037$$

$$m(\{\text{I}, \text{II}, \text{III}\}) = p(\{\text{I}, \text{II}, \text{III}\}) + \hat{k} \times \varepsilon \times q(\{\text{I}, \text{II}, \text{III}\}) + \hat{k} \times (1 - \varepsilon) = 0.478$$

(4) Gaussian Mass Function Based on Li Bicheng Combination Rules

Using formula (16), obtain

$$K = m_1^{10.99}(\text{III}) \times m_2^{11.19}(\text{II}) = 0.841$$

$$q(\text{II}) = \frac{1}{2} \times [m_1^{11.19}(\text{II}) + m_2^{10.99}(\text{II})] = 0.467$$

$$q(\text{III}) = \frac{1}{2} \times [m_1^{11.19}(\text{III}) + m_2^{10.99}(\text{III})] = 0.451$$

$$q(\{\text{II}, \text{III}\}) = \frac{1}{2} \times [m_1^{11.19}(\{\text{II}, \text{III}\}) + m_2^{10.99}(\{\text{II}, \text{III}\})] = 0.083$$

$$p(\text{III}) = m_1^{11.19}(\{\text{II}, \text{III}\}) \times m_2^{10.99}(\text{III}) = 0.060$$

$$\begin{aligned}
p(\text{II}) &= m_1^{11.9}(\text{II}) \times m_2^{10.99}(\{\text{II}, \text{III}\}) = 0.092 \\
p(\{\text{II}, \text{III}\}) &= m_1^{11.9}(\{\text{II}, \text{III}\}) \times m_2^{10.99}(\{\text{II}, \text{III}\}) = 0.007 \\
m(\text{II}) &= p(\text{II}) + K \times q(\text{II}) = 0.485 \\
m(\text{III}) &= p(\text{III}) + K \times q(\text{III}) = 0.439 \\
m(\{\text{II}, \text{III}\}) &= p(\{\text{II}, \text{III}\}) + K \times q(\{\text{II}, \text{III}\}) = 0.076
\end{aligned}$$

In summary, the assignment of Gaussian mass functions based on various combination rules is shown in Table 1:

Table1 Gaussian mass function assignment table

Gaussian mass function	Combination Rules			
	Dempster	Yager	Sun Quan	Li Bicheng
$m(\text{I})$	0	0	0	0
$m(\{\text{I}, \text{II}\})$	0	0	0	0
$m(\text{II})$	0.580	0.092	0.261	0.485
$m(\{\text{II}, \text{III}\})$	0.042	0.007	0.037	0.076
$m(\text{III})$	0.379	0.060	0.224	0.439
$m(\{\text{I}, \text{II}, \text{III}\})$	0	0.841	0.478	0

According to Table 1, based on the obtained Gaussian mass function, the fusion results of the combination rules of Yager and Sun Quan are: $m(\{\text{I}, \text{II}, \text{III}\}) > m(\text{II}) > m(\text{III}) > m(\{\text{II}, \text{III}\})$, that is, based on the size of the mass function, it is impossible to determine which type of this fruit belongs to. The fusion results of the Dempster combination rule and Li Bicheng combination rule are both same: $m(\text{II}) > m(\text{III}) > m(\{\text{II}, \text{III}\})$. Then, based on the size of the mass function, the fruit can be determined as class II, which is same as the actual class standard. In addition, the mass function obtained by the Dempster combination rule is more pronounced than the fusion result by the Li Bicheng combination rule, it better distinguishes the final classification result. Therefore, the Dempster combination rule is chosen as the final combination rule.

4 Experiment Result and Analysis

Based on the analysis in the previous section, this study will use Gaussian mass function and Dempster combination rule for decision making in the evidence fusion of PNN and PLS prediction models. Firstly PNN and PLS models are used to predict 132 test set samples. Secondly, two Gaussian mass functions based on the predicted values are generated respectively. Then, the mass functions of the two models are fused using the Dempster combination rule to obtain the evidence fusion model. And finally simple decision is made based on the size of the mass function values in the fusion model to obtain the classification results.

The accuracy results of PNN and PLS classification models are shown in Figures 4 and 5. For analyzing the results more clear, their Confusion matrix are given in (17) - (18) respectively.

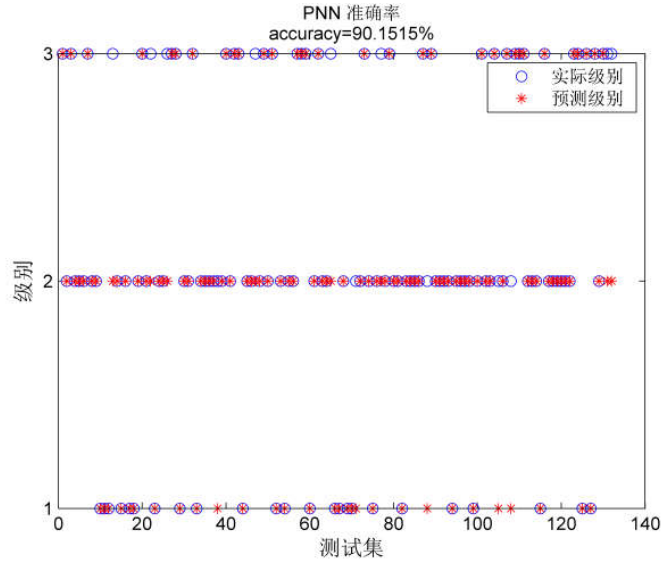


Fig.4 PNN classification accuracy

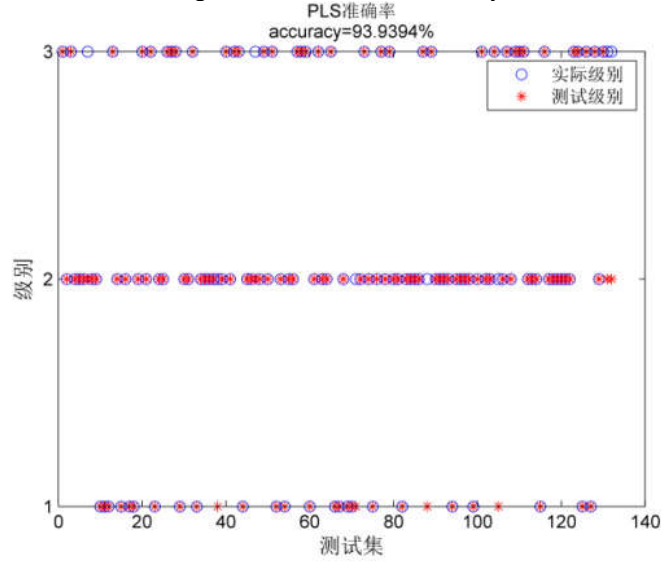


Fig.5 PLS classification accuracy

$$CM_{PNN} = \begin{bmatrix} 24 & 5 & 0 & 29 \\ 0 & 63 & 8 & 71 \\ 0 & 0 & 32 & 32 \\ 24 & 68 & 40 & 132 \end{bmatrix} \quad (17)$$

According to Fig. 4 and the Confusion matrix (17), 132 groups of data were classified by PNN method, 119 groups were accurately identified, 13 groups were incorrectly identified, of which 5 samples were wrongly classified from Class II to Class I, and 8 samples were wrongly classified from Class III to Class II. The overall classification accuracy rate was 90.1515%.

$$CM_{PLS} = \begin{bmatrix} 29 & 0 & 0 & 29 \\ 1 & 63 & 7 & 71 \\ 0 & 0 & 32 & 32 \\ 30 & 63 & 39 & 132 \end{bmatrix} \quad (18)$$

According to Fig.5 and the Confusion matrix (18), 124 groups were accurately identified and 8 groups were incorrectly identified. Among them, 1 sample was wrongly classified from the Class I to Class II, and

7 samples were wrongly classified from the Class III to Class II. The overall classification accuracy rate was 93.9394%.

The classification accuracy of fusion model by using Gaussian mass function and Dempster combination rule is shown in Fig. 6, and its Confusion matrix is shown in (19). It can be seen that after using the Dempster combination rule to fuse the classification results of PNN and PLS methods, 127 sets were accurately identified and 5 sets were incorrectly identified. Among them, 1 sample was mistakenly classified from Class II to Class I, and 4 samples were mistakenly classified from Class II to Class III. The overall classification accuracy reached 96.2121%. The accuracy of fusion model increases about 2.2727% and 6.0606% respectively compared to PLS and PNN models alone. The experimental results show that the combination of Gaussian mass function generation method and Dempster combination rule have the excellent effect on apple classification.

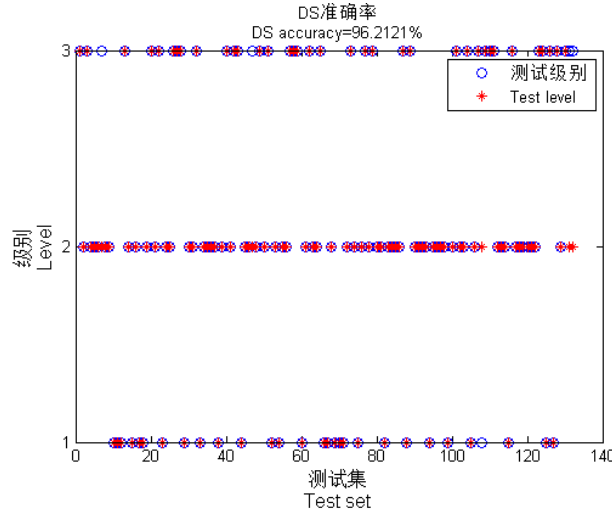


Fig.6 Fusion model classification accuracy

$$CM_{DS} = \begin{bmatrix} 28 & 0 & 0 & 28 \\ 1 & 63 & 4 & 68 \\ 0 & 0 & 36 & 36 \\ 29 & 63 & 40 & 132 \end{bmatrix} \quad (19)$$

5 Conclusion

In order to address the issues of low classification accuracy and model instability caused by poor reliability of data and inherent errors in prediction models in near-infrared spectroscopy technology, evidence theory was introduced into apple multi classification model fusion. In the study, a nonlinear Gaussian mass function was designed, which better reflects the support of SSC for classification compared to the linear triangle mass function proposed in previous studies. At the same time, in order to explore the impact of different combination rules on the evidence fusion effect of apple multiple models, this study was based on the established apple PNN and PLS prediction models. Based on the generated Gaussian mass function, a comparative analysis was conducted using the Dempster combination rule, Yager combination rule, Sun Quan combination rule, and Li Bicheng combination rule, respectively. The experimental results show that the fusion model combining Gaussian mass function and Dempster combination rule has a significant effect in apple classification. Moreover, after conducting experiments with 439 sets of apples, it was found that the classification accuracy of PNN and PLS models was 90.1515% and 93.9394%, while the classification accuracy of the fusion model was improved to 96.2121%. Research has shown that applying evidence theory to multi classification fusion of apples can not only better describe the uncertainty of apple classification, but also integrate the advantages of multiple prediction models, improve model accuracy and reliability, and ensure the quality of apples on the market.

Declarations

- Funding/This work by S. Bi was supported by the Natural Science Foundation of Shandong Province (ZR2020MF067, ZR2021MF074, ZR2023MF094).

- Conflict of interest/The authors declare that there is no competing financial interest or personal relationship that could have appeared to influence the work reported in this paper.
- Ethics approval/Not applicable
- Consent to participate/Not applicable
- Consent for publication/Not applicable
- Availability of data and materials/Not applicable
- Authors' contributions/ All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [Shuhui Bi], [Xue Li] and [Liyao Ma]. The first draft of the manuscript was written by [Xue Li] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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