Electronic nose-based technique for rapid detection and recognition of moldy apples

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Abstract:

In this paper, PEN3 electronic nose was used to detect and recognize fresh and moldy apples (inoculated with *Penicillium expansum* and *Aspergillusniger*) taken Golden Delicious apples as model subject. Firstly, the apples were divided into two groups: apples only inoculated with different molds (Group A) and mixed apples of inoculated apples with fresh apples (Group B). Then the characteristic gas sensors of the PEN3 electronic nose that were most closely correlated with the flavor information of the moldy apples were optimized and determined, which can simplify the analysis process and improve the accuracy of results. Four pattern recognition methods, including linear discriminant analysis (LDA), backpropagation neural network (BPNN), support vector machines (SVM) and radial basis function neural network (RBFNN), were then applied to analyze the data obtained from the characteristic sensors, respectively, aiming at establishing the prediction model of flavor information and fresh/moldy apples. The results showed that only the gas sensors of W1S, W2S, W5S, W1W and W2W in the PEN3 electronic nose exhibited strong signal response to the flavor information, indicating were most closely correlated with the characteristic flavor of apples and thus the data obtained from these characteristic sensors was used for modeling. The results of the four pattern recognition methods showed that BPNN presented the best prediction performance for the training and validation sets for both the Group A and Group B, with prediction accuracies of 96.29% and 90.00% (Group A), 77.70% and 72.00% (Group B), respectively. Therefore, it first demonstrated that PEN3 electronic nose can not only effectively detect and recognize the fresh and moldy apples, but also can distinguish apples inoculated with different molds.

Keywords: Electronic nose; apple; mildew; pattern recognition; artificial neural network; nondestructive examination

1. Introduction

Apples are widely consumed because of their rich vitamin, water, and dietary fiber contents. The apple industry, with an annual total output of more than 40 million tons, has become the first major fruit industry in China. Unfortunately, because of improper storage after harvesting, apples are vulnerable to diseases induced by various internal and external factors and infections by pathogenic microorganisms, resulting in serious post-harvest losses [1, 2]. A few moldy apples, which can be difficult to find from the surface in time, may lead to greater losses in the absence of a prompt solution. Therefore, development of a rapid and nondestructive detection method for moldy apples will help to guarantee the safety and quality of apples during storage and improve the competitiveness of Chinese apples in the global market. And it will help fruit farmers reduce their economic losses and help satisfy consumers by assuring the quality of the apples.

Methods such as gas chromatography [3], gas chromatography–mass spectrometry [4], stable isotope identification, and fluorescence spectroscopy have long been used to analyze the variety and concentrations of single substances in materials under test. However, these methods require expensive instrumentation and fail to evaluate the tested materials comprehensively [5], despite their high accuracy. Most importantly, they are time-consuming and are ineffective in rapid detection applications. The electronic nose technology that imitates the functions of the human olfactory system has seen rapid development in recent years. It can realize recognition of the characteristic information of complex flavors [6, 7] and provide superior performance in terms of response time, detection speed, evaluation range, and repeatability [8]. An electronic nose consists of two parts: a gas sensor array and a pattern recognition system [9, 10]. The gas sensor array collects the flavor characteristic information of the sample under test and sends the resulting data to the pattern recognition system. The pattern recognition system then processes the data and outputs the detection results for specific qualities of the samples. Commonly used pattern recognition methods used for electronic noses include principal component analysis (PCA) [11], linear discriminant analysis (LDA) [12, 13], support vector machines (SVM) [14, 15] and artificial neural networks (ANNs) [16, 17].

There have been numerous reports of the application of electronic noses in different agricultural product detection. For example, Russo et al. investigated the classification of red onion varieties using the ISE Nose 2000 electronic nose (Airsense Company, Germany) [18]. The analysis

accuracy of the DFA (Deterministic Finite Automaton) model used in their research was as high as 97.5%. Konduru et al. tested onions with sour skin disease using an electronic nose composed of nine metal oxide sensors, and the prediction model established attained an accuracy of 85% [19]. Biondi et al. used a PEN3 electronic nose (Airsense Company, Germany) in a survey of common ring rot and brown rot in potatoes [20]. The prediction model in their research achieved the recognition accuracy of 81.3%. Cheng et al. studied tomato seedlings that had been infected with early blight using a PEN2 electronic nose (Airsense Company, Germany) and obtained an optimum model accuracy of 87.5% [21]. In addition, electronic noses have also be applied to mildew detection in grain crops. Yin et al. explored the effects of different features combination characterizations for identifying the moldy maize by using a homemade electronic nose [22]. And a positive judgment rate of 96% was obtained with Fisher discrimination analysis. Lippolis et al. used the ISE Nose 2000 electronic nose to wheat mold detection by using the fungal volatile metabolite deoxynivalenol (DON) of wheat as the detection index [23]. The DFA model used in this research yielded a recognition rate of 86.7% for durum wheat.

Until now, researchers are also working on fruit disease detection using electronic noses [24]. For example, Zhu applied the PEN3 electronic nose to classify and identify strawberries that had been artificially inoculated with three pathogens and obtained satisfactory results [25]. In addition, researches with regard to the application of electronic noses to the volatile flavor characteristics information of apples are currently well-established. However, the researchesare mostly focused on differences among varieties [26], freshness identification [27], and storage time prediction of the apples [28, 29], along with the detection, analysis, and application of quality and nutrition information [30]. While little attention has been paid to the detection of mildew in apples, especially discrimination of different mildew.

Therefore, inspired by previous researches, PEN3 electronic nose (It has 10 different built-in metallic oxide gas sensors that can realize the detection and identification of various common gases, shown in Table 1) was used to detect and recognize fresh and moldy apples (artificial inoculation with *Penicillium expansum* and *Aspergillusniger* on Golden Delicious apples) in this study. To simplify the analysis process and improve the prediction accuracy, the gas sensor arrays of the PEN3 electronic nose were optimized and determined. And four pattern recognition methods, including LDA, backpropagation neural network (BPNN), SVM and radial basis function neural network

(RBFNN), were respectively compared to analyze the characteristic flavor data for establishing the prediction model of flavor information for fresh/moldy apples.

Table 1. Performance of the sensor arrays of the PEN3 electronic nose

Nos. in Array	Sensor Name	Reaction compound	Typical Targets
R1	W1C	Aromatic compounds	$C_6H_5CH_3$
R2	W5S	Oxynitride	NO_2
R3	W3C	Aromatic constituents, mainly ammonia	C_6H_6
R4	W6S	Hydrogen	H_2
R5	W5C	Alkanes, aromatic compounds	C_3H_8
R6	W1S	Broad Methane	CH_3
R7	W1W	Sulfides and organic sulfides	H_2S
R8	W2S	Broad Alcohols	C_2H_5OH
R9	W2W	Aromatics, organic sulfides	H_2S
R10	W3S	Alkanes, especially methane	CH_3

2 Materials and methods

2.1 Materials

The apples samples used in the experiments were Golden Delicious apples picked from an orchard in the Changping District in Beijing. And the apples were mature and fresh, all had a similar color, and were without surface damage and diseases. The inoculated molds were *Penicillium expansum* and *Aspergillus niger*; potato agar was used as the culture medium (Sinopharm Chemical Reagent Beijign Co., Ltd, China, Analytical grade). All other solutions were prepared with Milli-Q water (18.2 MΩ/cm resistivity) from a Millipore Milli-Q system (Thermo Scientific EASYpure II). All glassware ware was pre-washed three times with Milli-Q water and then dried in an oven.

2.2 Method of mold inoculation

2.2.1 Culture and purification of the molds

Firstly, the molds were made into suspensions using the pour plate method; these suspensions were then diluted using sterile water into proportions of 1:10, 1:100, and 1:1000. We took 1 ml from each diluted solution and mixed each solution with sterilized but uncondensed potato agar (acting as the culture medium). After being evenly shaken, the mixed solutions were poured into culture dishes and kept until natural coagulation occurred. The mold plates made as described above were then cultured at 25°C using the plate streak method. Finally, the pure colonies of *Penicillium expansum* and *Aspergillus niger* were obtained about five days later. The filamentous single colonies

obtained were then sealed in sterile environments and preserved in a refrigerator at 2 °C for direct use in the future experiments.

2.2.2 Mold inoculation of apples

Firstly, the apple samples were aired naturally on a sterile workbench after being cleaned using alcohol with purity of 75%. Each apple was then drilled with four holes located at different positions on the surface using an inoculation needle. The holes were filled with the pure colonies of *Penicillium expansum* and *Aspergillus niger* from the culture dishes by using an inoculation ring and were then covered using sterile seal films. The inoculated apples were placed into sterile beakers and sealed using further seal films. The samples were then placed into a thermostat incubator (25 °C) and cultured for five days until mildew appeared. Before the experiments began, the inoculated apples were carefully observed to ensure that they had been impregnated by the molds.

2.3 Apples sample set division

Before PEN3 electronic nose measurement, the apple samples were divided into two groups: individual apple only inoculated with/withoutone mold (single sample group, Group A) and mixed apples of inoculated apples with fresh apples (canned sample group,Group B). The canned sample group consisted offresh apples and moldy apples (inoculated with single molds of *Penicillium expansum* and *Aspergillus niger*, respectively) with a 9:1 ratio, and placed in a sealed canenvironment. Further, the apple samples of Group A and Group B were randomly divided into training set and validation set, training set A (TA) and validation set A (VA) for Group A and training set B (TB) and validation set B (VB) for Group B, respectively. The training set was used for building the prediction model, and the validation set was used for validating the prediction model.

2.4 Characteristic data collection of apples using electronic nose

The PEN3 electronic nose is applied to collecting the characteristic flavor of the apples. Briefly, the inoculated apples were sealed and placed at room temperature for 30 min after they were removed from the incubator. And headspace sampling was then initiated using the PEN3 electronic nose by inserting the sampling and pressure-stabilizing needles into the headspace of the beaker and drawing the flavor from the beaker for 150 s after cleaning for 70 s. Using the PEN3 detection figure, it was found that the response value of the sensor tended to be stable after 50 s, based on comparison and analysis. Therefore, the data acquired after 60 s was used as the effective data for the data analysis procedure (pre-experimental data not shown).

2.5 Data preprocessing of the electronic nose

The data preprocessing system is as an important link in the electronic nose system. The sampled signals were transmitted to the data preprocessing system for analysis and processing, while the pattern recognition system is used to realize qualitative identification of the gas. An effective data preprocessing algorithm can reduce the data errors and improve system reliability [31]. Simultaneously, it contributes to acquisition of more accurate analysis results and thus more believable conclusions.

When the gas under test reaches a stable contact state with the gas sensor array, the response value gradually tends to reach a constant level. However, slight fluctuations are unavoidable because of noise inference during data collection. Therefore, preprocessing using a data preprocessing algorithm is a necessary step. The main denoising methods that are commonly used in the electronic nose system include the smoothing method and the baseline correction method.

2.5.1 Six-point smoothing algorithm

The data curve obtained using a metal-oxide-semiconductor (MOS) sensor shows that the six-point smoothing algorithm is effective for denoising. The operator for the six-point smoothing algorithm is expressed as:

$$g(i) = \frac{\text{sum}\big(f(i\text{:}\,i+h-1)\big) - \text{max}\big(f(i\text{:}\,i+h-1)\big) - \text{min}(f(i\text{:}\,i+h-1))}{h-2}$$

where:

f(i:i+h−1) refers to all response values between *f(i)* and *f(i+h−1)*;

f(i) represents the response value at time point *I;*

g(i) is the response value at time point *i* after smoothing; and

h denotes the smoothing step size.

Data preprocessing using the above algorithm can effectively reduce the interference produced by noise.

2.5.2 Baseline correction

The baseline of the electronic nose refers to the variation curve of the blank background with time in the case where no test gas is in contact with sensor, which is generally regarded as noise interference [32]. Because the electronic nose is used in detection applications, the air inlet chamber of the electronic nose may unavoidably contain some residual gases as the number of tested samples

increases, thus resulting in environmental changes. It is therefore necessary to conduct baseline correction of the data to explore the response values between the gas sensor and its environment, while also ensuring the repeatability and accuracy of the experiments. During baseline correction, the datum $Y(i)$ obtained at the selected time point $X(i)-MinX(i)$ is used as the response value at time point t.

3 Results and disscussion

3.1 Mold culture and inoculation on apple

As described in section 2.2.1, the molds of *Penicillium expansum* and *Aspergillus niger* were first cultured in the culture dishes with potato agar as the culture mediumby using the plate streak method. Keeping at 25°C and five days later, the filamentous single pure colonies of *Penicillium expansum*, *Aspergillus niger* were obtained (shown in Figure 1b, 1c, respectively). The pure colonies obtained were then sealed in sterile environments and preserved in a refrigerator at 2 °C for direct use in the future experiments.

a)   b)   c)
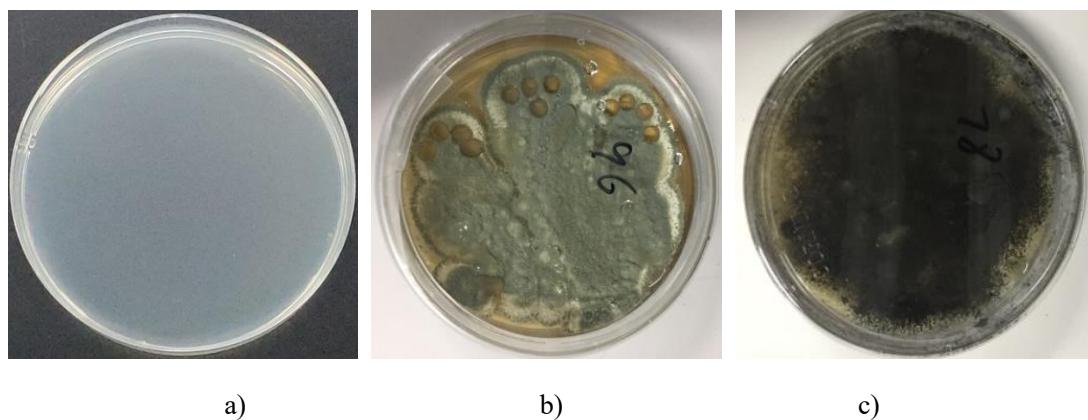
Figure 1. Cultured molds: a) culture medium without mold b) *Penicillium expansum*; c) *Aspergillus niger*. (Conditons: culture at 25°C for 5 days）

Next, the pretreated apples were inoculated with the cultured pure molds by filling the holes drilled at the apple surface using the inoculation ring (the left holes after sampling shown in Figure 1). The inoculated apples were placed into sterile beakers, sealed using further seal films, and kept at 25 ℃. As shown in Figure 2, the mildew appeared on the apple surface (Figure 2b, 2c) after five days, which also confirming the apples were successfully impregnated by the different molds. And then, the inoculated apples was used for PEN3 electronic nose anlysis.

| a) | b) | c) |
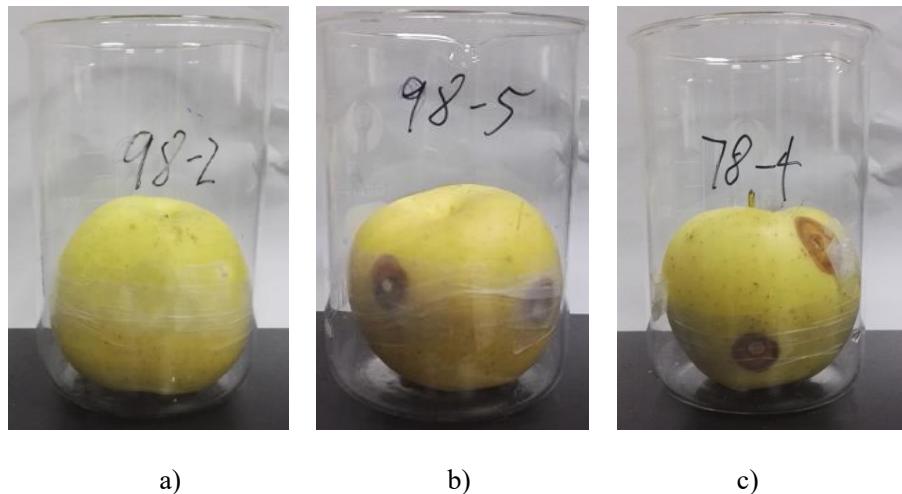
Figure 2. Apple samples inoculated with different molds: a) No mold (fresh apple); b) *Penicillium expansum*; c) *Aspergillus niger*. (Conditons: kept at 25°C for 5 days）

3.2 Determination of Characteristic flavorgas sensors
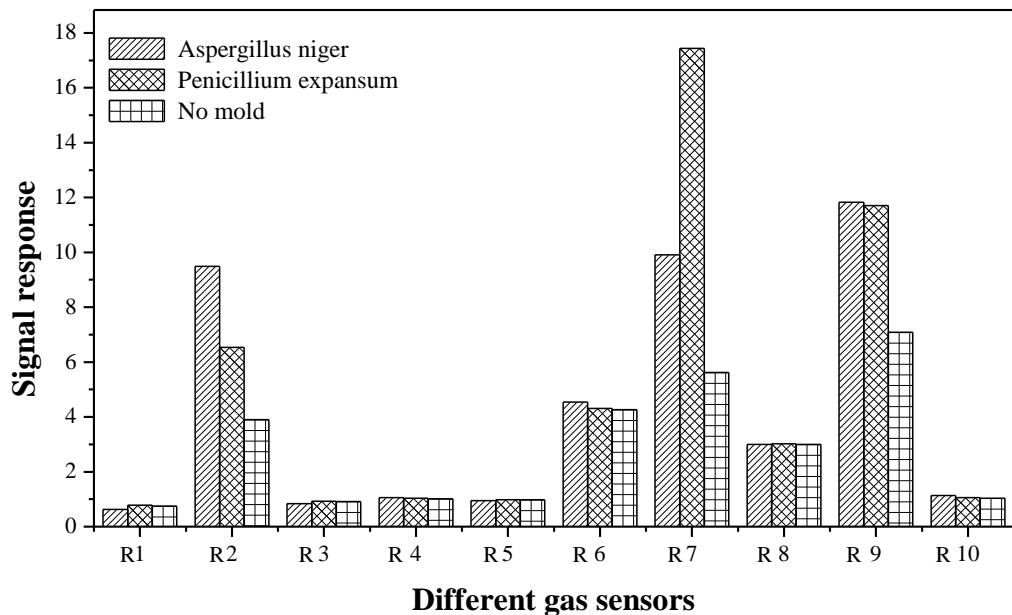
Figure 3. The gas sensors responses of PEN3 electronic nose to apples inoculated with different mold

As shown in Table 1, PEN3 electronic nose has 10 different built-in metallic oxide gas sensors, and it will simultaneously collect 10 sets of data information in one measurement. However, some of these data information are not characteristic flavor information for fresh/moldy apples. To simplify the subsequent analysis process and improve the prediction accuracy, the gas sensor arrays of the PEN3 electronic nose were first optimized to determine the characteristic flavor sensors for fresh and moldy apples. Then the response of PEN3 electronic nose to the fresh and moldy apples (apples inoculated separately with *Aspergillus niger* and *Penicillium expansum*) were explored and the characteristic values were extracted from the collected data of the ten sensors. As shown in

Figure 3, it can be noticed that the sensors give different signal for the four sets of samples measured, and only sensors of nos. R2, R6, R7, R8, and R9 (namely W5S, W1S, W1W, W2S and W2W) exhibited strong responses to the four sets of apple samples, indicating these sensors are the characteristic flavor gas sensors for apples. Therefore, the data collected from the sensors of W5S, W1S, W1W, W2S and W2W were used for data analysis in our study.

3.4 Data analysis

Four pattern recognition methods of including LDA, BPNN, SVM and RBFNN were respectively applied to analyze the data obtained from the characteristic sensors optimized for the prediction model of flavor information and fresh/moldy apples.

3.4.1 LDA analysis

The purpose of LDA is to find a projection that maps the original sample space to the low-dimensional space, so that the projection of high-dimensional data on the low-dimensional space can make the samples within the class more clustered, and the samples of different categories are separated to the greatest extent. Suppose data set $D=\{(x_1,y_1),(x_2,y_2),...,((x_m, y_m))\}$, where any sample x_i is an n-dimensional vector, $y_i \in \{0,1\}$. Define N_j (j = 0, 1) for the number of sample j, X_j (j = 0, 1), for the collection of sample j, and μ_j (j = 0, 1) for the mean vector of sample j, define $\sum_j$ (j = 0, 1) for the covariance matrix of sample j.

μ_j is expressed as:
$$\mu_j = \frac{1}{N_j} \sum_{x \in X_j} x \, (j = 0,1) \tag{1}$$

$\sum_j$ is expressed as:
$$\sum_j = \sum_{x \in X_j} (x - \mu_j)(x - \mu_j)^T \, (j = 0,1) \tag{2}$$

Assuming that our projection line is the vector ω, then the projection of any sample x_i on the line ω is $\omega^T x_i$, and the projection of center points of two categories μ_0, μ_1 in the line ω is $\omega^T \mu_0$ and $\omega^T \mu_1$.

Optimization objective is:

$$\underset{\omega}{\arg\max} J(\omega) = \frac{\left\| \omega^T \mu_0 - \omega^T \mu_1 \right\|_2^2}{\omega^T \sum_0 \omega + \omega^T \sum_1 \omega} = \frac{\omega^T (\mu_0 - \mu_1)(\mu_0 - \mu_1)^T \omega}{\omega^T (\sum_0 + \sum_1) \omega} \tag{3}$$

Generally, the intra-class divergence matrix S_ω is defined as:

$$S_\omega = \sum_0 + \sum_1 = \sum_{x \in X_0} (x - \mu_0)(x - \mu_0)^T + \sum_{x \in X_1} (x - \mu_1)(x - \mu_1)^T \tag{4}$$

Meanwhile, the inter-class divergence matrix S_b is defined as:

$$S_b = (\mu_0 - \mu_1)(\mu_0 - \mu_1)^T \tag{5}$$

Thus, our optimization objective can be rewritten as:

$$\underbrace{\arg\max}_{\omega} j(\omega) = \frac{\omega^T S_b \omega}{\omega^T S_\omega \omega} \qquad (6)$$

By using LDA algorithm, the test results of prediction accuracies were analyzed and shown in Table 2. As listed in Table 2, it can be seen that the LDA algorithm obtained the prediction accuracies of 79.63% for TA, 68.35% for TA of the training sets, 66.67% for TB, 64.00 for VB of the validation sets. The prediction accuracies were all lower than 80%, and lower than 70% for sets of TB, VA, VB, indicating that the LDA algorithm showed poor performance, and was not suitable for fresh/moldy apple discrimination.

Table 2 The test results of LDA algorithm

Sample Groups	Training set		Accuracy	Validation set		Accuracy
	Training samples	Correct samples		Training samples	Correct samples	
Group A	162	129	79.63%	30	20	66.67%
Group B	139	95	68.35%	25	16	64.00%

3.4.2 SVM analysis

Support Vector Machine (SVM) is a generalized linear classifier that carries out binary classification on data according to supervised learning, and its decision boundary is the maximum-margin hyperplane that is solved for learning samples.

The feature values extracted by the PEN3 electronic nose are taken as the input, and the category as the output. The model is built by LibSVM toolbox. Usually, (x, y) is based on the difference between the model output of f(x) and the real value y_i to calculate the loss is, if and only if f(x) = y_i, loss is zero. The basic idea is to allow the deviation between the predictive value of f(x) and y_i maximum to ε, when |f(x)-y_i| <ε, indicating correct prediction, regardless of the loss; only when the |f(x)-y_i| >ε, then calculate the loss. SVM problem can be described as follows:

$$\min_{\vec{\omega},b}(\frac{1}{2}\|\vec{\omega}\|^2 + C \sum_{i=1}^{n} L_\varepsilon (f(\vec{x}) - y_i)) \qquad (7)$$

$$\gamma = \frac{2}{\|\vec{\omega}\|} \qquad (8)$$

The punishment coefficient C=10, and the regular coefficient γ=0.1

In the selection of kernel functions, different kernel functions are tried, and the kernel function with the minimum inductive error is the best kernel function. In this paper, the core function uses the radial basis kernel function. TA and TB apple samples were used to build a characteristic

relationship model based on SVM, while VA and VB apple sampleswere used as validation sets. The prediction results were presented in Table 3.

Table 3 The test results of SVM algorithm

Sample Groups	Training set		Accuracy	Validation set		Accuracy
	Training samples	Correct samples		Training samples	Correct samples	
Group A	162	153	94.44%	30	24	80.00%
Group B	139	98	70.50%	25	16	64.00%

As shown in Table 4, the yielded prediction accuracies with SVM algorithm were 94.44% for TA, 80.00% for VA, and 70.50% for TB, 64.00% for VB, respectively. The results indicated that SVM algorithm showed good performance for discrimination of Group Aapple samples inoculated with different molds (validation accuracy 80.00%), but bad recognition performance for Group B apple samples (validation accuracy 64.00%).

3.4.3 RBFNN analysis

Fistly, the parameters were set for RBFNN analysis. The learning rate was set to 0.08, the momentum factor to 0.1, the maximum iteration epoch to 10000, and target accuracy to 0.02. Then the training data were input into the RBFNN, and the network structure was initialized to train the network. By judging threshold results of the stable error, adjusting the center and the weight of the hidden layer, and increasing the number of training epochs. Finally, the training set was predicted when the error was reduced below the pre-set threshold. The result of the RBFNN iteration process for the moldy apple samples was shown in Figure 4.
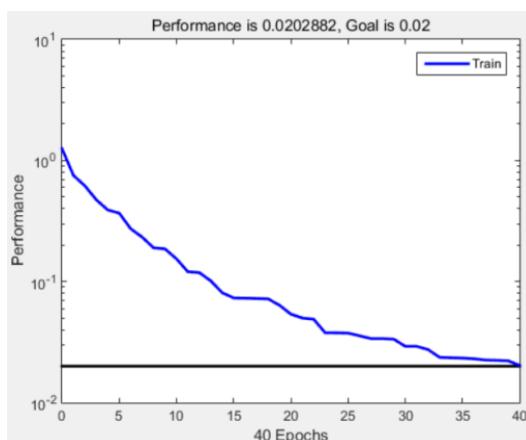
Figure 4. Diagram of the RBFNN iteration process result

As shown in Figure 4, the training error tends to become stable with a mean square error of

0.020 after 40 training epochs, which meets the maximum error requirements. Furthermore, constantly increasing the training epochs had little effect on the final recognition results obtained after 40 epochs (data not shown), and was time-consuming. Therefore, the designated training epoch number was set at 40 epochs. Then the RBFNN model was constructed for the TA, VA, TB and VB sets, respectively. The prediction results were listed in Table 3 below.

Table 4 The test results of RBFNN algorithm

Sample Groups	Training set		Accuracy	Validation set		Accuracy
	Training samples	Correct samples		Training samples	Correct samples	
Group A	162	144	88.89%	30	24	83.33%
Group B	139	100	71.94%	25	17	68.00%

As shown in Table 4, the RBFNN algorithm yielded prediction accuracy of 88.89% for TA, 83.33% for VA, and 71.94% for TB, 68.00% for VB, respectively. The validation accuracy was as high as 83.33% for Group A, but was only 68.00% for Group B (a little higher than that of LDA, SVM), indicating the RBFNN algorithm also showed bad recognition performance for discriminating moldy apples of *Penicillium expansum* and *Aspergillus niger*, if mixed with fresh apples.

3.4.4 BPNN analysis

BPNN, which learning processis realized by constantly error backpropagation. In this process, the input information propagates forward, while the errors propagate backward. By a process of constant iteration, training is finally suspended when the error accuracy is reduced to below a preset value or the number of training epochs is maximized.

The input and output in the BPNN are related as follows:

$$\text{Input} \quad net = \sum_{i=1}^{n} X_i W_i \tag{9}$$

$$\text{Output} \quad y = f(net) = \frac{1}{1 + e^{-net}} \tag{10}$$

As the convergence speed can be changed by adjusting the value of *net* in Equation (10), so the value of *net* should be controlled within a rapid convergence range during the calculations. Similarly, in this experiment, data of TA and TB was used to build a characteristic relationship model, while data of VA and VB was used as prediction sets. The prediction results were presented in Table 5.

Table 5 The test results of BPNN algorithm

Apple Groups	Training set		Accuracy	Validation set		Accuracy
	Training samples	Correct samples		Training samples	Correct samples	
Group A	162	156	96.29%	30	27	90.00%
Group B	139	108	77.70%	25	18	72.00%

As listed in Table 5, the judgement accuracies were 96.29% for TA, 90.00% for VA, and 77.70%

for TB, 72.00% for VB, respectively. It showed that higher prediction accuraciesof 90.00% and

validation accuracies of 72.00% were respectively obtain for Group A and Group B apple samples

by using BPNN algorithm. The results also confirmed that the PEN3 electronic nose showed good

recognition performance for discriminating fresh and moldy apples, moldy apples inoculated with

different molds (*Aspergillus niger*, *Penicillium expansum*).

Table 6 Comparison of the recognition accuracies of the four algorithms for the two groups

Sample Groups	Algorithm	Recognition rate of training set	Recognition rate of validation set
Group A	LDA	79.63%	66.67%
	SVM	94.44%	80.00%
	RBFNN	88.89%	83.33%
	BPNN	96.29%	90.00%
Group B	LDA	68.35%	64.00%
	SVM	70.50%	64.00%
	RBFNN	71.94%	68.00%
	BPNN	77.70%	72.00%

For better comparison, an overview of the performance of the four algorithms for moldy apples

recognition was listed in Table 6. As shown in Table 6, it's obvious that the BPNN algorithm showed

the best performance for recogniston fresh/moldy (*Aspergillus niger*, *Penicillium expansum*) apples

compared to the other three algorithm, so BPNN algorithm should be firstly considered as the

optimized algorithm in the future study. However, the recognition accuracies of the four algorithm

for Group B apple samples (canned sample group) were all lower than those of the Group A apple

samples (single sample group), this could be explained the collected flavor information of the

mildew infected apples was more or less influenced by the mixed fresh apples. But the later was

more closer to the real storage environment of apples.

4 Conclusions

In this study, PEN3 electronic nose system was used to detect and recognizemoldy apples inoculated with *Penicillium expansum and Aspergillusniger*. Based on the results discussed above, it could be described as follows:

(1) Firstly, the pure molds of *Penicillium expansum* and *Aspergillus niger* were cultured using the plate streak method and used for apples inoculation. Then, the apple samples were divided into two groups: individual apple only inoculated with single mold (single sample group) and mixed apples of inoculated apples with fresh apples (canned sample group).

(2) Secondly, the gas sensor arrays of the electronic nose system were optimized to determine the characteristic sensors that most closely correlated with the flavor information of the mildew infected apples (designated the W5S, W1S, W1W, W2S, and W2W), and then applied for data collection, which greatly simplifed the analysis procedure and improved the results accuracy.

(3) Thirdly, four pattern recognition methods, including LDA, BPNN, SVM and RBFNN, were respectively used to model the date obtained from the characteristic sensors. The results showed that BPNN presented the best recognition accuracy for the two Groups, and a higher recognition accuracies was abtained for Group A apple samples.

In conclution, the findings in this study proved that PEN3 electronic nose could not only effectively detect and recognize fresh and moldy apples, but also can distinguish moldy apples inoculated with *Penicillium expansum* and *Aspergillusniger*. Furthermore, the electronic nose technology can meet the demands of rapid, low-cost, nondestructive detection merits, which also provide references for developing detection equipment of mildew apple in the future.

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Author Contributions

Gang Liang principally conceived the idea for the study, and was in charge of the project management, revising this manuscript, and approval of the manuscript. Wenshen Jia, Hui Tian, Cihui Wan performed the experiments. Hui Tian, Cihui Wan Jing Sun analyzed the data. Gang Liang, Wenshen Jia was responsible for the preparation of this manuscript. All authors participated in some form in the concept, experimentation, writing, and editing of this manuscript. All authors read and approved the manuscript.

Conflicts of Interest The authors declare no conflict of interest.

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