

Applying Electronic Nose Based on Odour Classification and Identification Technology in Detecting the Shelf Life of Fresh Fruits

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The purpose of this study is to improve the market competitiveness and food safety of fresh fruit products. To this end, the methods of literature analysis, comparative analysis and experimental detection were adopted and the electronic nose (e-nose) technology based on odour classification and identification was introduced to study the non-destructive testing (NDT) method for the shelf life of fresh fruits. Besides, according to the optimized e-nose sensor array, the support vector machine (SVM), BP neural network model and the chlorophyll prediction model for the shelf life detection of fresh fruits were established respectively to make spinach freshness grade discrimination and chlorophyll quantitative prediction by taking the spinach as example. Finally, the experimental results show that the e-nose technology based on odour classification and identification can better realize the shelf life detection of fresh fruit.

1. Introduction

The various fresh fruits necessary for the residents' diet are rich in important elements such as minerals and vitamins (Natale et al., 2002). However, if fresh fruit is not sold or eaten in time, it will easily lead to loss of water and freshness (Brezmes et al., 2005), affecting its commodity value and food quality. With the continuous improvement of residents' living standards and life quality, the freshness and shelf life of fresh fruits have gradually become the focus of residents' purchasing. Therefore, in order to reduce the loss of fresh fruits after harvesting and ensure their food quality, it is in urgent need of one fast and effective non-destructive testing (NDT) method for detecting the shelf life of post-harvesting fresh fruit (Gobbi et al., 2010). NDT technology for agricultural products (Pan et al., 2014) is using the physical method to detect and analyse its internal and external quality by acquiring the information such as odour, composition, and colour etc. related to the quality of the object to be tested. It has been studied extensively by the researchers because of its advantages of non-destructiveness and timeliness, speediness and accuracy. At present, e-nose technology, machine vision technology, acoustics, optics, and electrical analysis are commonly used NDT methods for fresh fruits (Qiu and Wang, 2017). E-nose technology (Zhang et al., 2016) is an electronic system that simulates the animal olfactory organs using the response pattern of the sensor array for odour identification. It can also detect the overall volatile odour of agricultural products by means of stoichiometry. Due to its fast, objective, accurate judgment, it has become an important means of detecting fresh fruits. Moreover, by experiments, some researchers have demonstrated that e-nose technology is superior in the detection of fruit and vegetable quality and vegetable maturity detection (Solivafortuny and Martinbelloso, 2003), and it can also make early detection of special pollutants such as *Escherichia coli* (Ahvenainen, 1996), with broad application prospects.

Based on the above analysis, this paper attempts to use the e-nose as NDT technology to detect the shelf life of fresh fruits (Miao, 2018). By optimizing the sensor array, the appropriate qualitative and quantitative prediction models were established respectively to make the freshness level and chlorophyll prediction by taking the spinach as example. The comparative analysis of the experimental results indicates that the e-nose technology can well predict the spinach freshness grade.

2. Relevant theoretical basis

2.1 Shelf life detection of fresh fruit

After harvesting, the fresh fruits cannot get the nutrient compensation from the soil by using their root system, which shall lead to water loss, loss of freshness, weight loss, quality degradation, etc., and eventually result in the loss of commodity value and edible value (Beghi et al., 2017). Traditional methods for detecting fresh fruits include (Valdez and Guti  rrez, 2016): (1) Sensory evaluation method, which mainly uses the colour, traits and odour of fresh fruits as evaluation indicators, but it's impacted greatly by the testers' subjective feelings and environment, and the quality cannot be accurately described by exact numbers. (2) Physical and chemical testing methods, including chemical analysis, physical analysis and instrumental analysis. With the continuous development of science and technology, NDT methods have been widely used in the detection of fresh fruits in recent years, including acoustic analysis, optical analysis, electrical analysis, electronic nose technology and machine vision detection technology etc. Fig.1 shows the method for detecting the shelf life of fresh fruits.

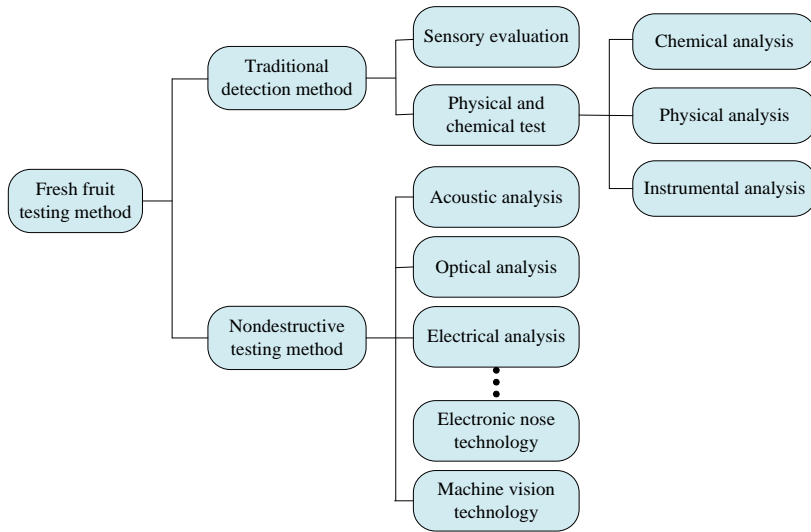


Figure 1: Fresh fruit shelf life detection method

2.2 Electronic nose technology and its application in the detection of fresh fruit shelf life

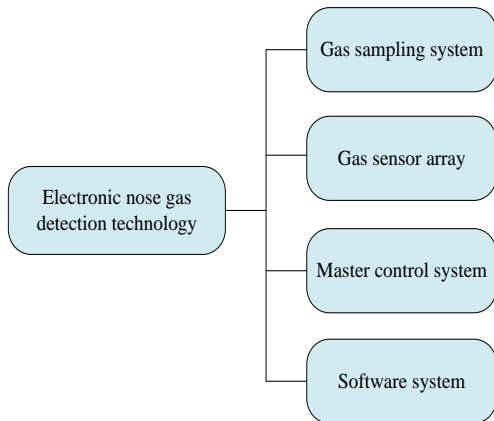


Figure 2: Electronic nose gas detection system

The e-nose is an intelligent sensory instrument that simulates the human olfactory system and combines pattern recognition technology with gas sensors to analyse, identify and detect complex volatile components (Valero et al., 2002). The e-nose gas detection system consists of the gas sampling system, gas sensor array, main control system and software system (Dahmani-Mardas et al., 2010), as shown in Fig.2. Due to its advantages of low detection cost, high cost performance, high sensitivity, high safety, ability to detect multiple

samples and the objective and accurate detection results free from external interference etc. (Chatchawal et al., 2009), it has been widely used in the quality test of fresh fruits, beverages, and dairy products, etc. At certain maturity stage of fresh fruits, it shall have some volatile gases. These gases are important factors in evaluating the freshness of fresh fruits (Calderonsantoyo et al., 2013). Therefore, the e-nose can be used as a means to achieve the detection of fruit shelf life.

3. Detection of fresh fruit shelf life based on odour classification and identification technology

3.1 Testing materials and methods

From 8:00 am to 9:00 am, 144 whole spinach plants of similar size and maturity were picked from the local vegetable garden and stored in a refrigerator at 4 °C. For the detection of e-nose headspace sampling, 12 spinach samples were selected as test samples every day; each plant was placed in a 500ml clean beaker and sealed with plastic wrap.

3.2 Electronic nose sensor array optimization

The gas sensor is the core component of the e-nose. With the amount of data increased, the higher requirements of the sensor are made for later processing. Therefore, it is necessary to optimize the sensor. In this paper, SPSS18.0 was used to analyse the load factor of the sensor array (Zhang et al., 2008), and according to the analysis results (Fig.3), the new sensor array consisting of sensors 1, 3, 4, 8, 9, 10, 11 was determined for the shelf life of fresh fruits (Zhang and Liu, 2018).

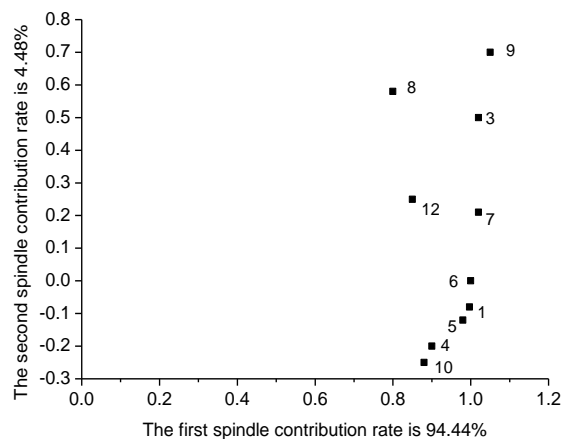


Figure 3: Factor load analysis chart

3.3 E-nose detection of fresh fruit shelf life based on odour classification and identification technology

3.3.1 Support vector machine model for the detection of spinach shelf life

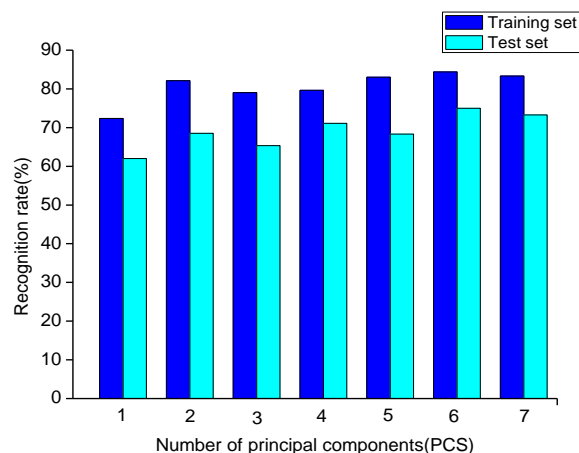


Figure 4: Support vector machine model discrimination results under different principal component numbers

Support Vector Machine (SVM) is a linear classifier based on the VC dimension theory of structural minimum principle and statistical theory, also known as the maximum edge region classifier. In this paper, 144 experimental samples were divided into two parts: training set and test set, at the ratio of 2:1, and each part contains samples of each freshness level. Fig.4 shows the discrimination result of SVM model under different principal component numbers. The experimental results show that when the number of principal components is 6, the identification rates of training set and test set are 84.37% and 74.49%, respectively, which are the best, indicating that it is feasible to use SVM for detecting the shelf life of spinach.

3.3.2 BP neural network model for the determination of spinach shelf life

The BP neural network model based on odour classification and identification technology was established. In view of different number of hidden layer nodes in the model and different accuracy of discrimination obtained, the exploratory method was used to determine the optimal hidden layer nodes. Table 1 lists the discriminant results of BP neural network model with different number of hidden layer nodes, indicating that at the number of hidden layer nodes 14, the discriminative accuracy of the training set and the test set samples is the highest, so 14 is selected as the number of hidden layer nodes. Then, based on this, the BPNN model with different principal components as inputs was established.

Table.1 Discriminant results of BP neural network model with different number of hidden layer nodes

Number of hidden layer nodes	Training set recognition rate (%)	Test set recognition rate (%)
5	86.45	79.16
6	84.37	79.16
7	87.49	81.24
8	83.32	74.49
9	86.45	77.07
10	84.37	77.07
11	88.53	79.16
12	86.45	81.24
13	84.37	81.24
14	88.53	81.24
15	86.45	79.16
16	85.41	74.49
17	88.53	81.24
18	85.41	79.16
19	84.37	79.16
20	85.41	79.16

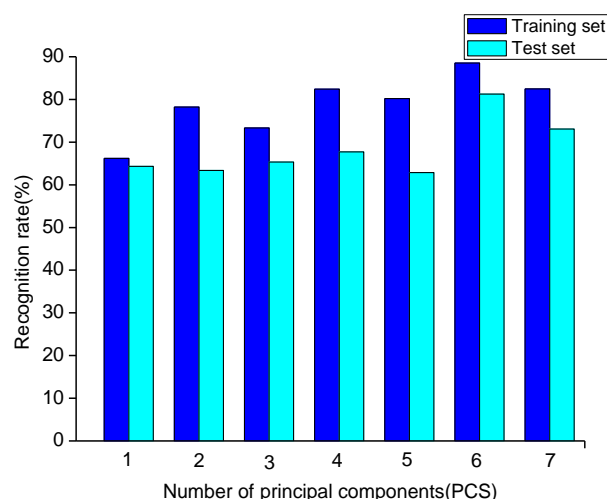


Figure 5: Discriminant results of BPNN model under different principal component numbers

Fig.5 shows the discrimination results of BPNN model under different principal component numbers. It can be seen from the figure that when the principal component is 6, the discrimination rates of the training set and the

test set are 88.53% and 81.24%, respectively, which are the best. Thus, it is feasible to use the BPNN model for the shelf life detection of spinach.

3.3.3 Quantitative detection of chlorophyll in spinach based on odour classification and identification technology

A three-layer BP neural network model for chlorophyll quantitative prediction based on odour classification and recognition technology was established. The input and output values were the main component score and chlorophyll chemical detection value, and 144 spinach experimental samples were divided into the training set and test set at the ratio of 2:1.

After several model trainings, with the main factor of 4 and the number of hidden layer nodes of 13, the root mean square error of the training set and the test set are 0.3119 and 0.3023, respectively, as shown in Fig. 6.

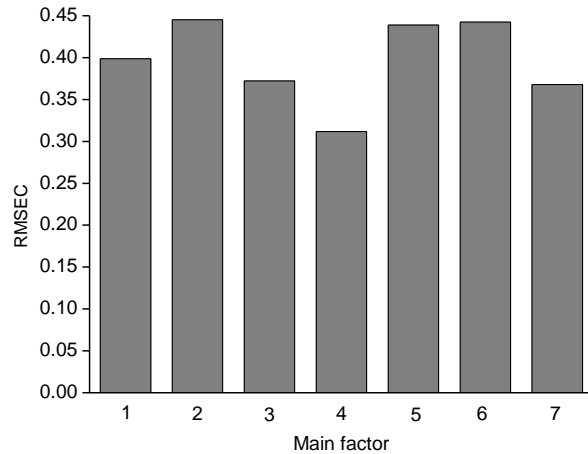


Figure 6: RMSEC under different principal factors in BP model

The correlation coefficient R_c is 0.7013 and 0.6905 respectively. Fig.7 and 8 show the BP model prediction results of the training set and the test set. The results indicate that the BP neural network model based on odour classification and identification technology is feasible in determining the chlorophyll content with common effects.

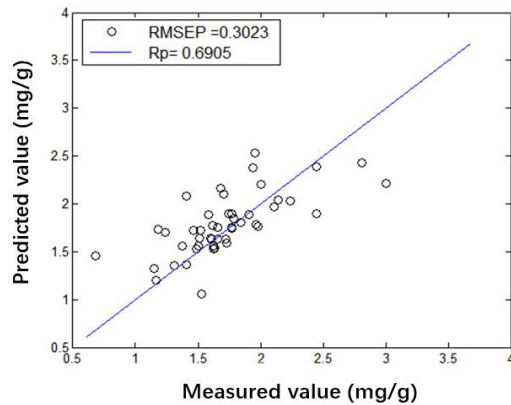


Figure 8: Forecast sample BP model prediction results

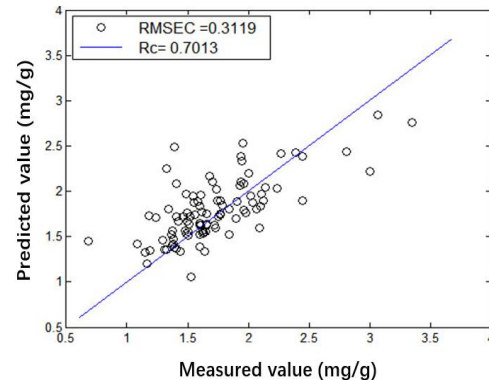


Figure 7: Training sample BP model prediction results

4. Conclusions

After harvesting, various fresh fruits are prone to water loss, rot, etc. due to their own physiological metabolic activities, which affect both the sales value and the nutritional value. Therefore, this paper aims to study the application of the electronic nose based on the odour classification and identification technology into the shelf life detection of fresh fruits. The specific conclusions are as follows:

- (1) The sensor array was optimized by factor load analysis method. Thus, the shelf life detection model of fresh fruit based on vector machine (SVM) and BP neural network model was established.
- (2) A BP neural network model for quantitative prediction of chlorophyll based on odour classification and recognition technology was established.
- (3) The models established in this paper were applied to make the experiments by taking spinach as an example. The experiment results show that the detection method of fresh fruit shelf life based on e-nose technology is better than BP neural network model, and the BP data network model based on e-nose technology has certain quantitative prediction ability of Chlorophyll.

References

- Ahvenainen R., 1996, New approaches in improving the shelf life of minimally processed fruit and vegetables, *Trends in Food Science & Technology*, 7(6), 179-187, DOI: 10.1016/0924-2244(96)10022-4
- Beghi R., Buratti S., Giovenzana V., Benedetti S., Guidetti R., 2017, Electronic nose and visible-near infrared spectroscopy in fruit and vegetable monitoring, *Reviews in Analytical Chemistry*, 36(4), DOI: 10.1515/revac-2016-0016.
- Brezmes J., Fructuoso M.L.L., Llobet E., Vilanova X., Recasens I., Orts J., 2005, Evaluation of an electronic nose to assess fruit ripeness, *IEEE Sensors Journal*, 5(1), 97-108, DOI: 10.1109/jsen.2004.837495
- Calderonsantoyo M., Bautistarosales P.U., Lunasolano G., Ghommidh C., Ragazzosanchez J.A., 2013, Monitoring of lactic fermentation with a coupling electronic nose and gas chromatography, *Engineering*, 5(9), 13-19, DOI: 10.4236/eng.2013.59a002
- Chatchawal W., Mario L., Teerakiat K., 2009, Detection and classification of human body odor using an electronic nose, *Sensors*, 9(9), 7234-49, DOI: 10.3390/s90907234
- Dahmani-Mardas F., Troadec C., Boualem A., Lã@Vãªque S., Alsadon A.A., Aldoss A.A., 2010, Engineering melon plants with improved fruit shelf life using the tilling approach, *Plos One*, 5(12), e15776, DOI: 10.1371/journal.pone.0015776
- Gobbi E., Falasconi M., Concina I., Mantero G., Bianchi F., Mattarozzi M., 2010, Electronic nose and alicyclobacillus spp, spoilage of fruit juices: an emerging diagnostic tool. *Food Control*, 21(10), 1374-1382, DOI: 10.1016/j.foodcont.2010.04.011
- Miao J., 2018, Rfid-based key technology for fresh food quality inspection, *Chemical Engineering Transactions*, 66, 1363-1368, DOI: 10.3303/CET1866228
- Natale C.D., Zude-Sasse M., Macagnano A., Paolesse R., Herold B., D'Amico A., 2002, Outer product analysis of electronic nose and visible spectra: application to the measurement of peach fruit characteristics, *Analytica Chimica Acta*, 459(1), 107-117, DOI: 10.1016/s0003-2670(02)00107-1
- Pan L., Zhang W., Zhu N., Mao S., Tu K., 2014, Early detection and classification of pathogenic fungal disease in post-harvest strawberry fruit by electronic nose and gas chromatography–mass spectrometry, *Food Research International*, 62(8), 162-168, DOI: 10.1016/j.foodres.2014.02.020
- Qiu S., Wang J., 2017, The prediction of food additives in the fruit juice based on electronic nose with chemometrics, *Food Chemistry*, 230, 208-214, DOI: 10.1016/j.foodchem.2017.03.011
- Solivafortuny R.C., Martinbelloso O., 2003, New advances in extending the shelf-life of fresh-cut fruits: a review, *Trends in Food Science & Technology*, 14(9), 341-353, DOI: 10.1016/s0924-2244(03)00054-2
- Valdez L.F., Gutiã©Rrez J.M., 2016, Chocolate classification by an electronic nose with pressure controlled generated stimulation, *Sensors*, 16(10), 1745, DOI: 10.3390/s16101745
- Valero D., Martı́nez-Romero D., Serrano M., 2002, The role of polyamines in the improvement of the shelf life of fruit, *Trends in Food Science & Technology*, 13(6–7), 228-234, DOI: 10.1016/s0924-2244(02)00134-6
- Zhang H., Wang J., Ye S., 2008, Prediction of soluble solids content, firmness and ph of pear by signals of electronic nose sensors, *Analytica Chimica Acta*, 606(1), 112-118, DOI: 10.1016/j.aca.2007.11.003
- Zhang H., Liu F., 2018, Spatial and temporal disparities in agricultural carbon emissions in xinjiang and decomposition of impact factors, *Chemical Engineering Transactions*, 66, 553-558 DOI:10.3303/CET1866093
- Zhang W., Pan L., Zhao X., Tu K., 2016, A study on soluble solids content assessment using electronic nose: persimmon fruit picked on different dates, *International Journal of Food Properties*, 19(1), 53-62, DOI: 10.1080/10942912.2014.940535