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Development stage prediction of flat peach by SVR model based on changes in characteristic taste attributes

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Abstract

Prediction of the development stage of flat peach is very important to determine the harvest time and guarantee high quality peach fruit. The objective of this study was to predict the development stage of flat peach by applying the SVR model based on characteristic taste attributes changes. Seven development stages were divided into immaturity stage (F1-F5) and maturity stage (F6-F7) according to PIs analysis. Both human sensory evaluation and electronic tongue showed that sourness and bitterness significantly decreased, while sweetness increased during seven development stages ($P < 0.05$). PCA result revealed that sourness and sweetness attributes had a high correlation between human sensory evaluation and electronic tongue. HCA classified seven development stages as two clusters, which was consistent with the PIs analysis. Seven development stages of flat peach were accurately predicted by the SVR model and the correct rate (CR) was 93.9%. The mean squared error (MSE) of each evaluation index was around 0.14 and the squared correlation coefficient (SCC) was over 0.99, which indicated the model performed well. This study proved that taste attribute could be used as an index combined with the SVR model to accurately predict the development stage of flat peach.

Keywords: flat peach; human sensory evaluation; electronic tongue; development stage prediction; SVR.

Practical Application: Developing an informatization method to accurately determine the harvest period and guarantee the harvest quality of flat peach fruit.

1 Introduction

Flat peach (*Prunus persica* L. Batsch. var. *compressa* Bean) is a climacteric stone fruit,which becomes softened once it reaches the ripening period because of the extreme increase in ethylene (Amoros et al., 1989). Peach quality at harvest is the main factor that will affect the consumer decision. However, the lack of experience in selecting a proper picking stage usually causes the low harvest quality of fruit, which results in a limited market value. Therefore, it is urgent to develop an informatization method to accurately determine the harvest period and guarantee the harvest quality of fruit.

Flesh firmness (FF) and physiochemical indexes such as soluble solids concentration (SSC), dry matter content (DMC) and titratable acidity (TA) are usually used as standards to assess the harvest quality of fruit (Crisosto & Crisosto, 2005; Moing et al., 2001). Nascimento et al. predicted peach maturity based on SSC and fruit firmness in low-chilling peach combined with a partial least square (PLS) model (Nascimento et al., 2016). However, SCC and fruit firmness are affected by many factors, such as variety, growing conditions and precipitation, which will result in the uncertainty of maturity prediction. Taste is generally accepted as an indicator of fruit quality, which directly reflects the actual consumer preferences (Evrendilek, et al., 2016; Pereira et al., 2020). Le Lievre et al. indicated that flavor components (starch, sugars and acids) in fruit affected the taste as perceived by consumers, which revealed the practicability of taste as an indicator of fruit quality (Le Lievre, 2017). Previous studies mainly focused on the analysis of taste attributes and flavor compounds (Oruna-Concha et al., 2007; Zhu et al., 2020;), but there have been few studies on the development prediction based on taste changes.

Flavor, sweetness, and acidity are three major parameters to evaluate the sensory quality of fruit (Oraguzie et al., 2009; Harker et al., 2002; Sohrabpour et al., 2021). Fruit taste changes can be efficiently sensed by sensory evaluation, which can provide a comprehensive analysis of the perceived flavor of products, such as aroma, and taste (Blahopoluchna & Liakhovska, 2021). However, there are some limits in human sensory evaluation because it perceives product features by experience and can hardly be automated (Bleibaum et al., 2002). As an objective, accurate, simplistic, and cost-effective method, electronic tongue combined with human sensory evaluation can be used to evaluate fruit flavor quality comprehensively (Phat et al., 2016).

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Despite numerous attempts of using electronic tongues for the taste analysis of fruit, juice, wine, tea, etc. (Qiu & Wang, 2015; Tan et al., 2021; Rudnitskaya et al., 2010; Chen et al., 2008), the application of the electronic tongue combined with machine learning for quality prediction remains scarce.

Multivariate statistical model and machine learning have been applied to predict fruit internal quality and ripeness (Zhang et al., 2017; Minas et al., 2021; Guedes et al., 2020; Kamruzzaman et al., 2012). The purpose of multivariate statistical models is to explore the relationship between data and variables, while machine learning aims to obtain a model that can be used to predict repeatedly. As a supervised machine learning model, support vector regression (SVR) can estimate a relationship between the input and output of random variables on the condition that the joint distribution of the variables is completely unknown. For a low number of samples with a high input space dimension, SVR can provide sparse solutions for regression problems, where only the most relevant samples of the training data need to be weighted in low memory requirements and computational cost. SVR has been used as a prediction model to solve problems in many research fields, such as water temperature prediction and COVID19 cases prediction (Quan, et al., 2020; Parbat & Chakraborty, 2020). In the food field, SVR was commonly applied to predict fruit quality and maturity during storage (Sanaeifar et al., 2016; Cho et al., 2021).

In the present study, we aim to analyze the changes in characteristic taste attributes of flat peach by using human sensory evaluation coupled with an electronic tongue and further establish a prediction model for the development stage of flat peach. Furthermore, the correlation between human sensory evaluation and electronic tongue will be explained by a PCA model, and the potential ability of electronic tongue in predicting the development stage of flat peach will be evaluated by comparing with human sensory evaluation. This study will provide fruit farmers with a rapid method to predict the development stage of fruit and further determine a proper harvest time.

2 Materials and methods

2.1 Flat peach material

Flat peach (No.1 Xinpan) was hand-picked from a commercial orchard in Shihezi, Xinjiang province, China (85°58'10.9698"E, 44°15'29.1636"N), from 3 July to 2 August 2020. The flat peach under the study was tagged once it started fruit set. Flat peach of different development stages (F1- F7) was harvested at the interval of five days beginning from 90 to 120 days after the fruit set. For each group, 100 fruits of the approximately same size and without any skin damage were transported to the laboratory for further analyses.

2.2 Flat peach sample preparation

A total of 80 fruits of each development stage were selected randomly and divided into four groups. One group was used for physiochemical indexes analysis, human sensory evaluation, and electronic tongue test. The other groups were used for electronic tongue analysis to provide training datasets for SVR model. Each group's flat peach was stored at 4 °C overnight. The horizontal diameter and single fruit weight of 20 individual fruit per development stage were first recorded, then they were washed, peeled, cut into small pieces. Subsequently, the pieces were crushed and blended by a juicer (Supor Co., Ltd., TJE06A-400; Shaoxing, China) at a speed of 45 rpm. A part of the prepared samples were immediately used for physiochemical indexes and the others were stored at -20 °C for further sensory evaluation analysis and electronic tongue test.

2.3 Physiochemical indexes (PI) analysis

Determination of soluble solid content (SSC)

The measurement of SSC was conducted to obtain the organic sugar content by a saccharimeter (MASTER-4M, ATAGO, Japan). Before determination, the Brix of the saccharimeter was adjusted to zero using distilled water at 20 °C and the prism was wiped with a soft flannelette. Then, 2-3 drops of the sample were evenly distributed on the surface of the prism and then the Brix of the sample was recorded. For each group, the experiment was measured in three parallel.

Determination of pH

The pH of flat peach samples was measured using a digital pH metre (PHS-3E, INESA Scientific Instrument Co., Ltd., Shanghai, China) according to International Standardization Organization (1975). The pH metre was firstly calibrated with commercial buffer solutions at pH 6.86 and 4.00. 20 mL of sample was placed in a 50 mL beaker and measured at 25 ± 0.5 °C. Sufficient time was allowed for equilibration before the pH metre reached a stable value. The experiment of each group was repeated in three parallel.

Determination of titratable acidity (TA)

Titratable acidity (TA) of flat peach samples was determined as described by Xu et al. with some modifications (Xu et al., 2019). Firstly, 10 g of flat peach sample was transferred to a 50-mL volumetric flask and diluted with distilled water to the volume, and mixed. Subsequently, the mixture was incubated in a thermostat water bath at 90 °C for 30 min. After that, the solution was centrifuged at a high speed of 2000 rpm. Three drops of phenolphthalein were added to 10 mL of the supernatant. The mixture was titrated with standardized 0.1 M NaOH until the phenolphthalein end-point (pH = 8.2) was observed, and then the dosage of NaOH was recorded. The analysis was conducted in three parallels for each group. TA was calculated according to the Formula 1 below:

$$\text{Titratable acidity}(\%) = \frac{V_1 \times C \times k \times V_2}{m \times V_0} \tag{1}$$

V_1: the dosage of NaOH (mL); C: the concentration of NaOH (0.1M); k: the reduction factor of malic acid (k = 0.067); V_2: the volume of the flat peach sample after dilution (50 mL); m: the weight of the sample (10 g); V_0: the titration volume of the sample (10 mL).

2.4 Human sensory evaluation

Sensory evaluation of flat peach was conducted according to the method of the previous study with some modifications (Hayashi, et al., 2020). The sensory panel comprised of six assessors (3 males and 3 females, aged from 22 to 26 years old) were recruited from the College of Food Engineering and Nutritional Science of Shannxi Normal University, Xi'an, Shannxi. All of the panelists were experienced in descriptive sensory analysis and trained well before sensory profiling. The sensory evaluation was comprised of three sessions. Firstly, panelists were required to evaluate and discuss the taste of flat peach until they reached a consensus on the taste characteristics. Six taste attributes for flat peach samples, including astringency, juiciness, bitterness, sweetness, sweet overall, and sourness were determined to describe the taste of flat peach samples by the sensory panel. Juiciness was defined as the amount of juice released during chewing the flat peach fruit. Secondly, panelists were trained to recognize and quantify tastes with reference standards of samples for at least one weeks. The standard samples were determined by the availability of the range that could be found in the flat peach samples. Thirdly, 30 mL of flat peach samples were placed in a 100-mL opaque disposable plastic cup and then given three-digit labels in random order. The panelists evaluated the flat peach samples with a 11-percentage point scale (0 = not perceivable, 1 = weak, 5 = significant, 10 = extremely strong). The sensory evaluations were conducted in an air-conditioned room (22 °C), nose clips were used to suppress olfactory sensations. Between samples, oral cavity cleaning was enforced with water over 30 s. Sensory panelists were given a 15 min break to minimize sensory fatigue after every sample. The sensory evaluation of falt peach was conducted in triplicate for each group and completed in one week.

2.5 Electronic tongue analysis

Electronic tongue analysis was performed using TS-5000Z E-tongue (Insent Company, Japan) according to the methods of Hayashi et al. (2013). Six basic tastes (sourness, saltiness, umami, bitterness, sweetness, astringency) and three aftertastes (richness, after-bitter, after-astringency) of flat peach in different development stages were analyzed by using the system consisted of an Ag/AgCl reference electrode and multichannel lipid/polymer membrane electrodes. Before electronic tongue detection, 100 g of pulp was mixed with 100 mL of pure distilled water and then centrifuged at 3000 rpm for 5 min at 4 °C. 25 mL of the water-soluble extract of each sample was used for electronic tongue measurement. The sensor analysis was automatically carried out at 25 °C. Firstly, three cleanings were performed lasting 90 s, 120 s, and 120 s, respectively. Secondly, sensor probes were dipped into the sample solutions for 30 s balancing and 30 s measurement. Then, these probes were cleaned twice for 3 s in 30 mM KCl and 0.3 mM tartaric acid and returned to the reference solution to measure the aftertaste value. The taste intensity of the flat peach sample was defined as the membrane potential difference between each coated sensor probe and the reference electrode. Each fruit sample was measured four times with five sensors by the auto-sampler. The reference solution (artificial saliva, tasteless sample) was composed of 30 mM KCl and 0.3 mM tartaric acid. Therefore, the tasteless points of sourness, saltiness, and others were -13, -6, and 0, respectively. When the taste value was below the tasteless point, the taste of the sample could not be detected.

2.6 Development of SVR model

SVR model was developed for development stage prediction based on changes in taste attributes of flat peach during fruit development. Totally 28 experiment datasets were used to develop the SVR model, 21 samples were used for training datas and 7 samples were used as test datas. For each dataset, electronic tongue (including 9 taste attributes) and human sensory (including 6 taste attributes) datas were used as input parameters, and the development stages of flat peach were used as output parameters. For the training data $X = \{(xi, di), i = 1, ..., l\}$, where $xi \in R^N$ is the i^{TH} input vector for the i^{TH} training data, $di \in R$ is the target value for the i^{TH} training data and l is the number of training data, the regression estimation can be formalized as a problem of inferring a function $y = f(x)$. Establishing the SVR model is equivalent to finding a regression function of the form, as shown in Formulas 2 and 3:

$$f(x) = \sum_{i=1}^{l} \left(\alpha_i - \alpha_i^*\right) k(x_i, x) + b \quad (2)$$

Where $\alpha = (\alpha_1, \alpha_2, ..., \alpha_l)^T$, $\alpha^* = (\alpha_1^*, \alpha_2^*, ..., \alpha_l^*)^T$ and b are the parameters of the model, $k(x_i, x)$ is a kernel function, which can be linear or nonlinear (Benkedjouh et al., 2015). The kernel function can transform nonlinear regression into linear regression by mapping the inputs into a higher dimensional feature space. For example, the partition hyperplane for the XOR problem can be found when the characteristic space is extended from two dimensions to three dimensions, which is shown in Figure 1. To abtain more precise results, a nonlinear kernel (Gaussian function) was employed in our study. Its form is given by the following Formula 3:

$$k(x_i, x) = \exp\left(-\frac{\| x_i - x \|^2}{\sigma^2}\right) \quad (3)$$

Where $\sigma > 0$ is the width of the kernel.

In our implementation, SVR was performed by libSVM version 2.89 and conducted by use of MATLAB version 6.5 (Mathworks Inc., Natick, USA), where soft-margin SVM with a Gaussian kernel was adopted. The steps in our experiment can be summarized by the following steps:

(1) Defined the data for learning and testing;

(2) Invoked the svmtrain function of LibSVM toolbox to cross-validate on the testing data to find the optimal penalty parameter c and kernel function parameter g;

(3) Established the SVR model based on parameters c and g;

(4) Predicted the newly input data and evaluated the performance of the regression model.

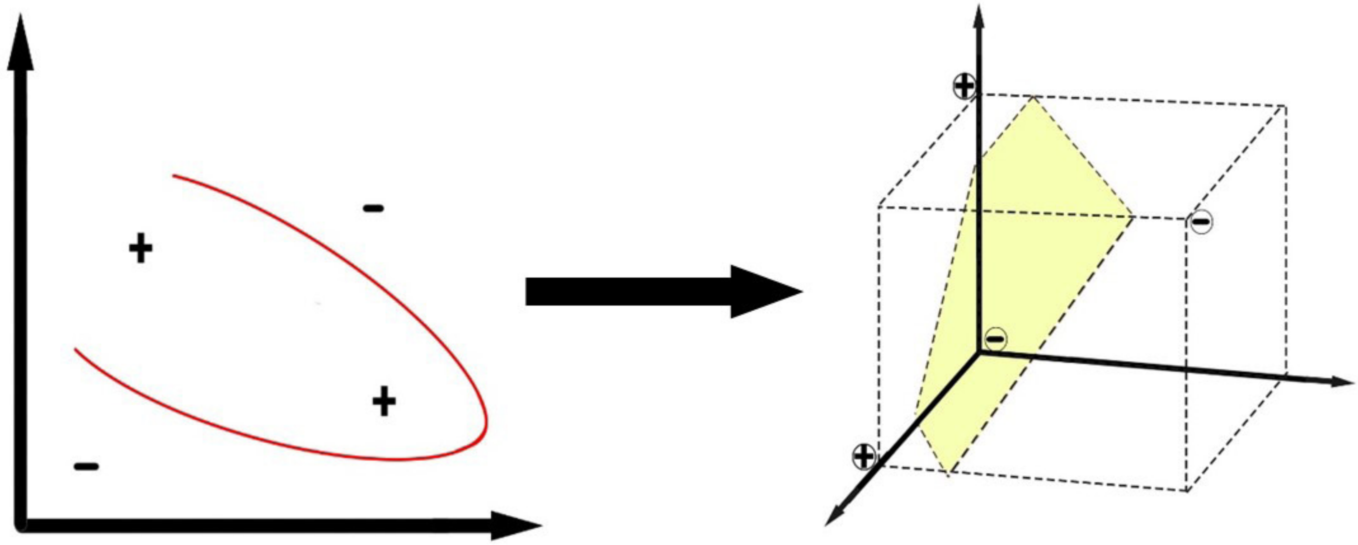

Figure 1. XOR problem and nonlinear mapping.

2.7 Statistical analysis

The radar images were plotted using Origin 2018 software. Principal component analysis (PCA) and Hierarchical clustering analysis (HCA) were conducted to group the samples and obtain an overview of the variation between different groups. In this paper, the One-way ANOVA test, PCA, and HCA were performed by using SPSS vs 18.0.

3 Results and discussion

3.1 Changes in physiochemical indexes (PIs) during flat peach development

Fruit development and ripening is a continuous process that goes through a complex series of biochemical changes, which determine the qualitative traits, such as appearance, flavour and texture (Janssen et al., 2008; Lombardo et al., 2011). To characterize and assess the development level of flat peach, data related to physiochemical changes were obtained. Figure 2 showed the evolution of various PIs during flat peach development.

The PIs including single fruit weight, horizontal diameter, SSC, TA, and pH significantly changed ($p \leq 0.05$). As shown in Figure 2A, the weight and horizontal diameter of flat peach increased rapidly at F1-F4, while the fruit size increase slowed down after F4, especially F5-F7. The starch was accumulated continuously during fruit early development (Zhu et al., 2017), which increased fruit weight and volume. By contrast, the most obvious changes in other parameters (SCC, AT, and pH) were observed after F4 (Figure 2B). The increase of SSC and decrease of AT were caused by the conversion from organic acids to sugar during fruit ripening. The development process of stone fruits can generally be divided into four recognized stages (S1-S4). At the first stage (S1), cells divide and elongate rapidly and fruit enters the fast growth phase. At the second stage (S2), the stone begins to form and fruit weight hardly increases. Stone fruit reached the second exponential growth phase at stage 3 (S3). At the final stage (S4), ripening takes place and fruit enters the harvest period (Chalmers & Ende, 1975; Tonutti et al., 1997; El-Sharkawy et al., 2007). According to the typical growth pattern (double-sigmoid pattern) of stone fruits (Chalmers & Ende, 1975), F1-F5 belonged to the S3 (immaturity) in which

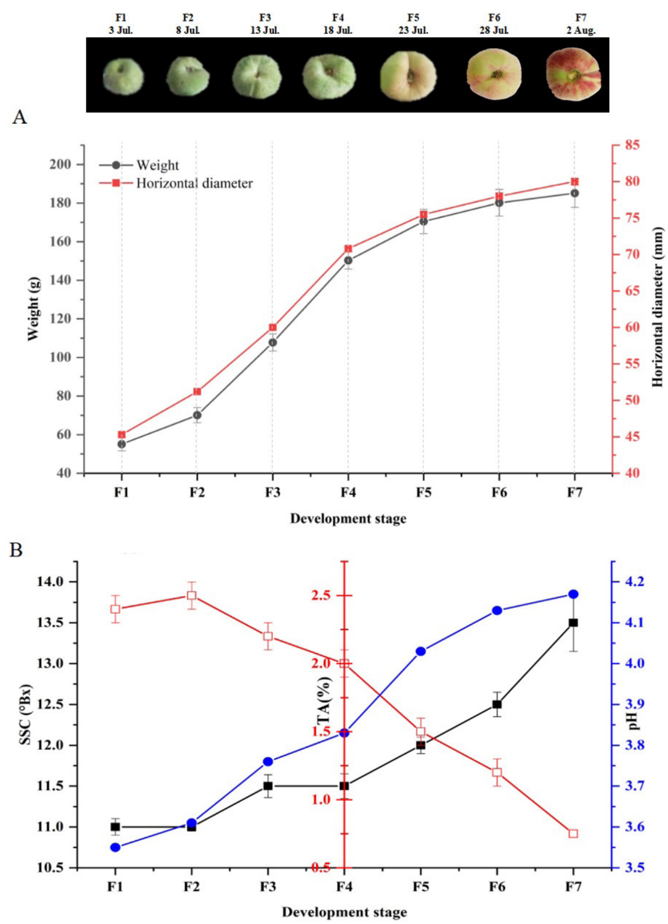

Figure 2. Changes in physiochemical indexes (PIs) of flat peach during development: changes in weight and horizontal diameter(A); changes in SSC, TA, and pH (B).

fruit size increased rapidly, and F6-F7 reached S4 (maturity) in which the fruit ripen rapidly. The development level of flat peach was preliminarily evaluated by PIs, and then the taste would be analyzed to assess the palatability and acceptability.

3.2 Changes in characteristic taste of flat peach during different development stages

Human sensory evaluation analysis

Human sensory evaluation was conducted to quantificationally characterize the taste properties of flat peach by six sensory panelists. The taste profile of flat peach in seven development stages was shown in Figure 3A. Six taste attributes significantly differed among the seven samples ($P < 0.05$). The scores of astringency, bitterness and sourness decreased with peach fruit growth, while those of juiciness, sweetness, and sweetness overall increased. F7 obtained the highest scores in good sensory attributes and the lowest levels in other unacceptable taste descriptors. Sensory evaluation and PI analysis indicated that F7 has superior taste and a higher degree of acceptability. An opposite situation was observed from F1 to F5, which had lower levels in above acceptable sensory attributes but higher levels in astringency, bitterness, and sourness. The highest taste intensities of astringency and sourness were found in samples F1 and F2. Samples F3 to F5 also showed higher levels of sourness. The changes in taste attributes were associated with the metabolism of some non-volatiles, such as amino acid, sugar, or organic acid. Therefore, the taste coupled with physiochemical indexes could monitor the changes in the substance metabolism and further indicate the maturity of flat peach.

Electronic tongue analysis

The electronic tongue was carried out to evaluate the taste of flat peach in different development stages. As shown in Figure 3B, there were significant differences in the intensities of sourness, bitterness, aftertaste-bitterness, and sweetness, whereas those of astringency, aftertaste-astringency, umami, saltiness and richness only changed slightly. The intensity of the sourness attribute decreased, while sweetness intensity increased with flat peach development. F6 and F7 exhibited the highest sweetness but lowest sourness intensity, and the lowest sweetness but highest sourness level was observed in F1 and F2. The changes in sweetness, sourness and bitterness were consistent with human sensory evaluation. To sum up, the peach fruits with a low score in sourness taste appeared to have a relatively high sweetness score. However, the astringency and aftertaste-astringency changed slightly and featured relatively similar levels during flat peach development. The electronic tongue test differed in astringency attribute from the human sensory evaluation, which indicated that the human sensory receptor was more sensitive than the electronic tongue sensor in evaluating the astringency taste. Therefore, the astringency note may made a minor contribution to predicting the maturity of flat peach. The saltiness scores of F3-F7 were below the tasteless point because of the decrease of inorganic salts with peach fruit growth.

3.3 Correlation among physicochemical indexes, human sensory evaluation, and electronic tongue test

PCA was performed to reveal the relationships among the human sensory evaluation, electronic tongue test, and physicochemical indexes. As shown in Figure 4, two principal components (PC1 and PC2) were obtained from the PCA model, with the cumulative variance being 87.467%. The X-matrix was composed of peach fruits with seven development stages, sensory attributes and physicochemical indexes were designated as the Y-matrix. All the sensory attributes and physicochemical indexes can be accurately identified and well explained by the PCA model, indicating that the proposed PCA model was scientific and reliable.

Figure 4 showed that all the indexes/taste notes were clustered into three groups, namely, group 1 (juiciness, sweetness, peach fruit weight, umami E, sweetness E, sweet overall, horizontal fruit diameter, pH, and SSC), group 2 (bitterness E, aftertaste-bitterness E, and astringency E), and group 3 (saltiness E, sourness E, sourness, astringency, aftertaste-astringency E, TA,

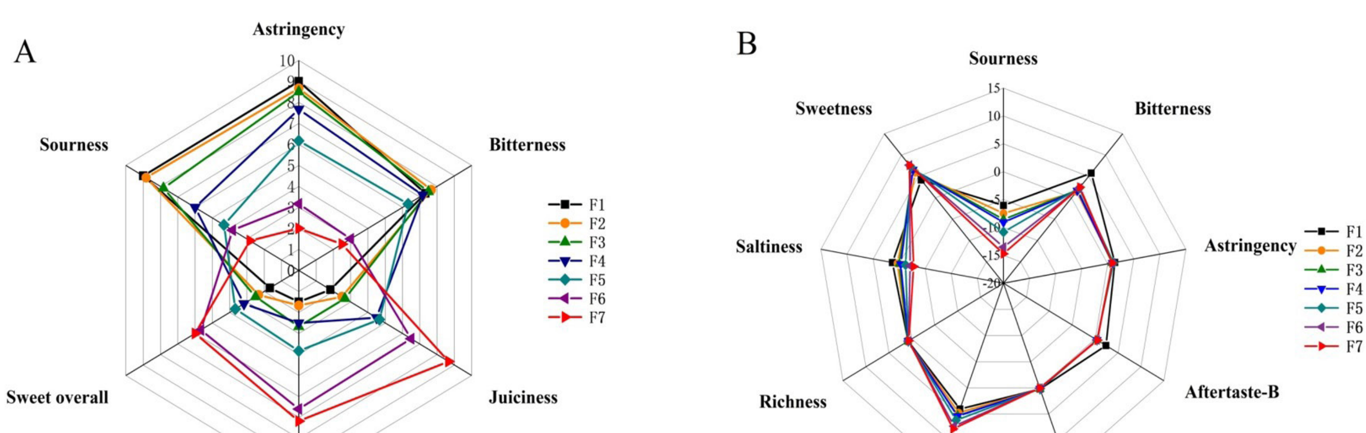

Figure 3. The taste profile of flat peach in seven development stages evaluated by human sensory evaluation (A) and electronic tongue test (B).

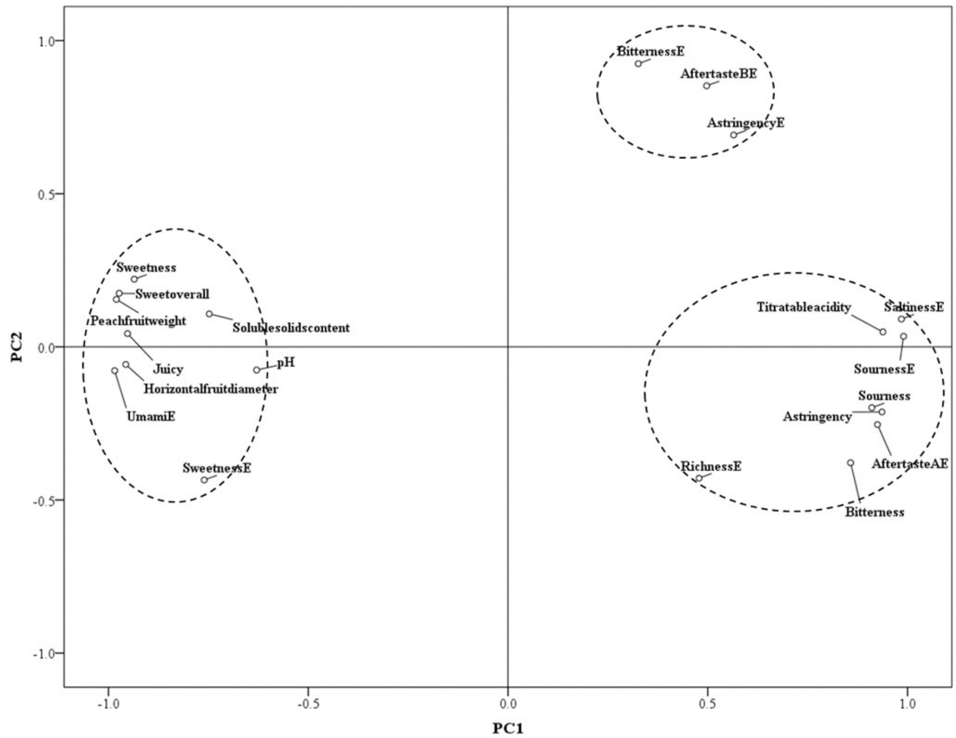

Figure 4. PCA of physicochemical indexes and taste attributes

bitterness, and richness E). As indicated in Figure 4, groups 1 and 3 were distributed on the left and right sides of the load diagram respectively, and group 2 was located on the upper right corner of the PCA load diagram. Variates with a close distance indicate that they have a positive correlation, while variates with an opposite location indicate that they have a negative correlation. Therefore, groups 1 and 3 had a negative relationship, meanwhile, groups 1 and 2 also had the same relationship. Whereas, a positive correlation was found between groups 2 and 3. In brief, except richness E, most of the good attributes were clustered into one group, and the unpleasant taste attributes were clustered closely. Moreover, the good tastes had a significant correlation with the single fruit weight, horizontal fruit diameter, pH, and SSC, and the unpleasant tastes presented a positive correlation with TA, which indicated that the flavor quality was associated with the physicochemical indexes during flat peach development. However, there were some attributes of human sensory evaluation such as astringency and bitterness that were not highly correlated with the electronic tongue test result. The phenomenon may be caused by the low sensitivity of the electronic tongue sensor in some taste notes. For most taste attributes (sourness, sweetness, and bitterness), the electronic tongue test had a high correlation with sensory evaluation, thus having the potential to predict these attributes. Therefore, the electronic tongue can provide a fast and precise tool to predict the palatability and acceptance of flat peach.

3.4 HCA of human sensory evaluation and electronic tongue test data

HCA was performed to explore and visualize the relationships among different samples and further assess the prediction ability of human sensory evaluation and electronic tongue test according to the development stage of flat peach. The dendrograms of HCA for human sensory evaluation and electronic tongue test were presented in Figure 5. Fruit samples in different development stages were clustered based on Euclidean distance.

As shown in Figure 5A, seven samples were divided into two significant clusters when the Euclidean distance was 2. F1-F5 belonged to the first level, named group 1, and the others belonged to the second level (group 2). In Figure 5B, all the samples have been partitioned into three statistically significant clusters when the distance was 5. F1 was solely classified into one group (group 1), F2, F3, F4 and F5 belonged to the second cluster (group 2). The third group (group 3) was composed of F6 and F7, which was consistent with group 3 for human sensory evaluation data. Moreover, samples were classified into two clusters (F1-F5, F6-F7) when the Euclidean distance was 18, which was consistent with the clustering result for human sensory evaluation data. In brief, human sensory evaluation and electronic tongue test could classify seven development stages of flat peach as S3 (immaturity) and S4 (maturity). Therefore, HCA results demonstrated the potential ability of the electronic tongue to predict the development stage of flat peach when compared with the clustering results of human sensory evaluation.

3.5 Development stage prediction of flat peach via SVR model

The SVR model combined with sensory eveluation was applied to predict the development stage of flat peach. Each development stage could be predicted with the taste attribute as model input. The result of the prediction for taste attribute

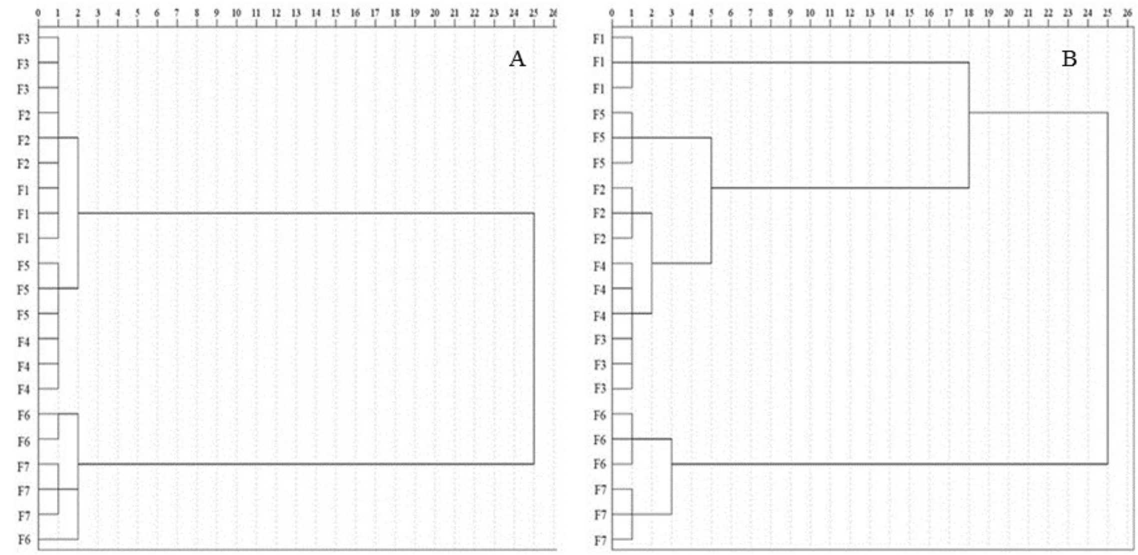

Figure 5. HCA of seven development stages of flat peach based on human sensory evaluation (A) and electronic tongue test (B).

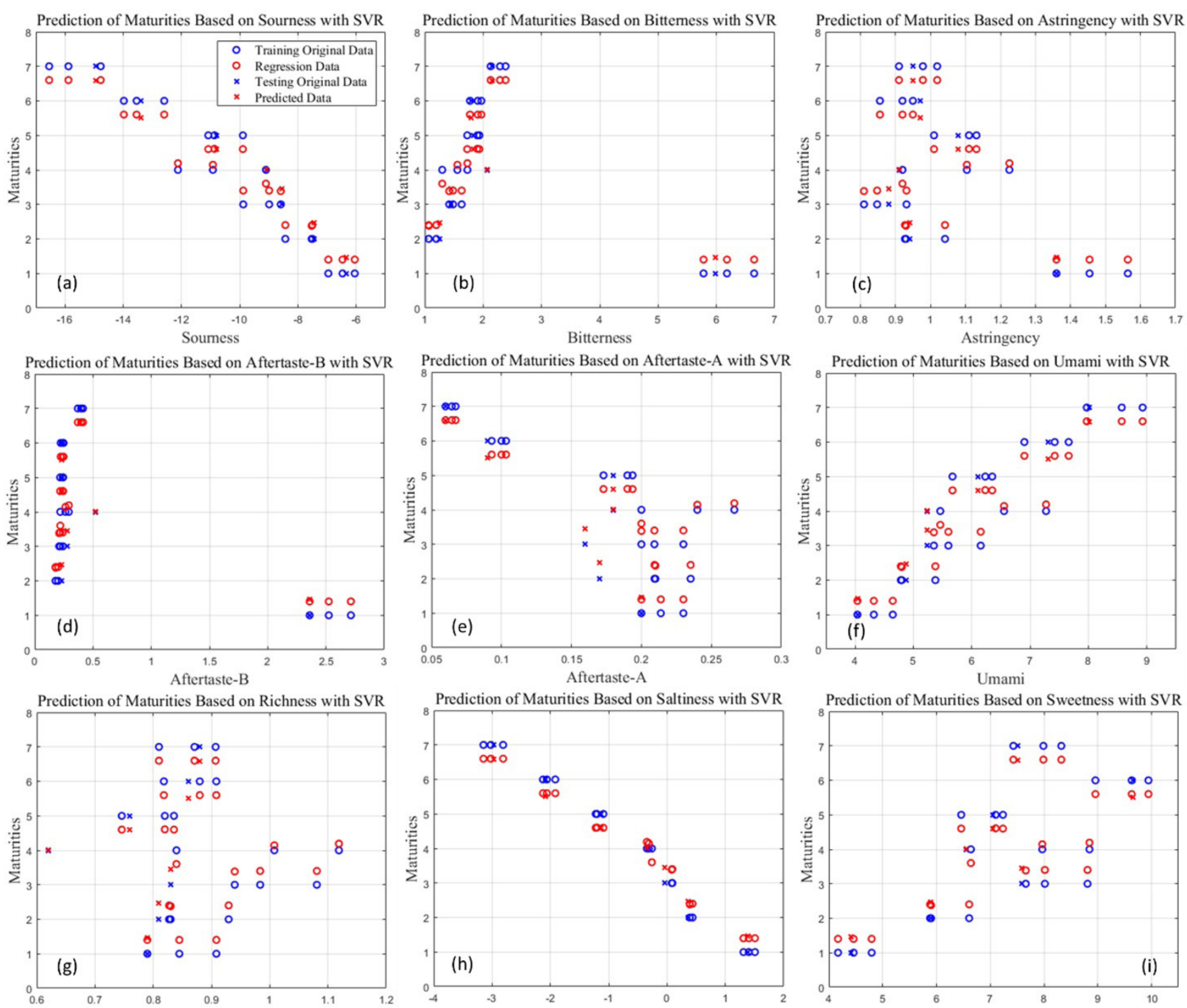

Figure 6. Development stage prediction of flat peach based on electronic tongue and SVR model.

(electronic tongue) based on the SVR model was presented using nine subfigures.

As shown in Figure 6, blue circles and blue crosses respectively represented original data in the training and testing datasets, while red circles and red crosses respectively represented regression data in the training phase and predicted data in the testing phase. In the first subfigure, the ordinate presented development stage and abscissa represented intensity of sourness attribute. The group in the lower right corner contained training and testing data of F1. In this development stage, the training values of the sourness attribute were represented by blue circles. With these data as inputs, the regression data represented by red circles were 1.4001, 1.4003 and 1.3998. The data exhibited by cross showed the test result. As the sourness value shown by blue cross input, the prediction result represented by the red cross was 1.455. For each sensory attribute, if the distance between the prediction value and real value was less than one, it would be regarded as a correct evaluation, which could be used to predict the development stage. Other cases were regarded as wrong evaluations. The demonstration of prediction for other taste attributes was omitted to save space, all of which had been implemented in our MATLAB code. The MATLAB code employed to construct the model and the experimental data have been published on GitHub (https://github.com/997948259/SVR-model-based-on-electronic-tongue-test).

The mean squared error (MSE) of our model for the development stage was around 0.14, while the squared correlation coefficient (SCC) was over 0.99, which indicated that our model performed well on the whole. Moreover, the correct rate (CR) was 93.9%, which indicated that our SVR model was reliable.

4 Conclusions

The development level of flat peach fruit could be divided into immaturity (F1-F5) and maturity stage (F6-F7) and was consistent with the double-sigmoid pattern. Sourness and bitterness significantly decreased, while sweetness increased with peach fruit growth ($P < 0.05$), especially in F4-F5. Electronic tongue could accurately discriminate the development level of flat peach and had a potential ability to predict the development stages by comparing with human sensory evaluation. The SVR model based on taste attribute was developed and verified. Seven development stages of flat peach could be accurately predicted by inputting the value of taste attribute with SVR model. This work provided an informatization method to efficiently determine the fruit picking stage and improve the efficiency of agricultural production.

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