Rapid quality determination of cherry fruit (Prunus spp.) using artificial olfactory technique as combined with non-linear data extraction model

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ABSTRACT
In this article, quality rapid determination of cherry fruit (Prunus spp.) using artificial olfactory technique (AOT) combined with non-linear data extraction model was studied. AOT system was developed and used for cherry quality detection. AOT system responses to cherry samples stored at 4°C were recorded. At the same time, physical/chemical indexes, such as human sensory evaluation (HSE), firmness, color, pH, total soluble solids (TSS), and reducing sugar content (RSC), were examined to provide quality references to the cherry samples. AOT data was analyzed by principal component analysis (PCA), and bilayer stochastic resonance (BSR) models. PCA only partially discriminated the cherry samples. The signal-to-noise ratio (SNR) maximum values (SNR-Max) generated by BSR successfully discriminated all the samples. Multiple variable regression (MVR) between cherry physical/chemical indexes and BSR SNR-Max values was conducted. Results indicated that BSR was suitable for cherry quality rapid evaluation. Cherry quality examination model was built based on linear fitting regression on BSR eigen values. Validation tests results indicated that the developed model has good forecasting accuracy. The proposed method had some advantages, such as rapid responses, high accuracy, easy operation, etc.

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Introduction
Cherry fruit (Prunus spp.) are the fruits with rich content of vitamin C, potassium, carotenoids, phenolic acids, and anthocyanins.\(^\text{[1-3]}\) There are over 30 species of cherries that are cultivated worldwide. Among them, almost two species are planted for food usage: tart cherry and sweet cherry. Both species are rich in energy content, fiber, vitamin C, vitamin E, and potassium.\(^\text{[4-6]}\) Usually, sweet cherry has a considerably higher amount of anthocyanins and total sugar than tart cherry. Also, the content of phenolic acids, β-carotene, and vitamin A is greater in both species.\(^\text{[7,8]}\) Due to its rich nutrition content, the cherry is easy to get deteriorated during transportation after harvest. If the deteriorated fruit is taken by people, it is possible to cause great harm to human body. So it is important to characterize cherry quality during storage and transportation.\(^\text{[9,10]}\)

Fruit quality examination methods usually include instrumentation method, standard protocol examination, and human sensory examination.\(^\text{[11,12]}\) Instrumentation methods, such as spectral technology, GC-MS, etc., are commonly used for fruits quality rapid determination in laboratory environment. Standard protocol examination methods depend on national fruit quality standard protocols for quality determination. Human sensory examination characterizes fruit quality by using human sensory organs, such as nose, eye, touch, etc.\(^\text{[13]}\) Although these methods realize the fruit quality determination, they also have some disadvantages, such as fuzzy operation, time-
consumption, and high cost, etc. Especially, the skilled operators are demanded to perform the instrumentation analysis. Standard protocol examination methods can determine fruit quality according to relative national standards. While these methods need complex experimental operations. The cost is also relatively high. Great demand for an effective, accurate, and low cost method for cherry quality rapid determination is needed.

In the recent past decade, AOT develops fast in rapid detection occasions. AOT consists of an array of some physical/chemical sensors towards certain gas components. It also needs proper pattern recognition model to proceed sensor array emitting data. Appropriate patterns from the gases emitted by the known samples are used as a training pattern so that the unknown gases can subsequently be judged by the training pattern. In the past decade, AOT and related data treatment methods were used in recognition and quality analysis of food samples, such as vegetables, fruits, fishes, etc.

Cherry fruit (Prunus spp.) quality detection by using AOT with non-linear data extraction model was studied in this paper. AOT system was designed for cherry quality analysis. AOT system responses to cherry samples were measured. Physical/chemical indexes were also examined to obtain references to the samples. AOT data was processed by PCA and BSR models. Cherry quality examination model was built based on linear fitting regression on BSR eigen values.

Materials and methods

Materials

Fresh cherry samples were obtained from an agro-product market in Tianjin. They were taken from the same package. The samples had the same weight (10.0 g (±1.0 g)) and curvature radius approximately. The samples were placed in non-hermetic box and stored at 4°C in a preservation box. In each day, 20 samples were randomly fetched out to conduct the experiments. 20 samples were used in AOT measurement. Physical/chemical indexes were examined by using 10 samples. The samples were fetched randomly. The experiments were conducted for 7 days. Another 100 cherry samples were used in validation experiments. Three samples were randomly fetched for AOT measurement each day.

Methods

Human sensory evaluation

The human sensory evaluation was conducted by several experienced panelists. Table 1 is the instruction for the human sensory evaluation method. The cherry samples are evaluated according to the four dimensions: (i) vision on cherry color, and skin wetness, (ii) touch estimation on cherry firmness and resilience by hand, (iii) taste estimation on cherry, (iv) odor estimation on cherry smell by panelist’s nose.

HSE experiments were evaluated by 10 experienced panelists (age from 30 to 40 years), and voting number was set at k, k ∈ (1,10). Cherry quality was divided into m levels, and the score of a specific level was set at hj, j ∈ (1,m). Cherry attributes were divided into n elements, and a specific element was

| Attributes          | Attribute degree          |
|---------------------|---------------------------|
|                     | 5             | 4           | 3           | 2           | 1           |
| Color               | Red            | Slight purple| Purple      | Dark purple | Purple brown|
| Skin wetness        | Very dry       | Dry         | Slight wet  | Wet         | Very wet    |
| Touch               | Very hard      | Hard        | Slight soft | Soft        | Very soft   |
| Taste               | Delicious      | No off-flavor| Slight off-flavor | Off-flavor | Strong off-flavor |
| Odor                | Fruity         | Slight fruity| Slight vinosity| Vinosity   | Strong vinosity |

Table 1. HSE index for cherry quality evaluation.
set at \( u_i, i \in (1,n) \). The contributory weight was decided by pairwise comparison of contribution weight of attributes was set at \( x_i (\Sigma x_i = 1) \). If there was a specific relationship between two objects of \( h_j \) and \( u_i \), the relation set (matrix) of \( f \) was calculated.

\[
F = \begin{bmatrix}
\frac{f_{11}}{k} & \frac{f_{12}}{k} & \cdots & \frac{f_{1m}}{k} \\
\frac{f_{21}}{k} & \frac{f_{22}}{k} & \cdots & \frac{f_{2m}}{k} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{f_{n1}}{k} & \frac{f_{n2}}{k} & \cdots & \frac{f_{nm}}{k}
\end{bmatrix}
\]

(1)

The overall acceptability was calculated by the weight grade method.

\[
Z = \sum_{i=1}^{n} x_i \cdot \sum_{m=1}^{m} \frac{f_{ij}}{k} h_j
\]

(2)

**Instrumental texture**

Texture Analyzer with flat cylindrical probe p/5 (5 mm diameter) was utilized to hold texture tests. TPA mode was selected. Testing speed in before and after measurement was 3 mm/s. Measurement speed was 1 mm/s. Compression degree was 50%. Data collection range was 200. Residence time interval was 5s. Load probe type was Auto-0.2 g.

**Color**

Color index was measured using a TES-135 chromatic meter. The index was reported as \( L^*, a^*, \) and \( b^* \) as CIELab coordinates. Parameters of \( L^* \), \( a^* \), and \( b^* \) indicate the lightness (the scale range of 0–100 points from black to white), red (+) or green (-), and yellow (+) or blue (-), respectively.

**pH**

In order to obtain pH index, 10 g cherry was smashed by a muller. A little purified water was added into the smashed sample to fully dissolve chemical substances. Cherry sample and water were poured into conical flask. The muller was flushed by purified water, and the flushed liquid was also poured into conical flask. The mixture in the flask was diluted to 100 mL, and left for a period of time. Then the mixture was filtered and the filtered liquid was tested by pH meter.

**Total soluble solids**

Cherry was grounded in a mortar and squeezed with a hand press for juice extraction. The juice was utilized for TSS testing utilizing refractometer (WZ113/ATC, China) at normal temperature.

**Reducing sugar content**

RSC index was tested based on China standard protocols GB/T 5009.7–2008: Determination of reducing sugar in foods. [29]

**AOT system**

Cherry samples were tested by a portable AOT system. It consists of three main parts: data acquisition unit (U1); gas sensor array unit (U2); power supply unit (U3), and the structure is displayed in Figure 1. U1 has eight metal oxide semiconductor (MOS) sensors with different chemical compositions towards different gases with different sensitivity and selectivity. The selectivity towards volatile compound species of MOS sensors is indicated by the provider: S1 (sulfide), S2 (flammable gases), S3 (ammonia gas), S4 (ethanol, aromatic hydrocarbons etc), S5 (hydrocarbon component gas, S6 (methane, propane, butane), S7 (propane, butane), S8 (nitrogen oxides). AOT responses are obtained as sampling voltage (V). Under proper temperature (300–450°C) heated by the electric resistance within the sensors, the volatile gases
transferred to the sensors are totally combusted to carbon dioxide and water, inducing the changes in the resistance of the sensor’s sensing materials. Each sensor room is independent. This structure avoids the cross-influence of the different inlet gas current.

AOT testing

Each cherry sample was placed into a vial with 50 mL volume. The vials were sealed with the membrane. The vials were balanced for 30 min at room temperature. Turn on the system power, then washing pump and valve 2 were started. The sampling pump and valve 1 remained close. Zero was obtained by filtering air gas using active carbon. The sensors reached their baseline by washing with zero gas. Then washing pump and valve 2 were closed. Then sampling pump and valve 1 were opened. The gases in cherry vial headspace were inhaled into gas sensor chamber at a flux of 350 mL/min for 40s. AOT measurement interval was 0.05 s. AOT real-time responses to cherry were measured. When testing was finished, the sensors were flushed by zero gas at a flux speed of 800 mL/min.

AOT data processing

Principal component analysis

The kernel idea of principal component analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. The principal components of a collection of points in a real coordinate space are a sequence of p unit vectors, where the i-th vector is the direction of a line that best fits the data while being orthogonal to the first i-1 vectors. Here, a best-fitting line is defined as one that minimizes the average squared distance from the points to the line. These directions constitute an orthonormal basis in which different individual dimensions of the data are linearly uncorrelated. In the mathematical transformation, we should make sure the total variance of all variates remains unchanged, and the variate that has maximum variance becomes the first variate. Similarly, the variate whose variance is just behind the maximum becomes the second variate, and make sure it has no relativity with the first variate and other variates.

Figure 1. AOT system.
Bilayer stochastic resonance

Classical stochastic resonance was proposed to explain the Earth climate periodical changes. It can be explained as following:

\[
dx/dt = -dV(x)/dx + k \times I(t) + p \times \xi(t) \tag{3}\]

Where \(CIRG\) is the position of the Brownian particle, \(t\) is the time, \(M\) and \(C\) are adjustable parameters, \(I(t) = S(t) + N(t)\) is an input signal \(S(t)\) with an intrinsic noise \(N(t)\), \(\xi(t)\) is the external noise, and \(V(x)\) is the simplest double-well potential with the constants \(a\) and \(b\).

\[
V(x) = -0.5ax^2 + 0.25bx^4 \tag{4}\]

Equation (3) can be transformed as

\[
dx/dt = ax - bx^3 + k \times I(t) + p \times \xi(t) \tag{5}\]

The minima of \(V(x)\) are located at \( \pm x_m \), where \(x_m = (a/b)^{1/2}\). A potential barrier separates the minima with the height given by \(\Delta U = a^2/4b\). The barrier top locates at \(x_b = 0\). Suppose the input signal is \(I(t) = A \sin(2\pi ft + \varphi)\), where \(A\) is signal intensity, \(f\) is signal frequency. \(p\) is external noise intensity. SNR is the common quantifier for SR and it can be approximately described as:

\[
\text{SNR} = \sqrt{2\Delta U (A/p)^2} e^{-\Delta U/p} \tag{6}\]

Noise intensity is a parameter in SR model. This model is used for e-nose data analysis. \(I(t) = A \sin(2\pi ft + \varphi) + aot(t) + N(t)\) denotes an input matrix. It has a sinusoid signal \(A \sin(2\pi ft + \varphi)\), AOT response data \(aot(t)\), and intrinsic noise \(N(t)\). SNR between the output and input is calculated. This model has been successfully used in food analytical applications. Under proper condition, signal amplitude is supposed to be relatively smaller \((A \ll 1)\). Then the particle is in one potential well. The energy of the particle drives it to jump from one potential well to another well. So Equation (4) can be written as:

\[
V(x, t) = -\frac{1}{2}ax^2 + \frac{1}{4}bx^4 + A \sin(2\pi ft + \varphi) + aot(t)x + N(t)x \tag{7}\]

Equation (7) indicates the potential function gets time dependence. Equation (8) displays the first-order and second-order derivation of \(V(x, t)\) with respect to \(x\), and let the equations equal to zero:

\[
\begin{cases}
\frac{\partial V(x, t)}{\partial x} = -ax + bx^3 + A \sin(2\pi ft + \varphi) + aot(t) + N(t) = 0 \\
\frac{\partial^2 V(x, t)}{\partial x^2} = -a + 3bx^2 = 0
\end{cases} \tag{8}\]

Setting noise intensity \(D = 0\) and \(\sin(2\pi ft + \varphi) = 1\), the critical amplitude value of the periodic signal can be obtained: \(A_c = \sqrt{4a^3/27b}\). Fourth-order Runge-Kutta numerical algorithm is utilized to solve Equation (3):

\[
x_{n+1} = x_n + \frac{1}{6}[k_1 + (2 - \sqrt{2})k_2 + (2 + \sqrt{2})k_3 + k_4], \quad n = 0, 1, \ldots, N - 1 \tag{9}\]

\[
k_1 = h(ax_n - bx_n^3 + sn_n) \tag{10}\]

\[
k_2 = h[a(x_n + \frac{k_1}{2}) - b(x_n + \frac{k_1}{2})^3 + sn_n] \tag{11}\]

\[
k_3 = h[a(x_n + \frac{k_3}{2}) - b(x_n + \frac{\sqrt{2} - 1}{2}k_1 + \frac{2 - \sqrt{2}}{2}k_2)^3 + sn_{n+1}] \tag{12}\]
\[ k_4 = h[a(x_n + k_3) - b(x_n - \frac{\sqrt{2}}{2} k_2 + \frac{2 + \sqrt{2}}{2} k_3)^3 + s_{n+1}] \]  

(13)

\( x_n \) is the \( n \)th numerical value of \( x(t) \), and \( s_{n} \) is the \( n \)th numerical value of \( S_n(t) \). \( h \) is the computation step. Much progress has been achieved on the applications of stochastic resonance in the past few decades. Single stochastic resonance system connected in series form the cascaded SR to obtain BSR. According to Equation (3), the relative Langevin equations can be written as:

\[
\begin{align*}
\frac{dx_1}{dt} &= ax_1 - bx_1^3 + M[A \sin(2\pi ft + \varphi) + EN(t) + N(t)] \\
\frac{dx_2}{dt} &= ax_2 - bx_2^3 + x_1(t) \\
&\cdots \\
\frac{dx_n}{dt} &= ax_n - bx_n^3 + x_{n-1}(t)
\end{align*}
\]  

(14)

**Results and discussion**

**Human sensory evaluation**

Human sensory of cherry is defined as 5 elements, and the preference levels are divided from 1 to 5. The higher preference level means a higher element score (see Table 1). Cherry human sensory analysis results are displayed in Figure 2. The samples start at 5, and the samples present bright color, dry and hard skin, delicious taste, and fruity odor. In day 2, the samples color get slightly dark than samples in day 1. In day 3, slight decay can be seen. Cherry skin gets slightly soft and wet. The samples get off-flavor. In day 6, obvious decay appears, and cherry skin gets softer and wet. The cherry loses its edible value. Generally, preference scores of the samples decline with the increase of time.
Firmness examination results are displayed in Figure 3. Firmness continuously decreases during the examination experiments. During storage, the total soluble content in the cherry continuously gets chemical changes. Also, pectin and cellulose are separated, causing the decrease in cherry firmness index. With the increase of storage time, the cherry flesh cells lose more water. The fiber in the fruit gets chemical changes at the same time. That’s a possible reason for firmness changes of the cherry fruit.

CIRG

Fruit quality changes can be characterized by CIRG parameters, such as L*, a*, and b*. According to previous reports, the hue angle (H) and the chroma (C) are defined in this research. 

\[ H = \arctan \left( \frac{b^*}{a^*} \right) \]

and 

\[ C = \left[ (a^*)^2 + (b^*)^2 \right]^{\frac{1}{2}} \]

Hue angle is distributed in the four quadrants of the \( a^*b^* \) plane, and chroma will be higher the further it is from the origin of the coordinates. Among them, 

\[ CIRG = \frac{180 - H}{L^* + C} \]

Calculating results are shown in Table 2. CIRG parameters gradually increase with the increase of time. CIRG value reaches 4.07 in day 6. Results demonstrate that CIRG effectively characterizes cherry surface color changes.

| Time (d) | \( L^* \) | \( H \) | \( C \) | CIRG |
|---------|-------|-----|------|------|
| 0       | 13.18 | 3.30| 22.34| 3.66 |
| 1       | 15.21 | 3.23| 25.50| 3.98 |
| 2       | 16.25 | 3.31| 26.12| 4.11 |
| 3       | 17.56 | 3.33| 21.65| 4.03 |
| 4       | 18.23 | 3.42| 22.80| 4.12 |
| 5       | 20.23 | 3.44| 24.38| 4.12 |
| 6       | 22.45 | 3.43| 23.66| 4.07 |
During storage, chemical environment within bayberry changes when its quality decreases. pH measurement results are displayed in Figure 4. pH value is about 2.42 on day. From day to day, pH increases quickly. In day, pH value is 2.76. During storage, the microbial get propagated, and the chemical content of cherry changes a lot, inducing the changes in pH index.

**Total soluble solids**

Soluble sugar relates to sucrose, glucose, and fructose in the fruit. The content of soluble sugar increases before harvest. Soluble sugar content declines after harvest. Cherry soluble sugar index decreases continuously during examination, and the results are shown in Figure 5. Soluble sugar is about 8.65% in day. TSS get 8.8% in day 1. From day 1 to day 6, TSS index persistently declines. The reason lies in that cherry gets ripen because of the individual respiration and metabolic activity.

**Reducing sugar content**

RSC index mainly focuses on the content of reducing sugar, such as glucose and fructose. RSC analysis results are shown in Figure 6. It increases from day to day 3. In day 4, RSC declines. The decline in RSC index possibly has relationship with chemical changes in cherry ripening procedure.

**AOT results**

**AOT responses and PCA**

AOT responses to cherry are shown in Figure 7(a). The feature gases emitted by the cherry samples are sensed by the gas sensors with AOT system. AOT signals induced by resistance changes are used to characterize the cherry olfactory properties. Different gas sensors present different responses and draw
Figure 5. TSS.

Figure 6. RSC.
Figure 7. AOT responses: (a) original responses; (b) PCA results; (c) BSR SNR curves; (d) Linear fitting regression.

feature fingerprint diagram for cherry samples. So AOT sensor array forms different responses to cherry fruit under different storage time. Sensor S1 presents the maximal stable value 1.36 V. S7’s stable value is about 1.14 V. S3, S5, and S6 present much lower stable values than S7 and S1. The other sensor S4, S8, and S2 present lower responses than S1, S7, S3, S5, and S6. PCA results are shown in Figure 7(b). Principal component 1 and principal component 2 totally capture 82.64% of data variance. Results demonstrate that the cherry samples of different storage time can not be qualitative classified from each other.

BSR analysis
Cherry AOT data processed by BSR as function of external stimulation intensity is shown in Figure 7(c). SNR curves first decline, and reach their minimum values. Then SNR curves fast increase with the increase of stimulation intensity. SNR peaks appear at more than 200. Cherry in different time can be classified by SNR peak values.

MVR between physical/chemical indexes and BSR maximal values
Quality is the overall characterization for fruits. The physical/chemical indexes have very close relationship to cherry quality. MVR results between physical/chemical indexes and BSR maximal values are shown as Table 3 and Equation (15). $R^2 = 0.99427$ indicates that BSR maximal values have good linear relationship with cherry physical/chemical indexes. $F = 34.67745$ demonstrates that BSR maximal values have significant linear relationship with physical/chemical indexes. BSR can be properly utilized to express cherry quality.
Table 3. Multiple variable regression between BSR eigen values and physical/chemical indexes.

| Index    | Value     | Error     | t-Value | P     |
|----------|-----------|-----------|---------|-------|
| Y-Intercept | −29.03159 | 61.88834  | −0.4691 | 0.72077 |
| Firmness  | −0.0348   | 0.06989   | −0.49787 | 0.70592 |
| pH       | −0.80247  | 11.17456  | −0.07181 | 0.95436 |
| CIRG     | 3.12068   | 16.24302  | 0.19212 | 0.87916 |
| TSS      | −1.78836  | 1.7736    | −1.00832 | 0.49736 |
| RSC      | −1.79305  | 2.4475    | −0.73261 | 0.59748 |

\[ F = 34.67745 \]

Table 4. Validation results (√ right; X wrong; not calculated).

| Sample No. | Detection value | Time | Error (%) | Results |
|------------|-----------------|------|-----------|---------|
| eva-1      | 1.874           | 2    | 6.3       | √       |
| eva-2      | 0.971           | 1    | 2.9       | √       |
| eva-3      | 2.731           | 3    | 8.97      | √       |
| eva-4      | 2.107           | 2    | 5.35      | √       |
| eva-5      | 3.875           | 4    | 3.125     | √       |
| eva-6      | 0.121           | 0    | /         | √       |
| eva-7      | 5.687           | 6    | 5.127     | √       |
| eva-8      | 4.578           | 5    | 8.44      | √       |
| eva-9      | 4.125           | 4    | 3.125     | √       |
| eva-10     | 2.106           | 2    | 5.3       | √       |
| eva-11     | 1.021           | 1    | 2.1       | √       |
| eva-12     | 3.214           | 3    | 7.133     | √       |
| eva-13     | 4.124           | 4    | 3.1       | √       |
| eva-14     | 1.874           | 2    | 6.3       | √       |
| eva-15     | 5.547           | 6    | 7.55      | √       |

\[
SR = -29.03159 - 0.0348 \times \text{Firmness} - 0.80247 \times \text{pH} \\
+ 3.12068 \times \text{CIRG} - 1.78836 \times \text{TSS} - 1.79305 \times \text{RSC} (R^2 = 0.99427)
\]

Cherry quality determination model

Cherry quality discrimination model is built by using SNR peak values and storage time in Figure 7(d). The model equation is shown as Equation (17), and the regression coefficients \( R = 0.97 \). After one-step’s calculation, Equation (18) is utilized as cherry storage time discrimination model. The input is SNR peak value processed using AOT data. The output is the cherry storage time. According to Table 3, the method is suitable for cherry quality discrimination.

\[
y = -77.3 + 1.34x; R = 0.97
\]

\[
\text{cherryquality} = (\text{SNRMaximal} + 77.3)/1.34
\]

Validating testing

Validating tests are conducted to validate detecting accuracy of the built model. Another 50 samples are made, and 15 samples are randomly selected for AOT detection. Results are shown in Table 4. The detecting accuracy is 100%. Validating tests indicate that this model has good accuracy.

Conclusion

Quality rapid determination of cherry fruit (Prunus spp.) using artificial olfactory technique combined with non-linear data extraction model was studied in this work. The following results were obtained. AOT system was designed and utilized for cherry fruit quality rapid determination. AOT system responses to cherry samples stored at 4°C were recorded. AOT data was analyzed by PCA, and BSR.
PCA only gives a qualitative discrimination for bayberry samples. SNR spectrum calculated by SR and DCSSR discriminates samples successfully. SNR eigen peak values increase with the increase of storage days. Physical/chemical indexes, such as HSE, firmness, color, pH, TSS, and RSC, were examined to achieve the exact quality of cherry. Results demonstrated that physical/chemical indexes changed with the increase of storage time. MVR between physical/chemical indexes (firmness, pH, CIRG, TSS, and RSC) and BSR SNR-Max values were conducted. Regression results demonstrated that BSR was more suitable for cherry quality expression. Cherry quality examination model (SNRMaximal + 77.3)/1.34 (R = 0.97) was developed. Validating tests results indicated that this method presents good accuracy for cherry quality discrimination. The proposed method in this work presents some advantages including rapid analysis, low cost, and good accuracy. It is promising in fruit quality fast analysis.

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References

[1] Sharafi, Y.; Jannatizadeh, A.; Rezapour Fard, J.; Aghdam, M. S. Morteza Soleimani Aghdam. Melatonin Treatment Delays Senescence and Improves Antioxidant Potential of Sweet Cherry Fruits during Cold Storage [J]. Sci. Hortic. 2021, 288, 1 10304. DOI: 10.1016/j.scienta.2021.110304.

[2] Calle, A.; Serradilla, M. J.; Wünsch, A. QTL Mapping of Phenolic Compounds and Fruit Colour in Sweet Cherry Using a 6+9K SNP Array Genetic Map [J]. Sci. Hortic. 2021, 280, 109900. DOI: 10.1016/j.scienta.2021.109900.

[3] Wöhner, T. W.; Emerewen, O. F.; Wittenberg, A. H. J.; Schneiders, H.; Vrienhoek, I.; Halász, J.; Hrotkó, K.; Hoff, K. J.; Gabriel, L.; Lempe, J., et al. The Draft chromosome-level Genome Assembly of Tetraploid Ground Cherry (Prunus Fruticosa Pall.) from Long Reads [J]. Genomics. 2021, 113(6), 4173–4183.

[4] Shakoor, N.; Adeel, M.; Zain, M.; Zhang, P.; Ahmad, M.; Farooq, T.; Zhou, P.; Azeem, I.; Rizwan, M.; Guo, K., et al. Exposure of Cherry Radish (Raphanus Sativus L. Var. Radculus Pers) to iron-based Nanoparticles Enhances Its Nutritional Quality by Triggering the Essential Elements [J]. NanoImpact. 2022, 8(1), e08788.

[5] Ćorković, I.; Pichler, A.; Buljeta, I.; Simunović, J., and Kopjar, M. Carboxymethylcellulose Hydrogels: Effect of Its Different Amount on Preservation of Tart Cherry Anthocyanins and Polyphenols [J]. Curr. Plant Biol. 2021, 28, 100222. DOI: 10.1016/j.cpb.2021.100222.

[6] Fan-lin, W. U.; De-hui, Q. U.; Wei, T. I. A. N.; WANG, M.-Y.; CHEN, F.-Y.; LI, K.-K.; Sun, Y.-D.; SU, Y.-H.; Yang, L.-N.; SU, H.-Y., et al. Transcriptome Analysis for Understanding the Mechanism of Dark Septate Endophyte S16 in Promoting the Growth and Nitrate Uptake of Sweet Cherry [J]. J. Integr. Agric. 2021, 20(7), 1819–1831.

[7] Kim, D.; Thanakkasaranee, S.; Lee, K.; Sadeghi, K., and Seo, J. Smart Packaging with temperature-dependent Gas Permeability Maintains the Quality of Cherry Tomatoes [J]. Food Biosci. 2021, 41, 100997. DOI: 10.1016/j.fbio.2021.100997.

[8] Villamor, D. E. V.; Pillai, S. S.; Eastwell, K. C. Systemic Infection and Symptom Development of agro-inoculated cDNA Clone of Cherry Rusty mottle-associated Virus in Sweet Cherry (Prunus Avium) [J]. Virus Res. 2021, 296, 198330. DOI: 10.1016/j.virusres.2021.198330.

[9] Hazel Álvez-Hernández, M.; Benito Martínez-Hernández, G.; Castillejo, N.; Martinez, J. A.; Artés-Hernández, F. Development of an Antifungal Active Packaging Containing Thymol and an Ethylene Scavenger. Validation during Storage of Cherry Tomatoes [J]. Food Pack. Shelf Life. 2021, 29, 100734. DOI: 10.1016/j.fspl.2021.100734.

[10] Zhang, Y.-L.; Cui, Q.-L.; Wang, Y.; Shi, F.; Liu, Y.-P.; Liu, J.-L., and Nie, G.-W. Effect of Carboxymethyl chitosan-gelatin-based Edible Coatings on the Quality and Antioxidant Properties of Sweet Cherry during Postharvest Storage [J]. Sci. Hortic. 2021, 289, 110462. DOI: 10.1016/j.scienta.2021.110462.

[11] Gonçalves, A. C.; Campos, G.; Pinto, E.; Oliveira, A. S.; Almeida, A.; de Pinho, P. G.; Alves, G., and Silva, L. R. Essential and non-essential Elements, and Volatile Organic Compounds for the Discrimination of twenty-three Sweet Cherry Cultivars from Fundão, Portugal [J]. Food Chem. 2022, 367, 130503. DOI: 10.1016/j.foodchem.2021.130503.
[12] Lahaye, M.; Tabi, W.; Le Bot, L.; Delaire, M.; Orsel, M.; Campoy, J. A.; Quero García, J., and Le Gall, S. Comparison of Cell Wall Chemical Evolution during the Development of Fruits of Two Contrasting Quality from Two Members of the Rosaceae Family: Apple and Sweet Cherry [J]. *Plant Physiol. Biochem.* 2021, 168, 93–104. DOI: 10.1016/j.plaphy.2021.10.002.

[13] Wähner, T. W.; Emeriewen, O. F.; Alexander, H. J.; Schneiders, H.; Vrijenhoek, I.; Halász, J.; Hrotkó, K.; Hoff, K. J.; Gabriel, L.; Lempe, J., et al. The Draft chromosome-level Genome Assembly of Tetraploid Ground Cherry (Prunus Fruticosa Pall.) from Long Reads [J]. *Genomics.* 10.1016/j.ygeno.2021.11.002. 2021, 113(6), 4173–4183.

[14] Fuentenalba, C.; Ejsmentewicz, T.; Campos-Vargas, R.; Saa, S.; Aliaga, O.; Chirinos, R.; Campos, D., and Pedreschi, R. Cell Wall and Metabolite Composition of Sweet Cherry Fruits from Two Cultivars with Contrasting Susceptibility to Surface Pitting during Storage [J]. *Food Chem.* 2021, 342, 128307. DOI: 10.1016/j.foodchem.2020.128307.

[15] Lamagna, A.; Reich, S.; Rodriguez, D.; Boselli, A.; Cicerone, D. The Use of an Electronic Nose to Characterize Emissions from a Highly Polluted River. *Sens. Actuators B Chem.* 2008, 131(1), 121–124. DOI: 10.1016/j.snb.2007.12.026.

[16] Zhu, L. M.; Seburg, R. A.; Tsai, E.; Puech, S.; Mifsud, J. C. Flavor Analysis in a Pharmaceutical Oral Solution Formulation Using an electronic-nose. *J. Pharm. Biomed. Anal.* 2004, 34(3), 453–461. DOI: 10.1016/S0731-7085(03)00651-4.

[17] Zhang, H. M.; Wang, J. Detection of Age and Insect Damage Incurred by Wheat, with an Electronic Nose. *J. Stored Prod. Res.* 2007, 43(4), 489–495. DOI: 10.1016/j.jspr.2007.01.004.

[18] Zheng, H.; Wang, S.; Ping, X.; Shao, C.; Zhou, H.; Xiang, B.; Li, J.; Lou, X.; Yi, X.; Guohua, H., et al. Study of Spinyhead Croaker (Collichthys Lucidus) Fat Content Forecasting Model Based on Electronic Nose and Non-linear Data Resolution Model[J]. *Food Anal. Methods.* 2019, 12(9), 1927–1937.

[19] Zheng, H.; Ying, X.; Wang, W.; Chen, Z.; Shao, C.; Zhou, H.; Wang, S.; Ping, X.; Li, J.; Yi, X., et al. Study of Sensitivity Evaluation on Ridgetail White Prawn (Exopalaemon Carinicauda) Quality Examination Methods. *Int. J. Food Prop.* 2019, 22(1), 942–951.

[20] Ning, J.; Ye, H.; Sun, Y.; Zhang, J.; Mei, Z.; Xiong, S.; Zhang, S.; Li, Y.; Hui, G.; Yi, X., et al Study on apple quality damage detecting method based on relaxation single-wavelength laser and convolutional neural network [J]. *Journal of Food Measurement and Characterization.* https://doi.org/10.1007/s11694-022-01429-8. 2022.

[21] Ameer, Q.; Adelouj, S. B. Polypyrrrole-based Electronic Noses for Environmental and Industrial Analysis. *Sens. Actuators B Chem.* 2005, 106, 541–552.

[22] Chennig, S.; Zheng, H.; Zhou, Z.; Li, J.; Lou, X.; Hui, G., and Zhao, Z. Ridgetail White Prawn (Exopalaemon Carinicauda) K Value Predicting Method by Using Electronic Nose Combined with Non-linear Data Analysis Model [J]. *Food Anal. Methods.* 2018, 11(11), 3121–3129.

[23] Zhiyi, H.; Chenchao, H.; Jiajia, Z.; Jian, L., and Guohua, H. Electronic Nose System Fabrication and Application in Large Yellow Croaker (Pseudosciaena Crocea) Farnessness Prediction [J]. *J. Food Meas. Charact.* 2017, 11(1), 33–40.

[24] Chanie, G. E.; Westad, F.; Jonsdottir, R.; Thalmann, C. R.; Basso, S.; Labreche, S.; Marcq, P.; Lundby, F.; Haugen, J. E. Prediction of Microbial and Sensory Quality of Cold Smoked Atlantic Salmon (Salmo Salar) by Electronic Nose. *J. Food Sci.* 2005, 70, 563–574.

[25] Jian, L.; Hailin, F.; Wei, L.; Gao, Y., and Hui, G. Design of A Portable Electronic Nose System and Application in K Value Prediction for Large Yellow Croaker (Pseudosciaena Crocea) [J]. *Food Anal. Methods.* 2016, 9(10), 2943–2951.

[26] Zheng, L.; Zhang, J.; Yu, Y.; Zhao, G., and Hui, G. Spinyhead Croaker (Collichthys Lucidus) Quality Determination Using multi-walled Carbon Nanotubes gas-ionization Sensor Array [J]. *J. Food Meas. Charact.* 2016, 10(2), 247–252.

[27] Liu, Y.; Feixiang, Z.; Bowei, Z.; Ruan, X.; Yi, X.; Li, J.; Gao, Y.; Hui, G. Effect of Sodium Lactate Coating Enriched with Nisin on Beef Strip Loins (M. Longissimus Lumborum) Quality during Cold Storage and Electronic Nose Rapid evaluation[J]. *J. Food Meas. Charact.* 2020, 14(6), 2998–3009. DOI: 10.1016/s11694-020-00548-4.

[28] Hui, G.; Lu, H.; Jiang, Z.; Zhu, D.; Wan, H. Study of small-cell Lung Cancer cell-based Sensor and Its Applications in Chemotherapy Effects Rapid Evaluation for Anticancer Drugs [J]. *Biosens. Bioelectron.* 2017, 97, 184–195. DOI: 10.1016/j.bios.2017.05.050.

[29] Determination of Reducing Sugar in Foods, (GB/T 5009.7-2008)