Biosensors and Bioelectronics: X 14 (2023) 100365

Contents lists available at ScienceDirect

Biosensors and Bioelectronics: X

journal homepage: www.journals.elsevier.com/biosensors-and-bioelectronics-x

Review on food quality assessment using machine learning and electronic nose system

Hassan Anwar[a,*], Talha Anwar[b], Shamas Murtaza[a]

[a] Department of Food Science and Technology, Faculty of Food and Home Sciences, MNS-University of Agriculture, Multan, 60000, Pakistan
[b] New Zealand College of Chiropractic, Auckland, 0600, New Zealand

ARTICLE INFO

Keywords:
Adulteration
Food quality assessment
Machine learning
Sensors

ABSTRACT

Quality evaluation in the food industry presents a significant challenge due to the necessity for high-cost equipment and extensive analysis to ensure that products reaching consumers are safe and of the highest quality. Existing technologies often require substantial resources, trained personnel, and complex analytical procedures, creating a demand for rapid, cost-effective solutions. Electronic nose technology is an emerging approach capable of detecting and differentiating between various aromas through an array of electronic sensors, demonstrating promising results when applied to diverse food items. Machine learning algorithms play a crucial role in analyzing the complex data collected by electronic nose systems, enabling accurate identification and assessment of food based on different odors. This review explores the combination of e-nose systems with machine learning algorithms, proposing a powerful nondestructive tool for food quality assessment. By integrating advanced data processing techniques with e-nose technology, this novel approach has shown the potential in overcoming traditional limitations related to subjectivity and time-consuming analysis procedures. Furthermore, the integration of electronic noses with machine learning applications is examined across key food categories such as meat, dairy, edible oil, fish, tea, and coffee products. Various case studies are presented to highlight the efficacy of this innovative method in addressing specific quality concerns within these sectors.

1. Introduction

Foodborne diseases affect millions of people and disrupt their daily lives. The world population is almost 7.8 billion, with 600 million suffering and 56 million dying yearly from different foodborne diseases (Ritchie and Roser, 2018). Common symptoms of foodborne diseases include nausea, diarrhea, abdominal cramps, headache, fever, and dizziness. Monitoring foodborne diseases is a fundamental component of food safety systems in developed countries.

The demand for accurate and rapid quality inspection of food commodities has increased significantly due to hygiene and safety considerations in the food supply chain. Highly perishable muscle foods such as meat, poultry, and fish are essential components of the human diet. Over the last few decades, food adulteration has become a common practice, especially in underdeveloped countries, posing a significant challenge to the food processing sector. Adulteration is the incorporation of cheaper substances with expensive ingredients. For adulteration, poisonous chemicals like calcium carbide and formalin are commonly used and found in dairy products, fish, meat and fruits (Gu et al., 2019; Li et al., 2018; Moosavy et al., 2019; Pandey, 2016). Other adulterants like urea, colour dyes and low qualities preservatives are used to increase the profit by compromising the quality. This can lead to chronic illnesses like liver disorders, cancer, and cardiovascular diseases. To overcome these issues, it is the need of time to monitor the food products throughout the entire food supply chain with an intelligent and low-cost system.

There are various methods to assess food quality. The most common and easy way is sensory evaluation but it can be biased and can be affected by human fatigue and mental state. Different lab scale techniques like microbial analysis, microscopic examination, gas chromatography-mass spectrometry, liquid chromatography, differential scanning calorimetry, Fourier Transform Infrared spectroscopy and nuclear magnetic resonance are used but most of these techniques are costly, time-consuming and required technical experts. Therefore, a low-cost, efficient, real-time rapid detection technique is required. Advancements in electronics, sensor technology and artificial intelligence (AI) have made it possible to develop instruments like the electronic nose (e-nose) system which is capable of characterizing quality factors

* Corresponding author.
E-mail address: hassan.anwarft@gmail.com (H. Anwar).

https://doi.org/10.1016/j.biosx.2023.100365
Received 31 March 2023; Received in revised form 15 May 2023; Accepted 1 June 2023
Available online 12 June 2023
2590-1370/© 2023 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

(Wilson and Baietto, 2009). The arrival of the e-nose system has provided a new option for non-destructive quality assessment of food commodities. It provides a rapid evaluation as compared to the conventional, high-cost time-consuming methods (Peris and Escuder-Gilabert, 2016).

In the 1980s research on machine olfaction led to the generally accepted definition of an e-nose as an instrument that comprised an array of heterogeneous electrochemical gas sensors with partial specificity and a pattern recognition system. An e-nose is an artificial olfactory system that is used for automated simulation of the sense of odor. It is cost-effective, portable, easy to handle and most importantly it provides analysis in a short time. E-nose instruments are feasible for several significant reasons such as relatively fast and small-sized headspace that can integrate easily into the current production process. Despite these benefits, there are still few applications of e-noses adopted in the food industry. This could be due to difficulties in the selection of the sensors and the need for pattern recognition algorithms which are difficult to embed in low-cost hardware devices. Regardless of these issues, the use of e-nose systems is still increasing rapidly and received notable significance in the food industry in the last few years. This progress coincides with an increased understanding of the biological mechanisms behind the human olfactory system (Loutfi et al., 2015). Keeping in view the advancement in the usage of e-nose in food quality assessment, this article focused on the latest development in the food quality domain. This paper specifically reviewed the progress of the e-nose system in the last 6 years in the following areas: meat, dairy, fish, edible oil, coffee and tea.

2. Electronic nose

All kinds of innovation are possible with inspiration. Image processing is inspired by the sense of sight, and the e-nose is inspired by the sense of smell. It is also known as a mechanical nose, aroma sensor, odor sensor, flavor sensor, artificial nose, odor sensing system and electronic olfactometry (Dymerski et al., 2011). The e-nose enables human beings to identify and grade food products with ease.

The human nose can analyze the quality of food before consumption and identify potential hazards. In many different industries like perfumes, cosmetics, pharmaceuticals and food; volatile components and food products are accessed by a sensory panel which is a group of people who fill out questionnaires based on the smell of these products. The human nose can rate an odor, but individual judgements vary based on biasness or other environmental factors. In addition, the human nose is not able to detect odorless toxic gases and has detection limits for gases. These limitations hinder the human nose from being a tool for all odor-related classification and discrimination.

An e-nose system consists of both software and hardware components. In e-nose, the released gases are absorbed by the sensor array that produces a signal. This signal can be differentiated using various statistical tools but with the advent of AI, machine learning (ML) algorithms are used to assess the food quality based on the signal.

3. Machine learning

The ability of a computer to learn without being programmed for a specific task is defined as machine learning and was first coined in 1959 (El Naqa and Murphy, 2015). Machine learning can be categorized into two main groups 1. Supervised Machine Learning, 2. Unsupervised Machine Learning.

In supervised machine learning, the input (features) and output (labels) of an event is known. The ML algorithm learns from the input and output, and next time they produce output when only the input is known. In the case of food quality assessment, the ML algorithm learns from input features which are sensor signals and output label which is food grade created by experts. The goal is to get the food grade during inference time when it is unknown and only input sensor signals are available.

Unsupervised machine learning uses a dataset with only inputs given and then the machine learning algorithm investigates the dataset and identifies the specific pattern by looking between data points. It clusters the data into groups, for example, it can group the freshness of a product into three categories i.e., fresh, semi-fresh, and spoiled. Owing to the fact, labels are unknown, there is no way to find the authenticity of the approach used as compared to supervised learning where we compared the predicted output with the actual output.

4. Application of electronic nose and machine learning models in food quality

Food quality is a vast domain, but this study focused mostly on reviewing the article related to freshness and adulteration of food products. Freshness is an issue related to a perishable commodity like meat, fish, vegetables, fruits, and milk while adulteration chances are high in nearly every food commodity like meat, oils, honey, dairy products, spices, tea and coffee. Table 1 summarizes the studies presented in this paper.

4.1. Meat

Meat is one of the best nutritional sources for human beings as it provides a good amount of protein which has a good amino acid profile and is consumed worldwide due to its good taste (Rahmati et al., 2016). The Organization for Economic Cooperation and Development and Food and Agriculture reported that the average annual global meat consumption crossed 327 million tons from 2018 to 2020 (Oecd/Fao, 2022). Unethical meat suppliers mix expensive meat with lower-priced meat like supplementing beef with pork meat due to differences in prices (Rohman, 2019). Forty-five million dollars loss occurred in Europe as beef was being adulterated with horse meat (Chen et al., 2020). In 2013, the horse meat scandal which was caused by the mixing of horse and beef meat shook the food chain supply of the European market (Premanandh, 2013). Besides this financial and economic loss, this fraudulent practice raised serious concerns about religion, ethics, public health and food safety.

In a study, PEN3 E-nose (Airsense Analytics GmbH, Schwerin, Germany) was used to collect data on adulterated meat. Fat and connective tissues were removed and then the sample was minced for 1 min in a blender. The minced beef was adulterated by mixing it with minced pork at seven distinct proportions by weight (0%, 10%, 20%, 30%, 40%, 50% and 60%). A novel framework called 1DCNN-RFR, combined a one-dimensional convolutional neural network (1DCNN) and a random forest regressor (RFR) is used for the quantitative detection of beef adulterated with pork. The 1DCNN backbone is responsible for extracting a sufficient number of features from the multichannel input matrix obtained from raw E-nose data, while the RFR enhances the regression performance due to its strong prediction ability. The effectiveness of the 1DCNN-RFR framework was demonstrated by comparing it to four other models; support vector regression model (SVR), RFR, backpropagation neural network (BPNN), and 1DCNN. The proposed 1DCNN-RFR framework outperformed the other models in the quantitative detection of beef adulterated with pork. The 1DCNN-RFR framework achieved an R2 of 0.9977, a root mean square error (RMSE) of 0.9491, and a mean square error (MSE) of 0.4619 (Huang and Gu, 2022).

Fresh steaks of beef and pork were purchased and minced separately using a commercial blender. Minced beef and pork samples were then adulterated at levels ranging from 0 to 100 at a 20% increment in each level. Data was collected using an e-nose made of a colorimetric sensor array, a reaction chamber, a camera and a computer. The researchers used Fisher linear discriminant analysis (F-LDA) and extreme learning machine (ELM) for the identification of ground pure beef, beef-pork mixtures, and pure pork. The results revealed that the ELM model

Table 1
Shows the classification and regression outcomes obtained from various machine learning models in previous research on food products.

Authors	Products	Techniques	Results
Meat			
Huang, C. and Gu, Y. (2022)	Beef adulteration with pork	1DCNN-RFR	R^2 0.997 RMSE 0.9491, MSE 0.4619
Han et al. (2020)	Beef adulteration with pork	ELM	87.5% accuracy
Sarno et al. (2020)	Beef adulteration with pork	SVM	98.10% accuracy
Tian et al. (2019)	Minced mutton with pork	CDA	93.10% accuracy
Wang et al. (2019)	Mutton adulteration with duck	LDA, multilayer perceptron network.	98.2%, 96.5% accuracy
Feyzioglu and Taspinar (2023)	Beef Spoilage	ANN	100% accuracy
Wijaya et al. (2022)	Beef spoilage	AdaBoost	99.8% accuracy
Wijaya et al. (2021)	Beef spoilage	DWT-LSTM, LTSM, SVM, KNN, LDA	Accuracy 94.83%, 85.14%,84.88%, 77.73%, 76.82
Anwar and Anwar (2021)	Beef Spoilage	Auto ML	Accuracy 96.4%
Mirzaee-Ghaleh et al. (2020)	Chicken freshness	KNN	Fresh chicken 95.2, and thawed 94.7% accuracy
Dairy			
Tohidi et al. (2018a)	Milk is adulterated with detergent	SVM	90% accuracy
Tohidi et al. (2018b)	Milk is adulterated with CH_2O, H_2O_2, NaClO	SVM	94.64%, 92.85%, 87.75% accuracy for CH_2O, H_2O_2, NaClO
Ayari et al. (2018a)	Ghee is adulterated with sunflower oil and cow body fat.	ANN	91.3% for sunflower oil and 82.5% for cow body fat.
Ayari et al. (2018b)	Margarine is mixed with cow ghee.	ANN	85.6% accuracy
Mu et al. (2020)	Milk quality is measured based on fat and protein.	RF regressor	R^2 0.9301 for fat and 0.9399 for protein
Putra et al. (2018)	Milk spoilage	Neural network	83% accuracy
Fish			
Grassi et al. (2019)	Fish spoilage	KNN and PLS-DA	83.3% and 84.4% accuracy
Vajdi et al. (2019)	Fish spoilage	Multilayer perceptron neural network and hyper disk model maximum margin optimum.	96.87% and 100%. accuracy
Grassi et al. (2022)	Fish products shelf life	KNN	100% accuracy
Edible Oil			
Wei et al. (2018)	Peony oil adulteration with low priced oil.	PCA	85% variance.
Zarezadeh et al. (2021)	Extra virgin olive oil adulteration with frying oil	Gradient Boosting Classifier, Naïve Bayes and SVM.	97.75%, 95.51% and 95.51% accuracy
Karami et al., 2020	Fresh sunflower oil is adulterated with expired oil.	ANN	Accuracy 96.5%
Karami et al., 2020	Shelf life of oil	SVM, Quadratic discriminant analysis and LDA	96.25%, 95.8% and 94.4% accuracy
Coffee			
Gonzalez Viejo et al., 2021	Coffee aroma	ANN	98% accuracy
Thazin et al., 2018	Coffee quality based on acidity level	ANN	95% accuracy
Wakhid et al. (2020)	Coffee classification based on civet and non-civet.	Decision tree	97% accuracy
Cui et al. (2020)	Composition of the volatile compound were explored at roasted, ground and brewed coffee.	PCA	97.3%, 92.5% and 93.8% variance respectively
Tea			
Chen et al. (2022)	Black Tea aroma	FDA and LDA.	95.2% and 78.6% accuracy.
Xu et al. (2021)	Black Tea leaf and tea infusion	SVM coupled with LDA	86% for tea leave and 91% for infusion.
Liu et al. (2019)	Green tea	MBPNN, SVM and RF	99%, 99% and 97% accuracy.

built was superior to the F-LDA model, with identification rates of 91.27% and 87.5% in the training and prediction sets, respectively. ELM is a feed-forward neural network characterized by high learning efficiency. For predicting the level of adulteration, the back propagation-artificial neural network (BP-ANN) model built showed a R^2 of 0.85 and an RMSE of 0.147 in the prediction set. The study concluded that the low-cost e-nose based on colorimetric sensors, coupled with chemometrics, has great potential in rapidly detecting beef adulterated with pork (Han et al., 2020).

Sarno et al. (2020) prepared beef samples mixed with pork in seven classes. First class was 100% beef while 7th was 100% pork. While other classes consisted of 10%, 20%, 50%, 75%, and 90% of beef in a 100-g sample respectively. Samples testing was carried out for 15 min for each sample using an e-nose consisting of nine MQ series sensors to detect different types of gasses. The sensors used were MQ2, MQ4, MQ6, MQ9, MQ135, MQ136, MQ137, MQ138 and a temperature sensor DHT 22. Researchers proposed the Optimized E-nose System (OENS) to accurately detect pork adulteration in beef. OENS offers several advantages, including proper noise filtering, an optimized sensor array, and optimized Support Vector Machine (SVM) parameters. Noise filtering was conducted through cross-validation with various mother wavelets, including Haar, coiflet, symlet, and Daubechies, which has been found to increase classification accuracy by 1%. The sensor array was optimized through principal component analysis (PCA), a dimensionality reduction technique, which effectively reduces the number feature size. The classification test results demonstrated an accuracy of 98.10% using the optimized SVM, indicating that OENS has a favorable performance for detecting pork adulteration in beef and is suitable for halal authentication (Sarno et al., 2020).

Minced mutton was adulterated with pork and odor was detected by utilizing a PEN 2 E-nose system composed of 10 sensors to identify the presence of pork in minced mutton samples. The data collection time by an e-nose was 80 s. The meat samples were stored at -18 °C before processing. Fat and connective tissues were removed from the samples, which were then cut into 1 cm^3 cubes and minced for 2 min. Adulterated mutton samples were prepared by mixing minced pork at levels of 0%, 20%, 40%, 60%, 80%, and 100% by weight with minced mutton. The optimized detection parameters for the E-nose system include placement of 10g of minced meat in a 250 mL beaker at 25 °C $\pm$ 3 °C for 30 min. The study utilized canonical discriminant analysis (CDA) and Bayesian discriminant analysis to analyze the data collected by the E-nose system. The results showed that the error rate was 10.835% when using CDA-linear discriminant function and the same error rate was observed when using the CDA-quadratic discriminant function. However, the Bayesian discriminant analysis yielded a lower error rate of 5.83% and the average percentage of misclassified samples was 9.16%. The system could collect data within 80 s and provide reliable results with a low error rate (Tian et al., 2019).

Wang et al. (2019) developed a method to reduce adulteration in meats by employing an E-nose and gas chromatography-mass spectrometer to identify adulterants in mutton. The study focused on duck meat as a model adulterant due to its lower cost, similarity in flavor to mutton, and frequent cases of adulteration in China. The researchers conducted qualitative and quantitative analysis using linear regression, F-LDA, and multilayer perceptron neural networks analysis (MLPN) on e-nose signals. The PEN 3 (AIRSENSE Analytics GmbH) e-nose system was used to collect data for 60 s, and this information was then processed through F-LDA classifier and multilayer perceptron network, reaching an accuracy of 98.2% and 96.5%, respectively. Additionally, GC-MS was employed to identify several fingerprint volatile organic chemicals to validate the e-nose results. Researchers performed multivariate partial least squares regression to study the relationships between GC-MS and e-nose. The results of GC-MS confirmed the effectiveness of E-nose in identifying duck adulteration in mutton, with a minimum detection ratio of 10%. The study demonstrated that rapid detection of mutton adulterated with duck meat using e-nose has high accuracy, significantly reducing detection time and improving detection efficiency (Wang et al., 2019).

The research discussed above is about the adulteration of different meat products. E-nose has also been widely used in shelf-life assessment. The main factor that consumers consider while choosing meat is aroma and color of which aroma is a more reliable indicator of quality. Simple sensory evaluation is not enough to determine that meat has passed its shelf life. As lab techniques like microbial count, gas chromatography and high-pressure liquid chromatography are time-consuming and required huge resources, therefore, industry requires a robust system to detect the quality of meat. For this purpose, e-nose is used to detect the freshness of meat and has achieved significant performance.

In a study conducted by Feyzioglu and Taspinar (2023), e-nose was used to identify the freshness of various beef cuts. The dataset used in the research consisted of four classes representing the quality of beef: excellent, good, acceptable, and spoiled. The Analysis of Variance method (ANOVA) was employed to determine the active features within the dataset, which contained data on 12 features. Subsequently, three active features that is total viable count, MQ137 and MQ5 were selected through ANOVA for classification purposes. Machine learning methods Artificial neural network (ANN), K nearest neighbor (KNN), and Logistic Regression (LR) were utilized for classification. The experimental results revealed that ANN achieved a classification accuracy of up to 100% using data obtained from all 12 cuts. Meanwhile, KNN and LR yielded accuracies of 98.8% and 98.6%, respectively (Feyzioglu and Taspinar, 2023).

Beef freshness was analyzed using an e-nose from fresh to spoiled. The researcher found that Adaboost got 99.8% accuracy while classifying beef from fresh to spoiled. The e-nose system that was employed to collect data consisted of the following 11 MQ sensors: MQ2, MQ3, MQ4, MQ5, MQ6, MQ8, MQ9, Mq135, MQ136, MQ137, MQ138 (Wijaya et al., 2022). With the same e-nose system, the authors collected beef data for spoilage detection. Different machine learning algorithms like linear discriminant analysis (LDA), KNN, SVM, long short-term memory (LSTM) and discrete wavelet transform-based LSTM network were used and achieved an accuracy of 76.82%, 77.73%, 84.88%, 85.14% and 94.83% respectively (Wijaya et al., 2021).

AutoML was also used to assess beef quality as it automates the workflow of a machine and eliminates the expertise of machine learning. An e-nose system composed of MQ135, MQ136, MQ2, MQ4, MQ6, MQ9 and DHT 22 was used to detect gasses from beef during the decay process. PCA was employed for dimensionality reduction, which helped remove noise from the data. The reduced data was then fed to AutoML, resulting in good performance in categorizing beef into fresh, semi-fresh, and spoiled classes. AutoML achieved an impressive 96.4% accuracy in classifying beef quality, demonstrating its effectiveness as a method for assessing meat quality (Anwar and Anwar, 2021).

The study by Mirzaee-Ghaleh et al. (2020) investigates the capability of an e-nose system, equipped with eight metal oxide semiconductor (MOS) sensors, to classify chilled and frozen-thawed chicken meat. Thawing loses important nutrients and fresh chicken demand is higher among people. The study highlighted the use of e-nose technology combined with the fuzzy KNN algorithm for intelligent classification of chicken meat samples. The sensors used in this study were from the MQ and TGS series, including MQ3, MQ9, MQ135, TGS822, TGS813, and TGS2620. The results demonstrated the high performance of the F–KNN algorithm, achieving an average accuracy of 95.2% for the classification of fresh-chilled chicken meat and 94.67% for frozen-thawed chicken meat (Mirzaee-Ghaleh et al., 2020).

The results achieved above show that an e-nose coupled with machine learning algorithms is a promising tool for quality evaluation like freshness, spoilage, and adulteration detection in meat.

4.2. Milk and dairy products

Milk plays an important role in human nutrition due to a good amount of protein, carbohydrates, fat, minerals and vitamins. Due to its high nutrition profile and consumption especially in children, the demand is high. The growing dairy market is facing adulteration issues by dishonest vendors and producers which leads to health issues. Different adulterations in milk are added for different purposes like water addition to increase its volume, and urea to increase protein. The detergent is added to raw milk as a regulator or coating of milk acidity. The use of detergent is harmful to human health and causes severe health issues.

An e-nose, comprising eight MOS gas sensors namely MQ3, MQ8, MQ136, TGS2602, TGS2620, TGS813, TGS 822 and a temperature humidity sensor; sensirion SHT75 sensor, was designed and assessed for its ability to detect formalin, hydrogen peroxide, and sodium hypochlorite in raw milk. The mixing ratio was 0.03%, 0.05%, 0.1%, 0.2% and 0.3% by weight. Sensor array responses were processed and then features were extracted for pattern recognition models. PCA demonstrated that the first two principal components (PC1 and PC2) accounted for 97%, 87%, and 83% of the variance within data for formalin, hydrogen peroxide, and sodium hypochlorite, respectively. LDA yielded relatively low classification accuracies of 79.16%, 70.83%, and 66.66% for these adulterants, respectively. In contrast, SVM achieved accuracy values of 94.64%, 92.85%, and 87.75% for formalin, hydrogen peroxide, and sodium hypochlorite, respectively. These findings indicate that an artificial nose, when coupled with pattern recognition techniques, can effectively detect these adulterants in raw milk (Tohidi et al., 2018a).

Acceptability of raw milk in dairy processing plants is based on microbiological load. Adulterants like hydrogen peroxide and formaldehyde were added to reduce microbial count (Jeong et al., 2015). Formalin, sodium hypochlorite, and hydrogen peroxide in raw milk were detected using an e-nose system. The equipment was made of SP3-AQ2, MQ3, MQ8, MQ136, TGS813, TGS822, TGS2602 and TGS 2620 sensors. Eight levels of hydrogen peroxide (0%, 0.01%, 0.02%, 0.03%, 0.05%, 0.1%, 0.2% and 0.3% were added to raw milk. Similarly, eight level of formalin (0%, 0.01%, 0.02%, 0.03%, 0.04%, 0.05%, 0.1%, and 0.2%) and seven level of sodium hypochlorite (0%, 0.05%, 0.08%, 0.1%, 0.2% and 0.3%) were tested. SVM showed an overall accuracy of 94.64%, 92.85% and 87.75% for formalin, hydrogen peroxide and sodium hypochlorite respectively. LDA showed low classification accuracy and resulted in a decrement in accuracy by 15.48%, 22.02% and 21.1% respectively (Tohidi et al., 2018a).

Clarified butter or cow ghee is a nutritive dairy product. It is an effective compound in increasing memory, muscular power and power to control senses (Kaushik et al., 2016). Ghee is an expensive commodity obtained from milk and its price is 7–10 times higher than edible vegetable oil. Therefore, ghee is prone to adulteration and has an adverse effect on health.

In a study, sunflower oil and cow body fat were heated for 10 min at 40–50 Celsius. E-nose system was used to analyze various levels of sunflower oil and cow body fat mixed with pure cow ghee (10%, 20%, 30%, 40%, and 50%). This e-nose was based on eight MOS sensors, including TGS (TGS813, TGS 822, TGS2602, TGS 2620) and MQ (MQ3, MQ9, MQ135, and MQ136) series sensors. The study utilized PCA and ANN methods to classify different levels of adulteration in cow ghee. The results of this research revealed that the PCA variance for sunflower oil and cow body fat was 96% and 97% respectively. Furthermore, ANNs successfully identified adulteration with sunflower oil and cow body fat with accuracies of 91.3% and 82.5%, respectively (Ayari et al., 2018a). The same researcher used the same e-nose to detect mixing of margarine in ghee. Data gathered from these sensors is analyzed using PCA and ANN. In this study, PCA analysis accounted for 98% of the total variance in the data set. ANN, on the other hand, achieved an accuracy rate of 85.6%. These findings underscore the potential of e-nose systems as an effective and reliable method for identifying adulteration in cow ghee samples (Ayari et al., 2018b).

Researchers employed e-nose consisting of seven MOS sensors: TGS822, TGS826, TGS832, TGS 2600, TGS2602, TGS2611 and TGS2620 to identify milk sources (dairy farms) and estimate the content of milk fat and protein, which are crucial indicators of milk quality. The e-nose was used in conjunction with machine learning algorithms, such as LR, SVM, and Random Forest (RF), to construct classification models for milk source identification. The results showed that the SVM model based on fusion features after LDA had the best performance, with an accuracy of 95%. The RF regressor model exhibited the best performance, yielding R^2 values of 0.9399 for milk fat and 0.9301 for milk protein. This study provides a strong technical foundation for predicting milk quality using non-destructive and cost-effective methods (Mu et al., 2020).

In a study, researchers employed a sensor system consisting of an array of semiconductor gas sensors, including MQ136, MQ137, and TGS 2602. These sensors have been shown to produce consistent responses in detecting the odor of milk samples. Milk samples were categorized into three groups: fresh (less than 6 h old), sour (6–16 h old), and spoiled (more than 16 h old). The gas sensor array was used to collect data from these samples, and the neural network was trained to recognize patterns associated with each category of milk quality. The study achieved an accuracy rate of 83% in assessing the quality of fresh, sour, and spoiled milk. The success rate of 83% demonstrated the feasibility of this approach, and future research could further improve the accuracy of the sensor system by incorporating additional data, such as the number of microorganisms present in the milk samples (Putra et al., 2018).

These studies show that the e-nose system has great potential to evaluate the quality of milk and dairy products using a machine learning algorithm.

4.3. Fish and seafood

Fish is one of the best sources of protein and nutrients and provides omega 3 and boosts immunity. Fish quality evaluation is an important parameter to check whether fish is safe for consumption or not. The increasing demand for quality and safety in the seafood industry has led researchers to explore innovative and rapid methods to monitor the freshness of various seafood products. In recent years, e-nose systems have emerged as a promising tool for assessing the freshness of seafood, particularly in the large-scale distribution chain.

Grassi et al. (2022) developed an e-nose system that employed a combination of four MOS sensors, a photoionization detector, and two electrochemical cells to monitor the freshness of three different seafood products: sole (Solea senegalensis) fillets, red mullet (Mullus barbatus) fillets, and cuttlefish (Seppia officinalis). The K-means partitional clustering method was applied to group samples into three freshness classes, then confirmed by microbial analysis. Two classification models based on KNN and partial least square-discriminant analysis (PLS-DA) were developed to classify the freshness of the seafood regardless of species. The KNN model provided 100% overall sensitivity, specificity, and precision in prediction, confirming the applicability of the e-nose system for informing retailers on product safety and quality (Grassi et al., 2022). Salmon and plaice fish samples were obtained and kept at low-temperature and classified as acceptable, unspoiled and spoiled. E-nose used in this study consisted of GGS sensors; GGS1430, GGS1530, GGS 2530, GGS4430, GGS3530, GGS5430, GGS6530, GGS7330, GGS8530 and GGS10530. KNN classifier achieved an accuracy of 83.3% while PLS-DA accuracy was 84%. Although algorithms sometimes misclassify acceptable and unspoiled, none of the spoiled fish was classified as acceptable and unspoiled (Grassi et al., 2019).

E-nose was developed to classify fish freshness during cold storage, utilizing seven sensors namely TGS813, TGS822, TGS825, TGS826, TGS831, TGS832 and TGS880 that detect fish volatiles. The study involved conducting total viable count and total volatile base nitrogen analyses to indicate fish quality status. Fish headspace was sampled, and patterns were obtained during a 15-day storage period at room temperature. Different odor parameters were selected, reduced to 5-dimensional vectors using PCA, and clustered samples into fresh, semi-fresh, and spoiled categories. The multilayer perceptron neural network and hyper disk model maximum margin optimum classifier were utilized for fish spoilage classification, yielding 96.87% and 100% accuracy, respectively (Vajdi et al., 2019).

The results demonstrated that the e-nose technology has the potential to be a promising tool in the food industry for diagnosing fish spoilage. KNN and hyper disk model maximum margin optimum classifier pattern recognition methods proved to be superior in modeling fish spoilage, providing the highest correct rates in the classification of test samples.

4.4. Edible oil

Tree peony, a well-known wood has been exploited as an oil seed plant (Xue et al., 2015). 90% of the oil is unsaturated fatty acids out of which α-linolenic acid constitutes up to 40% of the oil. α-linolenic acid is very important for human health as it protects against rheumatoid arthritis, ischemic heart diseases, stroke and cancer (Su et al., 2016). Wei et al. (2018) investigated the fatty acid composition of peony seed oil and its adulteration with four less expensive edible oils (soybean oil, corn oil, sunflower oil, and rapeseed oil) using gas chromatography-mass spectrometry and e-nose. Their study employed iodine values to estimate the extent of adulteration and utilized an e-nose combined with PCA or LDA for assessment. The results revealed that the iodine value of peony seed oil is capable of detecting some adulterants, but could not detect all four potential adulterants. In contrast, the E-nose rapidly identified adulterated peony seed oil by sampling vapor. Data analyses using PCA and LDA demonstrated that LDA was more effective in clustering data and discriminating between pure and adulterated oil, capable of detecting adulteration at the 10% level. This study concluded that the E-nose combined with LDA is a suitable method for detecting peony seed oil adulteration, even at very low (10%) levels, suggesting its potential as a rapid detection tool for adulterants in peony seed oil. The application of the PEN 3 E-nose in this study, along with PCA, showed an 85% cumulative variance, further highlighting the effectiveness of this method. (Wei et al., 2018).

Extra virgin olive oil (EVOO) is known for its oxidative stability, nutritional value, aroma and taste. Extra virgin olive oil is quite expensive and is often adulterated. Zarezadeh et al. (2021) detected extra virgin olive oil adulteration by using e-nose. EVOO was mixed with low price frying oil like canola oil, sunflower oil, and corn oil and the concentration used was set to 5%, 10%, 20%, 35% and 50% in mass. Gradient boosting classifier (GBC), SVM, LR, ANN, Naïve Bayes, KNN and AdaBoost were used to detect the adulteration. GBC achieved the highest accuracy among all classifiers with an accuracy of 97.75%. The accuracy of other classifiers is lower than GBC performance. AdaBoost resulted in the lowest accuracy among all which is 69.7%. E-nose employed in this study consisted of 5 MQ sensors namely MQ3, MQ4, MQ8, MQ135, and MQ136, two TGS sensors were TGS813, TGS822 and one FIS sensor (Zarezadeh et al., 2021).

Sunflower, soy and canola mixed oil with new production date and expiry date were procured. Five oil samples were made. The first sample is 100% fresh oil, the second, third and fourth ones contain 25, 50 and 75% oxidized oil while the last one is 100% oxidized. Data was collected via e-nose consisting of MQ3, MQ9, MQ135, MQ136 and TGS 813, TGS822, TGS2602 and TGS2620. ANN was used to classify the oil with an accuracy of 94.5% for fresh and 96.5% for oxidized. While for the 2nd, 3rd and 4th samples the classifier gave an accuracy of 96.5%, 97.3% and 96.2% respectively (Karami, et al., 2020).

The shelf life of edible oil was determined using a non-destructive method of e-nose and compared with the AOCS official method. Edible oil samples were purchased from a local market and stored for five months under normal conditions to determine their shelf life. The oil data was collected by an e-nose equipped with 8 MOS sensors namely MQ3, MQ136, MQ9, MQ135, TGS813, TGS822, TGS2602 and TGS2620. The study focused on two types of oil samples: newly-produced oils and those produced 6 months prior, assessing them for 150 days. Various data analysis methods were employed, including cluster analysis, LDA, quadratic discriminant analysis (QDA), SVM, and the AOCS official method. Based on the results, the classification accuracy of SVM, QDA, and LDA methods was 96.25%, 95.8%, and 94.4% respectively, all of which were consistent with the American Oil Chemists' Society (AOCS) results (Karami et al., 2020b).

The use of e-nose as a rapid detection tool for adulteration and shelf life determination of edible oils offers numerous benefits. However, the effectiveness of the method varies depending on the type and concentration of adulterants, as well as the classification algorithm used. The E-nose combined with LDA proved to be effective in detecting adulterants in peony seed oil, while GBC achieved the highest accuracy in detecting extra virgin olive oil adulteration. SVM, QDA, and LDA methods provided consistent results for determining the shelf life of edible oils.

4.5. Coffee

Considering the hot drinks category in 2020, coffee accounted for 52% of the total volume. Flavor and aroma are the most important organoleptic attributes for consumers when purchasing coffee (Flambeau et al., 2017; Sberveglieri et al., 2014). These characteristics are mainly dependent on coffee provenance and variety as well as the roasting process, temperature and time (Severini et al., 2015).

In a study, coffee intensity and aroma were measured using an e-nose and machine learning model. The e-nose used consisted of multiple sensors i.e., MQ3, MQ4, MQ7, MQ8, MQ135, MQ136, MQ137, MQ138 and MG811. Two different ANN models were used in the study. One model classified the sample into low, medium, and high intensity. Model 2 predicted the relative abundance of 45 different aromas. The proposed model effectively estimated the intensity of coffee with high accuracy of 98% and depicted the specific aroma with a high correlation coefficient of 0.99 (Gonzalez Viejo et al., 2021).

Researchers used e-nose, which consisted of an array of eight different semiconductor gas sensors. It was able to classify the acidity levels of various roasting degrees and produced results nearly identical to those obtained by human testers. The study highlighted the e-nose's capability for integration into gourmet robots, exploring its potential applications in robotic baristas, such as its ability to classify acidity levels and predict values according to human sourness level scores with around 95% accuracy using ANN. Moreover, the e-nose revealed that the temperature of liquid coffee had a significant effect on the coffee's aroma and taste. Thus, the e-nose technology showed great promise in enabling robotic chefs and baristas to possess the sense of smell and perform tasks once limited to humans, such as food tasting. (Thazin et al., 2018).

In another study, an e-nose was utilized to detect and classify the aroma of two types of coffee, Arabica and Robusta, based on gas data collected through the MQ135 sensor. The coffee samples were diluted for 20 min, yielding 288 gas data points, which were then classified using SVM and perceptron methods. Factors such as the distance between the sensor and the coffee, as well as the conditions within and outside the coffee container, greatly influenced the signal results obtained. From the 288 experiments conducted, the SVM and Perceptron methods achieved an accuracy of 71% and 57%, respectively, in classifying the coffee aromas, which shows potential of e-nose in classifying types of coffee. In the future more sensors and ensemble learning can enhance the accuracy for classifying coffee aroma (Magfira and Sarno, 2018).

In recent years, the demand for civet coffee has grown significantly due to its unique flavor and exclusivity. However, this high economic value has led to a proliferation of counterfeit products, making it essential to develop methods for detecting and distinguishing between genuine civet coffee and non-civet coffee. The present study investigated the use of e-nose for this purpose, utilizing sensors namely MQ2, MQ3, MQ4, MQ7 and MQ135. Six classes were created; Aceh civet coffee, Aceh non-civet coffee, Bengkulu civet coffee, Bengkulu non-civet coffee, Arjuno civet coffee and Arjuno non-civet coffee. The e-nose data was analyzed using different combinations of classification methods and statistical parameters, such as DT, LR, Naive Bayes, and SVM. The results demonstrated that the e-nose was capable of accurately recognizing and distinguishing between civet and non-civet coffee. Decision tree algorithm fed with average and standard deviation features achieved the best results. This combination yielded an impressive 97% accuracy for the six-class comparison, while a two-class (civet and non-civet coffee) comparison achieved 100% accuracy. Although the study presents promising findings, future research could explore the classification of more diverse coffee samples, such as mixtures of civet and non-civet coffee from different regions, to further improve detection methods and safeguard the integrity of the civet coffee market (Wakhid et al., 2020).

FOXα4000, Alpha MOS e-nose was used to explore the composition of volatile organic compounds in coffee at three different conditions i.e., roasted, ground powder and brewed coffee. PCA shows 97.3%, 92.5%, and 93.8% variances in roasted, ground powder, and brewed coffee, respectively (Cui et al., 2020).

It has been seen that e-nose has good potential while determining coffee quality using ANN and DT.

4.6. Tea

Tea is one of the most popular and widely consumed non-alcoholic beverages around the globe. Due to its abundant health-benefiting compound, it has been extensively explored. It contains amino acids, polyphenols, catechins and theanine that may help to prevent cardiovascular diseases, and gastritis and prevents oxidation (Xu et al., 2019).

Aroma analysis of black tea infusions was conducted using an e-nose system (Alpha M.O.S., Toulouse, France). Different incubation temperature, time and sample volume were three main factors that were evaluated to obtain good chromatographic information. F-LDA effectively classified the aroma quality of tea with 95.2% accuracy while PLS-DA was less effective comparatively and got an accuracy of 78.6% (Chen et al., 2022).

Electronic nose system (PEN3, Airsense Corporation, Germany) was used to evaluate tea quality grades by detecting different compounds of tea leaves and tea infusion samples. Longjing tea samples were plucked from March to May by skilled workers. Tea grade of Longjing tea is related to its plucking time and the tea leaves picked earlier means a higher tea grade and better price. Tea leaf samples were prepared by placing 5-g tea leaves in a 500 ml beaker. Tea infusion samples were prepared by pouring 250 ml boiled water into a 500 ml beaker with 5-g tea leaves and brewed for 5 min. E-nose data was then classified using SVM and LR. For tea leaf, LR gave 83% accuracy while for tea infusion the accuracy was reduced to 72%. If data dimension was reduced by LDA and classified using LR, then tea leaf and tea infusion accuracies were increased to 86% and 88% respectively. In the case of SVM, the accuracy was 86% for tea leaf and 85% for tea infusion. LDA reduced data with SVM had the same accuracy for tea leaf; the accuracy for tea infusion was increased by 6% (Xu et al., 2021).

Liu et al. (2019) explored the effectiveness of e-noses in classifying and evaluating organic green teas of different quality grades. The study utilized a multi-task model based on the back propagation neural network (MBPNN) alongside RF and SVM for classification, and partial least squares regression (PLSR), kernel ridge regression (KRR), and SVR for price regression. The E-nose system used in the study comprised various sensors, including W1C, W3C, W5C, W1S, W2S, W3S, W5S, W6S, W1W, and W2W. The results demonstrated that traditional PCA or LDA methods were insufficient for achieving a clear identification of tea quality grades. However, the MBPNN, SVM achieved 99% and RF exhibited 97% accuracy showing excellent performance in classification tasks. The PLSR model, on the other hand, showed poor price prediction for different tea quality grades, while the MBPNN model outperformed other nonlinear multivariate regression analyses, such as KRR and SVR. The proposed MBPNN model proved effective in representing the nonlinear relationship between aroma information and quality information of tea. It is capable of simultaneously classifying tea grades and predicting tea prices with remarkable performance. The study concluded that e-noses, when paired with an optimal pattern recognition algorithm, can be employed for classification and regression prediction of organic green teas (Liu et al., 2019).

5. Challenges and future Prospective

The promising results achieved by e-nose technology and machine learning algorithms in food quality assessment have paved the way for further exploration and development of these tools. Nevertheless, there are several challenges and future trends that need to be addressed to enhance the performance, applicability, and acceptance of e-nose devices in the food industry.

One of the main challenges faced by e-nose technology is the inability to recognize individual chemical compounds within gas odors, as well as the adverse implications of humidity and temperature on sensor responses. To overcome these limitations, research should focus on improving sensor selectivity and stability by developing new sensing materials, such as nanomaterials or hybrid materials, that can offer better discrimination performance and resistance to environmental factors.

E-noses may not entirely replace conventional analytical devices; however, they can complement them by providing rapid real-time detection and discrimination solutions. Future research should aim at integrating e-nose technologies with conventional analytical instruments like gas chromatography or mass spectrometry, which could provide more detailed information about gas mixture attributes and improve overall analysis.

A significant challenge for e-nose applications is the reluctance of some industrial partners to adopt new sensing techniques in their existing systems. To increase the acceptance of e-nose technology in industrial applications, efforts must be made to develop user-friendly devices with increased reliability and long-term durability. This includes addressing issues such as boundary properties, size differences, uniformity in gas concentrations, and thickness of sensing materials.

To further improve the performance of e-nose systems in food quality assessment, advanced machine learning algorithms should be explored and developed. This includes addressing the robustness of models to tackle sensor selectivity issues and developing algorithms that can efficiently handle large amounts of data generated by e-nose devices. Further such machine learning models need to be developed that can easily be integrated into embedded devices.

6. Conclusions

In recent years, a number of studies investigated the application of e-nose in the area of food quality assessment such as food adulteration and freshness measurement. These studies highlighted that significant improvement has been made regarding food quality assessment using e-nose and machine learning. The reason for the increasing trend in e-nose related studies and usage is due to the low cost and reproducibility of the system, improved performance and no need for human involvement to judge food quality. The latter two advantages are because of advancements in machine learning that improved the accuracy and reduced the biases involved in the manual assessment and human error. This paper studied the impact of the utilization of different combinations of gas sensors and machine learning models. Though the results in existing studies are quite promising, there is a need of making one window system for data collection by e-nose and quality assessment with machine learning.

Authors contribution

Hassan Anwar: conceptualization, drafted the manuscript and carried out revisions. Talha Anwar: conceptualization and revised the manuscript, Mian Shamas Murtaza: reviewed and edited the manuscript.

Funding

No funding was received for this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Anwar, T., Anwar, H., 2021. Proceedings of the 2021 Mohammad Ali Jinnah University International conference on computing. MAJICC 2021, 1–4.
Ayari, F., Mirzaee-Ghaleh, E., Rabbani, H., Heidarbeigi, K., 2018a. Int. J. Food Prop. 21, 1670–1679.
Ayari, F., Mirzaee- Ghaleh, E., Rabbani, H., Heidarbeigi, K., 2018b. J. Food Process. Eng. 41, e12806.
Chen, J., Yang, Y., Deng, Y., Liu, Z., Xie, J., Shen, S., Yuan, H., Jiang, Y., 2022. LWT 153, 112496.
Chen, X., Lu, L., Xiong, Xiaohui, Xiong, Xiong, Liu, Y., 2020. Sci. Rep. 10, 1–10.
Cui, D.D., Liu, Y., Chen, Y.P., Feng, X., Lu, Y., Yu, B., 2020. Flavour Fragrance J. 35, 541–560.
Dymerski, T.M., Chmiel, T.M., Wardencki, W., 2011. Invited Review Article: an odor-sensing system-powerful technique for foodstuff studies. Rev. Sci. Instrum. 82, 111101.
El Naqa, I., Murphy, M.J., 2015. What is machine learning?. In: Machine Learning in Radiation Oncology. Springer International Publishing, pp. 3–11, 2015.
Feyzioglu, A., Taspinar, Y.S., 2023. Sensors 23, 2222.
Flambeau, K.J., Lee, W.J., Yoon, J., 2017. Food Sci. Biotechnol. 26, 1245–1254.
Gonzalez Viejo, C., Tongson, E., Fuentes, S., 2021. Sensors 21, 2016.
Grassi, S., Benedetti, S., Magnani, L., Pianezzola, A., Buratti, S., 2022. Food Control 138, 108994.
Grassi, S., Benedetti, S., Opizzio, M., Di Nardo, E., Buratti, S., 2019. Sensors 19, 3225.
Gu, D.C., Liu, W., Yan, Y., Wei, W., Gan, J. hong, Lu, Y., Jiang, Z.L., Wang, X.C., Xu, C.H., 2019. nose. LWT. 101, 382–388.
Han, F., Huang, X., Aheto, J.H., Zhang, D., Feng, F., 2020. Foods 9, 193.
Huang, C., Gu, Y., 2022. Foods 11, 602.
Jeong, H.S., Chung, H., Song, S.H., Kim, C. Il, Lee, J.G., Kim, Y.S., 2015. Toxicol. Res. 31, 273–278.

Karami, H., Rasekh, M., Mirzaee-Ghaleh, E., 2020a. J. Food Process. Preserv. 44, e14696.
Karami, H., Rasekh, M., Mirzaee – Ghaleh, E., 2020b. Chemometr. Intell. Lab. Syst. 206, 104165.
Kaushik, R., Jain, J., Rai, P., 2016. Int. J. Pharmaceut. Sci. Res. 7, 1383.
Li, J., Wang, M., Liu, Q., Zhang, Y., Peng, Z., 2018. Int. J. Food Prop. 21, 1246–1256.
Liu, H., Yu, D., Gu, Y., 2019. IEEE Access 7, 172965–172973.
Loutfi, A., Coradeschi, S., Mani, G.K., Shankar, P., Rayappan, J.B.B., 2015. Electronic noses for food quality: a review. J. Food Eng. 144, 103–111.
Magfira, D.B., Sarno, R., 2018. International conference on information and communications technology. ICOIACT 645–650.
Mirzaee-Ghaleh, E., Taheri-Garavand, A., Ayari, F., Lozano, J., 2020. Food Anal. Methods 13, 678–689.
Moosavy, M.H., Kordasht, H.K., Khatibi, S.A., Sohrabi, H., 2019. Qual. Assur. Saf. Crop. 11, 491–498.
Mu, F., Gu, Y., Zhang, J., Zhang, L., 2020. Sensors 20, 4238.
Oecd/Fao, 2022. OECD-FAO Agricultural Outlook 2022-2031.
Pandey, S.K., 2016. J. Agric. Eng. 40, 35–39.
Peris, M., Escuder-Gilabert, L., 2016. Electronic noses and tongues to assess food authenticity and adulteration. Trends Food Sci. Technol. 58, 40–54.
Premanandh, J., 2013. Horse meat scandal – a wake-up call for regulatory authorities. Food Control 34, 568–569.
Putra, M.A., Rivai, M., Arifin, A., 2018. Proceeding - 2018 International seminar on intelligent technology and its application. ISITIA 2018, 409–412.
Rahmati, S., Julkapli, N.M., Yehye, W.A., Basirun, W.J., 2016. Food Control 68, 379–390.
Ritchie, H., Roser, M., 2018. Causes of death, our world in data. Available at. https://ourworldindata.org/causes-of-death.
Rohman, A., 2019. J. Adv. Vet. Anim. Res. 6, 9–17.
Sarno, R., Triyana, K., Sabilla, S.I., Wijaya, D.R., Sunaryono, D., Fatichah, C., 2020. IEEE Access 8, 221700–221711.
Sberveglieri, V., Ongo, E., Falasconi, M., Concina, I., Pulvirenti, A., Sevilla, F., 2014. Lect. Notes Electr. Eng. Springer Verlag, pp. 463–466.
Severini, C., Ricci, I., Marone, M., Derossi, A., De Pilli, T., 2015. J. Agric. Food Chem. 63, 2321–2327.
Su, J., Ma, C., Liu, C., Gao, C., Nie, R., Wang, H., 2016. J. Food Sci. 81, H1001–H1009.
Thazin, Y., Pobkrut, T., Kerdcharoen, T., 2018. 10th International Conference on Knowledge and Smart Technology: Cybernetics in the Next Decades, pp. 210–215. KST 2018.
Tian, X., Wang, J., Ma, Z., Li, M., Wei, Z., Díaz-Cruz, J.M., 2019. J. Food Qual. 2019.
Tohidi, M., Ghasemi-Varnamkhasti, M., Ghafarinia, V., Bonyadian, M., Mohtasebi, S.S., 2018a. Int. Dairy J. 77, 38–46.
Tohidi, M., Ghasemi-Varnamkhasti, M., Ghafarinia, V., Saeid Mohtasebi, S., Bonyadian, M., 2018b. Meas.: J. Int. Meas. Confed. 124, 120–129.
Vajdi, M., Varidi, M.J., Varidi, M., Mohebbi, M., 2019. J. Food Meas. Char. 13, 1205–1217.
Wakhid, S., Sarno, R., Sabilla, S.I., Maghfira, D.B., 2020. Int. J. Intell. Syst. 13, 56–65.
Wang, Q., Li, L., Ding, W., Zhang, D., Wang, J., Reed, K., Zhang, B., 2019. Food Control 98, 431–438.
Wei, X., Shao, X., Wei, Y., Cheong, L., Pan, L., Tu, K., 2018. J. Food Sci. Technol. 55, 2152–2159.
Wijaya, D.R., Afianti, F., Arifianto, A., Rahmawati, D., Kodogiannis, V.S., 2022. Sens. Bio-Sens. 36, 100495.
Wijaya, D.R., Sarno, R., Zulaika, E., 2021. Sensor. Actuator. B Chem. 326, 128931.
Wilson, A.D., Baietto, M., 2009. Sensors 9, 5099–5148.
Xue, J., Wang, S., Zhang, P., Zhu, F., Ren, X., Liu, C., Zhang, X., 2015. Sci. Hortic. 182, 92–101.
Xu, M., Wang, J., Zhu, L., 2021. J. Food Sci. Technol. 58, 1549–1561.
Xu, M., Wang, J., Zhu, L., 2019. Food Chem. 289, 482–489.
Zarezadeh, M.R., Aboonajmi, M., Varnamkhasti, M.G., Azarikia, F., 2021. Food Anal. Methods 14, 2199–2210.