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A comprehensive review of quality measurements of fruits using electronic nose and computer vision

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ABSTRACT

The quality of fruits is crucial for consumer demand, market acceptance and environmental health. Many studies have measured and predicted fruit quality using electronic nose (E-nose) and computer vision. However, reviews simultaneously covering both E-nose and computer vision research on fruit quality is scarce. A review of both E-nose and computer vision technologies is critical for advancing research and guiding practical applications in fruit quality assessment. Its primary objective is to provide an in-depth discussion of findings, limitations, and knowledge gaps, while highlighting the relevance of this field to environmental health. The review found that apples and strawberries were the most frequently studied fruits. Metal-oxide semiconductor (MOS) sensors were the most widely used in E-nose applications, with principal component analysis (PCA), linear discriminant analysis (LDA), and support vector machines (SVM) as the primary classification methods. In computer vision studies, RGB and hyperspectral imaging (HSI) were widely used, and White and Dark Reference Image Correction was the most common preprocessing method. PCA was the most frequently used machine learning method, followed by partial least squares discriminant analysis (PLS-DA), SVM, and convolutional neural networks (CNN). Research mainly focused on a few fruits, leaving many widely consumed types understudied. Existing methods were limited by sensor performance, small datasets, weak validation, little real-world testing, and little consideration of shelf life. We conclude that integrating suitable preprocessing with combined E-nose and computer vision techniques improves fruit quality classification, while accounting for shelf life and exploring environmental implications remain essential directions for future research.

1. Introduction

Approximately 1.05 billion tons of food were wasted globally in 2022, representing 19% of consumer food (The United Nations Environment Program, 2024). The Food and Agriculture Organization of the United Nations reports that around $400 billion, or 14% of the world's food, is lost each year between harvest and the point of retail(Food & Agricultural Organization of the United Nations, 2021). Food waste is linked not only to global food insecurity but also to significant environmental consequences, accounting for 8–10% of global greenhouse gas emissions and accelerating biodiversity loss(The United Nations Environment Program, 2024). Due to their perishable nature, fruits are among the leading contributors to food waste, with 46% of fruits and vegetables lost. Meanwhile, population growth and increasing health consciousness are driving higher demand for fruits, intensifying the dual challenges of food waste management and nutritional security (BALLARD BRIEF, 2022). Measuring and predicting fruit quality is therefore critical for reducing waste, protecting environmental health, and supporting social well-being.

Numerous studies have investigated non-destructive methods for measuring and predicting fruit quality using olfactory sensors (electronic nose) and imaging systems (computer vision)(Akter et al., 2024; Jia et al., 2024). Several recent reviews have summarized food quality assessment using E-nose technologies (Al-Dayyeni et al., 2021; Ali et al., 2023; Aline et al., 2023; Jia et al., 2024; Liu and Zhang, 2021; Pereira et al., 2021) and computer vision (Akter et al., 2024; Bhargava and

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Bansal, 2021; Wang et al., 2015). However, the majority of these reviews had a narrow scope and focused on a single approach (either e-nose or computer vision). One review has discussed the combined use of E-nose and computer vision for fruit quality detection; however, it lacked in-depth discussion on the most commonly studied fruit types, the specific sensor technologies applied, or the classification models used (Srivastava and Sadistap, 2018). Understanding the types of fruits and sensors used is essential for identifying data gaps and guiding future data collection. Moreover, evaluating the classification models applied is critical for improving prediction accuracy and informing

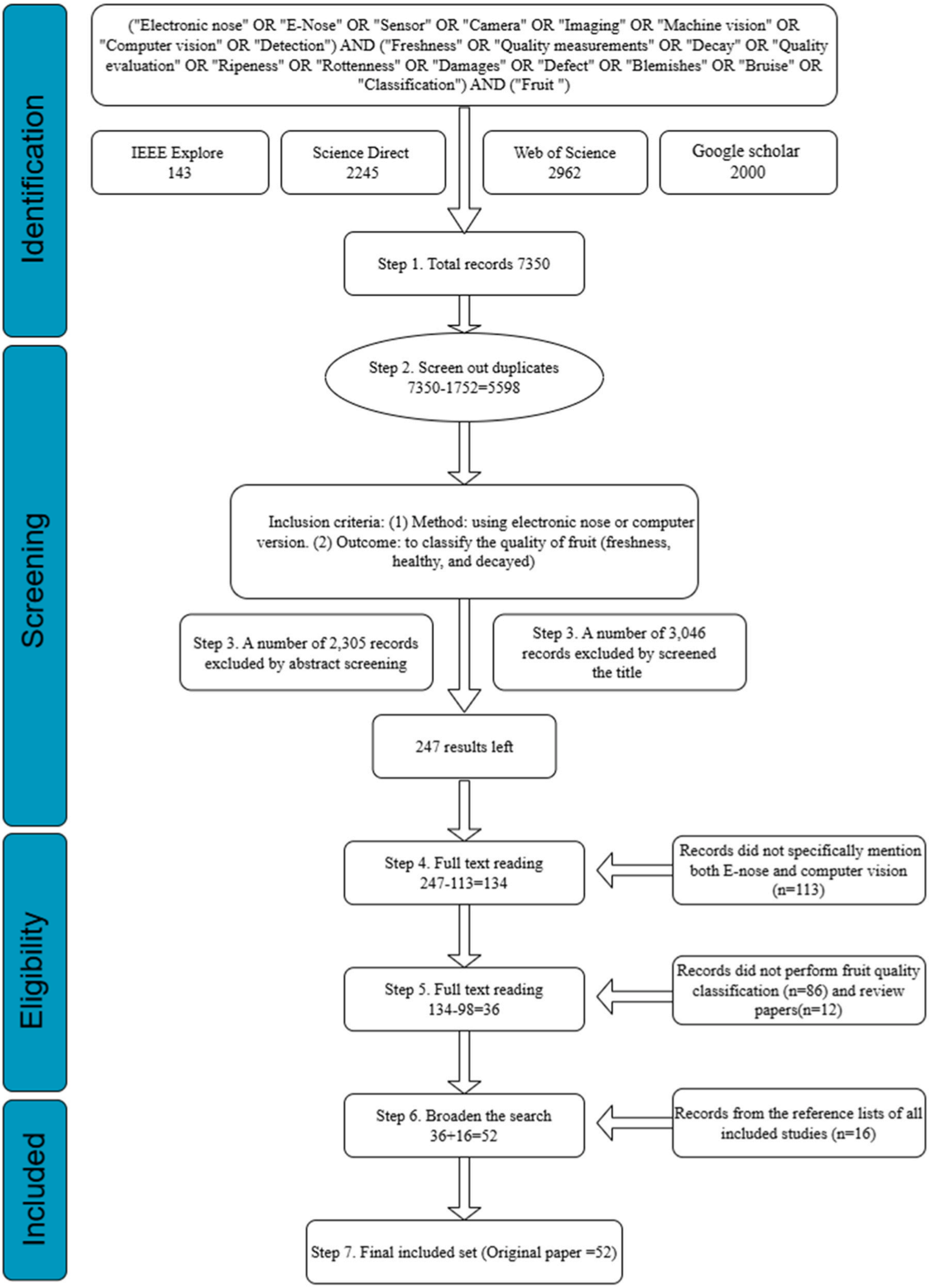

Fig. 1. The review process and associated articles based on the PRISMA guideline.

decision-making processes to reduce food waste. The in-depth analyses of assessed fruit types, sensor technologies and classification models are essential for summarizing the existing scientific advancement in using E-nose and computer vision for measuring fruit quality and for offering guidance to aid in further development. Beyond accurate prediction of fruit quality, it is essential to estimate the life shelf of fruits under specific environmental conditions, as this directly affects spoilage losses during transportation. Last, given the substantial environmental impacts of fruit waste, strengthening the connection between fruit detection technologies and environmental health is critical, yet this area remains largely unaddressed in the current literature.

To address these gaps, this study provides a comprehensive overview of the application of E-nose and computer vision technologies for fruit quality classification. The objectives are to: (1) summarize the sensors, imaging systems, detection conditions, preprocessing methods, processing techniques, and machine learning models used for fruit quality classification, with the goal of supporting application to underexplored fruit varieties; (2) identify existing knowledge gaps in enhancing fruit quality detection; and (3) highlight the connection between fruit detection technologies and environmental health.

2. Method

2.1. Data sources

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2010). The article selection and review process were conducted in seven steps, as illustrated in Fig. 1. Step 1: Articles on E-nose and computer vision technologies were retrieved from four major databases: IEEE Xplore Digital Library, ScienceDirect, Web of Science (WoS), and Google Scholar. Keywords were developed based on relevant methods and outcome definitions. The search covered publications from 2000 to 2025 and used combinations of method-related terms (“Electronic nose,” “E-Nose,” “Sensor,” “Camera,” “Imaging,” “Hyperspectral imaging,” “Machine vision,” “Computer vision,” “Detection”) with outcome-related terms (“Freshness,” “Quality measurements,” “Decay,” “Quality evaluation,” “Ripeness,” “Rottenness,” “Damages,” “Defect,” “Blemishes,” “Bruise,” “Classification,” “Fruit”). In Step 2, we eliminated duplicate studies from all databases. In Step 3, titles and abstracts were screened using predefined inclusion criteria: (1) Method: studies employing electronic nose or computer vision technologies; and (2) Outcome: studies focused on classifying fruit quality (e.g., freshness, healthiness, or decay). Articles deemed irrelevant were excluded. Step 4 involved a further review of the full texts of the remaining articles, excluding those that did not specifically mention either E-nose or computer vision. In Step 5, studies unrelated to fruit quality classification were removed. In Step 6 ensured comprehensiveness through a manual review of the reference lists of all included studies to identify additional relevant publications. Finally, in Step 7, the final set of articles was thoroughly evaluated, as shown in Fig. 1.

3. Results

3.1. Characteristics of included studies

A total of 52 articles were included in this study, of which 15 studies used E-nose to detect fruit quality, while 37 studies used computer vision for assessment. Among computer vision studies, 24 concentrated on defect detection, and 13 on ripeness. In contrast, E-nose studies investigated ripeness in 10 articles, defect detection in 4, freshness in 1, and shelf-life evaluation in 1. The current studies primarily include the following fruits: apples, strawberries, peaches, pears, nectarines, oranges, pineapples, mangoes, bananas, postharvest kiwifruits, white berries, blackberries, jackfruits, cantaloupes, longans, grapes, pomegranates, cucumbers, citrus fruits, blueberries, mandarins, and hawthorns. Seventeen studies focused on apples, of which 7 used E-nose and 10 used computer vision. Among the reported apple cultivars, ‘Fuji’ apples were the most frequently studied (7 occurrences), followed by ‘Red Delicious’, ‘Pink Lady’, ‘Golden Delicious’, ‘York’, and ‘Super Chief Red’ and apple harvesting or sampling predominantly occurred in autumn (September–October). Following apples, 9 studies focused on strawberries, with 8 using computer vision and only 1 used E-nose. Among the reported strawberry studies, the explicitly named cultivars were “Hong yan”, “Zhang Ji”, and “Chapter Ji”, each mentioned once. Several other studies reported strawberries without specifying the cultivar. Additionally, 8 studies involved peaches, and 6 focused on bananas. Among the reported peach cultivars, ‘Dabai’, ‘Royal Glory’, and ‘Pinggu’ were the most frequently studied, each appearing twice. Other cultivars, such as ‘Redhaven’ and ‘Big Top’ nectarines, as well as R. stolonifera, were reported only once. The main banana cultivars included the commercially important Cavendish (cv. Cavendish) and the wild or ornamental Musa basjoo Siebold var. formosana. All E-nose studies were conducted in a laboratory environment, while 7 computer vision studies were performed in natural environments.

3.2. Electronic nose

3.2.1. Principle of the electronic nose

An electronic nose is a sensor that mimics human olfactory sense to identify and differentiate odors, gases, or volatile organic compounds from substances like food, chemicals, explosives, and more(Mohamed et al., 2018). Typically, only individuals who have previously identified a specific gas can recognize it, as this requires both memorizing its characteristics and classifying it. To solve this limitation, the concept has been digitized in a device called the E-Nose, paired with a classification model. To illustrate this process, Fig. 2 shows the general architecture of E-Nose. In this system, the most critical components are the sensor array and the classification unit. The sensor array generates signals when exposed to gas and communicates with the classification unit to produce an output in a specific form. The sensor array and classification models used in previous studies are detailed in Sections 3.2.2 and 3.2.3.

Except for the experimental setup, other characteristics, such as fruit species, sample size, and the evaluation and detection environment, are also important for researchers conducting similar studies. Thus, as shown in Table 1, previous E-nose studies used between 15 and 500 fruits, depending on the type of evaluation. Furthermore, temperature and humidity are also important factors, as they can influence the ripening process of fruits. To minimize the effects of temperature and humidity, most studies maintain fruit samples in controlled environments. Across the included studies, experimental and storage conditions varied substantially, with temperatures ranging from −7.2 °C to 35 °C and relative humidity spanning approximately 25–99%. Most experiments (8 of 15) were conducted under room-temperature conditions (20–25 °C) with moderate humidity (50–80% RH). In contrast, some studies store fruits at lower temperatures (e.g., −7.2°C, 1°C, or 0.5–1°C) to investigate chilling injury and assess ripeness under cold storage conditions. One study did not control environmental conditions; instead, it recorded the ambient temperature and humidity and incorporated these variables into the classification process(Tyagi et al., 2023).

3.2.2. Gas Sensor

The sensor array is a key component of the electronic nose, designed to detect gases or odors present in volatile compounds, with each sensor responding to a specific gas individually. Table 2 summarizes gases and corresponding sensors used for various fruits. Sensor types used in previous studies included Metal oxide semiconductor (MOS) (Aghilinategh et al., 2020; Chen et al., 2018; Du et al., 2019; Ren et al., 2023; Ren et al., 2018; Sanaeifar et al., 2014; Tyagi et al., 2023) (Brezmes et al., 2005), carbon black organic polymer composite sensors (Tan et al., 2005), and internal thin film carbon black polymer composite sensors(Li et al., 2007). Studies conducted in 2014 and later

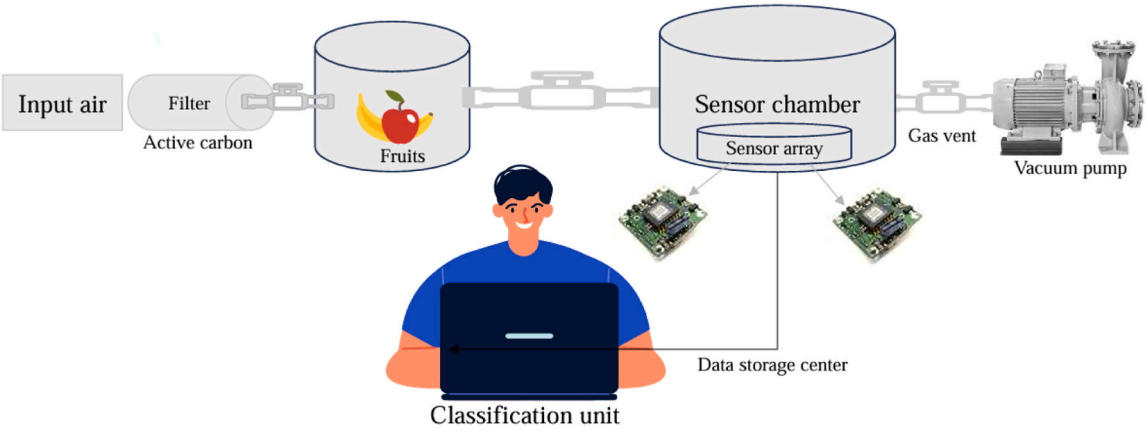

Fig. 2. Schematic of the experimental setup for fruit quality classification.

preferred to use MOS sensors. Fruit quality classification studies on apples typically used MOS sensors(Brezmes et al., 2000; Li et al., 2007; Ren et al., 2023; Ren et al., 2018). The ten most commonly detected gases in previous studies included ethanol, carbon monoxide, hydrogen sulfide, ammonia, methane, natural gas, hydrogen, LPG (liquefied petroleum gas), ethylene, and aromatic compounds.

3.2.3. *Classification*

Classification involves analyzing the electrical signals generated by gas sensors to distinguish among different odor or aroma profiles. In fruit quality assessment, this step enables researchers to estimate freshness levels based on sensors outputs. Preprocessing strategies are crucial for preparing sensor signals for subsequent classification, yet they varied across studies and no standardized pipeline was applied. Common steps included baseline correction and normalization to stabilize responses and reduce sensor variability. Most studies extracted static features, such as conductance increments, normalized responses, or first-order derivatives. Dimensionality reduction or transformation techniques, including PCA and LDA, were often employed for visualization or as feature preparation prior to classification. Overall, preprocessing and feature extraction methods were generally simple and highly study-dependent. Most studies employ machine-learning (ML) algorithms for classification (see Table 3). Because each algorithm has distinct strengths, its suitability depends on the specific evaluation task; while the choice of input features and target outputs have s significant influence on model performance. To ensure robustness and generalizability, rigorous validation method, such as cross-validation or testing on independent datasets, is required to ensure that the resulting models are both robust and generalizable.

The top 5 ML methods used in prior studies include Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). Only one study employed a deep learning model (CNN) for fruit quality detection. Studies on apples typically use the PCA model for fruit quality classification. However, due to the limitations of ML models, different models yield different results. Therefore, many studies used multiple ML models to perform classification. For example, Ren et al. used PCA, LDA, SDA, RBFN, MLPN, and BPNN to classify apples with different level of impact. They found that PCA accounted for 85% of the total variation, LDA accounted for 98.7%, SDA achieved accuracy ranging from 75% to 100%, MLPN achieved accuracy from 91.3% to 100%, RBFN accuracy ranged from 45.0% to 100%, and BPNN accuracy ranged from 90.0% to 100%. Overall, the LDA and MLPN achieved the best performance (Ren et al., 2018). Furthermore, combined algorithms has been shown to improve classification accuracy. Chen et al. performed PCA + KNN, PCA + SVM, LDA + KNN, and LDA + SVM algorithms to detect banana ripeness and found that the accuracy for PCA + KNN, PCA + SVM, LDA + KNN, and LDA + SVM was 98.10%, 95.24%, 99.05%, and 86.67%, respectively(Chen et al., 2018). Among these combination, LDA + KNN outperformed the others(Chen et al., 2018).

In studies on food ripeness detection, the PCA algorithm has often been used in combination with other ML models(Brezmes et al., 2005; Brezmes et al., 2000). As for ML inputs, prior research has primarily focused on sensor-derived measurements. These include conductance increment, sensor resistance, resistance ratios, sensor array values, raw E-nose signal data, waveform features of sensor responses, and relative sensor responses(Brezmes et al., 2005; Brezmes et al., 2000; Chen et al., 2018; Hui et al., 2012; Li et al., 2007; Ren et al., 2023; Ren et al., 2018; Tan et al., 2005; Torri et al., 2010; Tyagi et al., 2023; Zhang et al., 2012). This category appears most frequently, with six items. Additionally, data-related metrics have been used, including the total number of principal components, the signal-to-noise ratio (SNR) spectrum, and LDA matrices (Sanaeifar et al., 2014; Zakaria et al., 2012). Finally, response curve metrics have been considered, include the maximum or minimum values of each response curve, the difference between the maximum and minimum values, the 70th values of each response curve, and the response of the E-nose signal(Aghilinategh et al., 2020; Du et al., 2019). For ripeness studies, the ML outputs typically included unripe (green), mid-ripe, ripe, and over-ripe. For freshness, outputs were classified as were fresh, sub-fresh, and spoiled. For defect detection, the outputs were healthy and damaged. Most studies focused on two or three categories, with only three studies conducted on more than three categories, and all of them focused on fruit ripeness(Aghilinategh et al., 2020; Chen et al., 2018; Zakaria et al., 2012). Only one study simultaneously estimated both shelf-life and freshness under different environmental conditions (Torri et al., 2010).

The validation methods used in these studies primarily included Leave-one-out cross-validation (LOO) (Brezmes et al., 2000; Chen et al., 2018; Du et al., 2019; Sanaeifar et al., 2014; Tan et al., 2005), various train-test split ratios (such as 75%-25%, 80%-20%, etc.). These methods were applied to evaluate the model's performance on unseen data and assess generalizability. The main performance metrics used are accuracy, correlation, success Rate, classification error rate, and other specific metrics like precision, recall, F1-score, R^2, and RMSE, depending on the type of model and evaluation criteria.

3.3. *Computer vision*

3.3.1. *Principle of the computer vision*

Conventional computer vision systems first emerged in the late 1960s and have since become widely applied across various fields, including industrial automation, security inspection, intelligent transportation, medical imaging, and fruit quality and safety assessment. In

Table 1
The characteristics of fruit quality classification studies using E-nose.

Author/year	Food species	Number of fruits	Evaluation	Detection environment
Brezmes/2000	Peaches, pears, and apples	180 peaches, 60 pears, and 56 apples.	Ripeness	The peaches: 25°C. Pears: two of five were ripened under laboratory conditions, the left at 0.5–1°C. Apples, half were measured immediately, and the other half: refrigerator.
Brezmes/2005	Peaches, nectarines, apples, and pears	200 “pinklady” apples, 500 Doyenne du Comice pears, 60 Royal Glory peaches, and 60 BigTop nectarines	Ripeness	Apple: 20 ℃ and 50–60% relative humidity. Pear: 20 ℃ and 1 ℃ and relative humidity (90%); Peach: Keep at 20 ℃.
Tan/2005	Valencia oranges (Citrus sinensis (L.) Osbeck ‘Valencia’)	475	Defect detection	-7.2℃
Li/2007	Apple	456	Defect detection	20 ± 1℃
Torri/2010	Pineapple	Six lots of fresh-cut pineapple slices	Shelf-life evaluation	23 ± 1℃
Hui/2012	Peach	46 “Dabai” peaches	Ripeness	NA
Zakaria/2012	Mangoes	240	Ripeness	27(±1) °C and humidity of 80%
Zhang/2012	Peach	90	Ripeness	25 ± 1 °C and 50–60% relative humidity
Sanaeifar/2014	Banana	15	Ripeness	25°C and 25–35% RH
Chen/2018	Banana	A bunch of bananas weighing about 1.2 kg	Ripeness	20℃–25℃ and a relative humidity of 70–80%
Ren/2018	Apples	400	Defect detection	25℃
Du/2019	Postharvest kiwifruit	160	Ripeness	20 ℃± 0.5 C and relative humidity of 70% ± 5%.
Aghilinategh/2020	White berry and blackberry	120	Ripeness	30°C.
Ren/2023	Fruits (jackfruit, strawberry, cantaloupe, pear, longan, apple, grape, and banana)	-	Freshness	25 ∘C ± 2 ∘C and humidity of 25% ± 2%
Tyagi/2023	Apples, bananas, oranges, grapes, and pomegranates	30 samples for each fruit	Ripeness	The temperature and humidity of the chamber were also recorded

Table 2
The characteristics of gas sensors among included studies using E-nose.

Author/year	Food species	Sensor Type	Gases involved
Brezmes/2000	Peaches, pears, and apples	MOS: TGS825, TGS826, TGS822, TGS800, TGS882, TGS2610, TGS2611, TGS2620	Hydrogen sulphide, Ammonia, Alcohol, toluene, O-xylene, Air contaminants, Air contaminants, General hydrocarbons, Methane, natural gas, Alcohol, organic solvents
Brezmes/2005	Peaches, nectarines, apples, and pears	FIS(SB-series), Taguchi(8-series), and humidity and temperature sensors	Hydrogen, cigarette smoke, flammable vapors, organic solvents, toxic gas, combustible gas detection, and ethylene
Tan/2005	Valencia oranges (Citrus sinensis (L.) Osbeck ‘Valencia’)	Headspace gas sampling: carbon black organic polymer composite sensors. Internal gas sampling：carbon dioxide sensor and the ethanol sensor	Ethanol and Carbon dioxide
Li/2007	Apple	The E-nose (Smith Detection, Herts, UK) consists of 32 internal thin film carbon black polymer composite sensors. The zNose (Electronic Sensor Technology, Newbury Park, CA) consists of one capillary column and one surface acoustic wave (SAW) sensor.	-
Torri/2010	Pineapple	A commercial portable electronic nose (PEN 2 model, Win Muster Airsens Analytic Inc., Schwerim, Germany).	Aromatic compounds, broad-range compounds, polar compounds, nitrogen oxides, and ozone
Hui/2012	Peach	A self-developed E-nose system with eight metal oxide semiconductors gas sensor array	Smoke, Ethanol, Propane, butane, LPG, Nitrogen oxides, Carbon monoxide, Hydrogen, Methane, and Hydrogen sulfide
Zakaria/2012	Mangoes	The sensing elements consist of a 32 potentiometric sensor array made up of various conducting polymers, blended with carbon-black composite.	-
Zhang/2012	Peach	Eight commercial metal oxide sensors (6 TGS, Japanese Manufacturer Figaro; MQ-3 and MQ-7 of metal oxide sensors, Hanwei Electronics Co., Ltd., Henan, China)	Ethanol, Solvent vapor detection, Carbon monoxide, Air quality control, Toxic gas detection, Combustible gas detection, cooking control, and Hydrogen sulfide

(*continued on next page*)

Table 2 (*continued*)

Author/year	Food species	Sensor Type	Gases involved
Sanaeifar/2014	Banana	MOS	Alcohol, LPG, natural gas, coal gas, CO, and combustible gas, ozone, sulphureted hydrogen
Chen/2018	Banana	MOS: TGS2600, TGS2602, TGS2603, TGS2610, TGS2611, TGS2612, and TGS2620	Hydrogen, Carbon monoxide Ammonia, Hydrogen sulfide, Trimethylamine, Methyl mercaptan, Butane, LP gas, Methane, Natural Gas, Methane, Propane, Iso-butane, Alcohol, Solvent vapors
Ren/2018	Apples	10 metal oxide semiconductors (MOS, W1S, W5S, W3C, W6S, W5C, W1S, W1W, W2S, W2W, W3S)	Aromatic compounds, ammonia, hydrogen, Alkanes, methane, sulfur compounds, alcohols, and sulfur organic compounds
Du/2019	Postharvest kiwifruit	10 metal oxide semiconductor (MOS) gas sensors	Aromatic compounds
Aghilinategh/2020	White berry and blackberry	MOS gas sensors	Alcohol, LPG, CH4, Coal gas, CO and combustible gas, steam organic solvents, C4H10, LPG, CH4, Sulfide, hydrogen sulfide, ammonia, toluene
Ren/2023	Fruits (jackfruit, strawberry, cantaloupe, pear, longan, apple, grape and banana)	The sensor is a four-cantilever structure metal–oxide (MOX)–semiconductor gas sensor based on the MEMS technology.	Hydrogen sulfide, Ammonia, Ethanol, Ethylene, Hydrogen
Tyagi/2023	Apples, bananas, oranges, grapes, and pomegranates	Five MOS sensors and one DHT sensor	Natural gas, alcohol, hydrogen, Methane, solvent vapors, LPG and component gases, Air contaminants (VOCs and odorous gases)

Note: "-" indicates that the information is not available in the literature.

fruit research, Imaging techniques capture fruit images and extract spatial information in a manner analogues to the human visual system, allowing for data storage, sorting, and analysis. Consequently, computer vision has gained increasing prominence in a wide range of applications. Fig. 3 illustrates the general architecture of a computer vision system, which typically includes four key stages: image acquisition, preprocessing, machine learning, and classification.

3.3.2. *Image acquisition*

In fruit quality assessment, prior studies typically used Hyperspectral Imaging (HSI), RGB Imaging (RGB), Thermal Imaging (TI), Multispectral Imaging (MSI), Structured-Illumination Reflectance Imaging (SIRI), and Unmanned Aerial Vehicle (UAV) Imaging. HSI captures detailed spectral information; RGB relies on red, green, and blue channels for color images; TI detects heat emitted from objects; MSI captures images in specific wavelengths; SIRI enhances image resolution using specialized light patterns; and UAV involves imaging from unmanned aerial vehicles, often combined with near-ground imaging for high-resolution views. HIS (16 results) is the most common used method, followed by RGB (12 results). RGB imaging is commonly applied for strawberry detection in a natural environment, such as in a garden. For image classification, a suitable number of images is critical for researchers. As summarized in Table 4, the number of images ranged from 100 to 79,200. About 20 studies used fewer than 1000 images, 11 studies used between 1000 and 5000 images, and only 7 studies had more than 5000 images. The number of fruits per study ranged from 40 to 2000, with most studies using fewer than 400 fruits.

3.3.3. *Preprocessing, segmentation, and feature extraction*

In most vision systems, acquired images often contain undesirable high-frequency signals (random noise), leading to variations in intensity, illumination, and poor contrast. Preprocessing is therefore needed to enhance image quality by reducing distortions and enhancing features critical for analysis, thereby producing data more suitable for the intended application than raw images. Table 5 listed the preprocessing method used in previous studies. The pre-processing methods used in fruit quality analysis include White and Dark Reference Image Correction, Background Removal, Multiplicative Scatter Correction (MSC), First Derivative (1D) and Savitzky-Golay (SG) Smoothing, Standard Normal Variate (SNV), Image Enhancement (Pseudo-color enhancement), Gaussian Filter for Image Noise Removal, Image Normalization and Dark Current Reduction, Sensor Corrections, and Radiometric Calibration. Among them, White and Dark Reference Image Correction is the most commonly used in prior studies, followed by background removal.

After preprocessing, image segmentation is necessary to divide a digital image into separate regions. Proper segmentation is essential for effective image analysis, while poor segmentation can reduce classifier performance. A range of methods have been commonly used in fruit quality detection, including thresholding, edge-based, region-based, traditional segmentation algorithms, clustering-based, watershed-based, partial-differential-equation-based, and artificial neural-network-based approaches (Ismail and Malik, 2022). These methods have been extensively discuss in previous systematic reviews, so the current study does not provide a detailed discussion(Akter et al., 2024; Bhargava and Bansal, 2021). Subsequently, feature extraction was used to classify to recognize the input. Typically, used features include color and morphological features, which have been widely mentioned and explained in previous studies(Bhargava and Bansal, 2021). By combining multiple features of fruit data, deep neural networks may be more beneficial for classification compared to using a single feature.

3.3.4. *Classification*

The key feature for fruit quality evaluation is classification, which provides a framework for artificial simulation of human decision-making to assist quick, accurate, and consistent judgments. Summary of classification method is listed in Tables 6–7. Performance is typically reported using task-specific metrics such as defect detection and ripeness assessment. For defect detection, HSI achieves 37.3–100%, RGB imaging 74.4–90.9%, TI 44–98%, MSI 87.3–95.8%, and SIRI 65–98.6%. In terms of ripeness assessment, HSI reaches 70–100%, RGB 99.6–100%, TI 71.5–99.3%, and UAV-based methods demonstrate a precision of 0.80–0.94 (Table 6). E-nose systems are mainly applied under laboratory conditions, achieving accuracies of 45–100% for defect detection, up to 96.9% for freshness evaluation, and 66.7–100% for ripeness assessment. In comparison, computer vision methods are used in both laboratory and natural environments, with comparable laboratory accuracies for defect detection (37.3–100%) and ripeness assessment (70.0–100%), and consistently high performance for ripeness evaluation under natural conditions (74.4–98.7%) (Table S1). PCA is the most frequently used ML method, followed by PLS-DA, SVM, and CNN (Table 7). The input data for these models vary across studies. RGB images are the most common, reported in 8 studies. Since there is noise during image acquisition, prior studies prefer corrected images to make them more suitable for classification (Azadnia et al., 2023; Fan et al., 2017; Li et al., 2022; Luo et al., 2022; Tan et al., 2018; Tian et al., 2020).

Table 3
The characteristics of classification model and its performance.

Food species	Evaluation	ML algorithm for classification	ML Inputs	ML Outputs	validation	Model performance metrics	Model performance
Peaches, pears and apples	Ripeness	PCA and NNNA	The conductance increment	Green, Ripe and Overripe	Leave-one-group-out	Success rate	92.5%
Peaches, nectarines, apples, and pears	Ripeness	Apple: PCA; Pear: PCA, Fuzzy ART and Fuzzy ARTMAP; Peach: PCA	The conductance increment(▲G)	Apple: No classification; Pear: green or ripen; Peach: No	NA	Apple: Correlation; Pear: success rate and correlation; Peach: Correlation	Pear: 94.6% success rate
Valencia oranges (Citrus sinensis (L.) Osbeck 'Valencia')	Defect detection	CDA	NA	Freeze and non-freeze	Leave-one out cross-validation	Accuracy	57%-72%
Apple	Defect detection	PNN	Total number of principal components	Healthy and damaged	Training set (75%) and testing set (25%).	Classification error rate	1.5%-32.5%
Pineapple	Shelf-life evaluation	PCA and CA	Resistivity	Discontinuous method: "fresh pineapple" corresponding to 0–5 days at 5.3℃, 0–3 days at 8.6℃ and 0–1 day at 15.8℃; "old pineapple "for the other storage conditions.	NA	Recommended storage temperature	5 days at 4–5∘C
Peach	Ripeness	Max-SNR	Signal-to-noise ratio (SNR) spectrum of peach	Fresh and stale	Compared with peach freshness determined by peach firmness and contents of total soluble solids (TSS) indices.	Accuracy	85%
Mangoes	Ripeness	CLNN	LDA matrices	Pre-mature, mature 1, Mature 2, Early ripening, nearly ripe and Optimum ripeness	Training set (25%) and test dataset (75%)	Number of clusters detected % Correct Classification	66.7%-84.4%
Peach	Ripeness	PCR and PLS	Resistance of a sensor	Unripe, Ripe, and Half-ripe	Training set (66.66%) and test dataset (33.33%)	PCA correlation	R= 0.95
Banana	Ripeness	PCA+LDA, SIMCA and SVM	Values of the sensor array	Five groups for each ripening stage	Leave-one-out cross-validation	Accuracy	98.66%-100%
Banana	Ripeness	PCA+KNN, PCA+SVM, LDA+KNN, LDA+SVM	The sensor resistance ratio	Unripe (day 1); half-ripe (day 2 and day 3); fully ripe (day4, day5 and day6) and overripe (day7)	Leave-one-out cross validation method	Accuracy	86.67%-100%
Apples	Defect detection	PCA, LDA, SDA, RBFN, MLPN and BPNN	E-nose data sensor signals	Different degrees of impacted apples	Training set (80%) and test dataset (20%)	Accuracy	45%-100%
Postharvest kiwifruit	Ripeness	LDA	(1) The maximum or the minimum values of each response curve; (2) the difference between the maximum and minimum values of each response curve; and (3) the 70th s values of each response curve.	Time (from day1 to day7) and ripeness (Unripe, Mid ripe and Eating Ripe)	leave-one-out method and training set (75%) and test dataset (25%)	Accuracy for classification, the performances of PLSR, SVM, and RF were evaluated by two parameters: square correlation coefficient (R2) and root mean square error (RMSE).	Accuracy: 99.4%-100%
White berry and blackberry	Ripeness	LDA and ANN	Response of the e-nose signal	Ripe, close to ripeness, intermediate to ripeness, close to unripe, and unripe	Training set (75%) and test dataset (25%)	Accuracy	85.54%-100%
Fruits (jackfruit, strawberry, cantaloupe, pear, longan, apple, grape, and banana)	Freshness	CNN	Waveform of the sensor response as a feature,	Fresh, sub fresh, and spoiled	Training set (80%) and test dataset (20%)	Accuracy	96.9%
Apples, bananas, oranges, grapes, and pomegranates	Ripeness	ANN	Relative responses of sensors	Unripe, ripe, and over-ripe	Training set (80%) and test dataset (20%)	Precision, Recall, F1-score, and accuracy	Accuracy:95%

Notes: Principal component analysis (PCA); Principal component regression (PCR) and partial least-squares regressions (PLS); non-linear neural network algorithms (NNNA); fuzzy art neural networks (Fuzzy ART), Fuzzy ARTMAP neural network (Fuzzy ARTMAP); Canonical Discriminant Analysis (CDA); Probabilistic neural network (PNN); cluster analysis (CA); SNR maximums linear fitting regression (Max-SNR); LDA-Competitive Learning (CLNN); Soft independent modelling of class analogy (SIMCA); support vector machine (SVM); Linear Discriminant Analysis (LDA), Stepwise Discriminant Analysis (SDA), Radial Basis Function Neural Network (RBFN), Multilayer Perceptron Neural Networks (MLPN), and Back-Propagation Neural Network (BPNN); Artificial Neural Network (ANN).

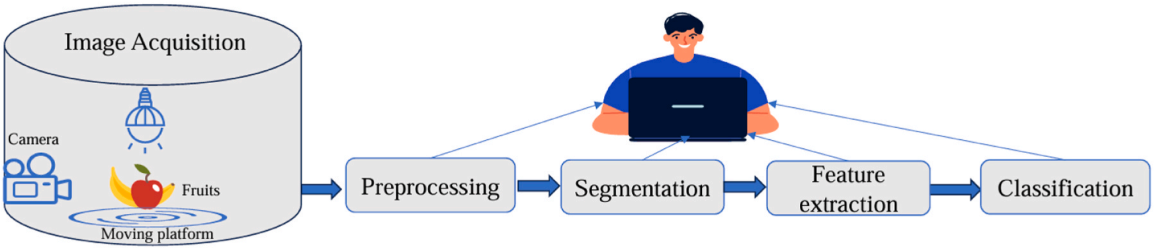

Fig. 3. The schematic diagram of the developed hyperspectral imaging system.

The output of the model also varies across studies, with "Healthy and bruised group" being the most frequently mentioned in defect detection. For ripeness detection studies, most of them focus on four categories with unripe, half-ripe, fully ripe and overripe(Chen et al., 2018; Wang et al., 2024; Zhu et al., 2024), followed by three categories: unripe, ripe, and overripe(Azadnia et al., 2023; Azarmdel et al., 2020; Chen et al., 2022; Wang et al., 2024). In the validation process, most studies split the dataset into training and testing groups, while other studies use K-fold cross-validation. It is also relatively common to perform 5-fold cross-validation and 10-fold cross-validation, dividing the data into 2:1 training and testing groups. Model performance was typically evaluated using a range of metrics, including accuracy, precision, recall, F1 score, sensitivity, specificity, success rate, coefficient (r), RMSE, R^2, MSE, MAP, and FPS, with multiple metrics often used in combination. Accuracy is the most commonly used performance metric among previous studies. Most studies show good model performance, with accuracy typically exceeding 86.6% in all cases for main results of them.

4. Discussion

4.1. *Needs of expanding quality detection for understudied fruits such as watermelons, oranges, and pears*

A total of 17 studies focused on apples, making them the most studied fruit, followed by strawberries, peaches, and bananas. This trend is noteworthy, as previous research has identified apples and bananas among the most commonly wasted fruits, contributing to substantial economic losses (FoodHero). According to the U.S. Department of Agriculture (USDA), bananas, apples, strawberries, and peaches were the most commonly consumed fresh fruits among U.S. consumers in 2010, with apples, bananas, and strawberries remaining the top choices by 2021(service, 2023). Many of these fruits require long-distance transportation to reach their target markets (MSC Group, 2024). Delays in the supply chain, coupled with limited preservation technologies, lead to significant quality and nutritional losses in fruits, causing economic and environmental impacts; thus, effective quality detection is essential for reducing post-harvest losses and supporting sustainable fruit supply chains. USDA reports indicate that oranges, grapes, pineapples, and watermelons are also among the most widely consumed fruits in the United States(USDA, 2021). A prior study found that the most wasted fruits include bananas (57%), strawberries (42%), apples (30%), raspberries (19%), oranges (19%), and pears (18%) (FRUCTIDOR.COM, 2025). Nevertheless, research remains limited, particularly with respect to watermelons, oranges, and pears.

4.2. *Needs of E-nose sensor advancement for assessing various fruits and large-scale applications*

Most studies on E-nose technology are typically equipped with MOS sensors, while computer vision studies relied on RGB images. MOS sensors are generally well-suited for fruit quality detection due to their low cost, broad gas detection range, durability, and fast response time. However, a major limitation of MOS sensors is their need for high operating temperatures (300–500 °C), which leads to increased power consumption compared to sensors based on other materials(Ali et al., 2023). Ali et al. and Sun et al. reviewed and discussed the advantages and limitations of several gas sensor technologies, including MOS sensors, metal oxide semiconductor field-effect transistors (MOSFET), piezoelectric crystal (PC), quartz crystal microbalance (QCM), electrochemical sensors, and surface acoustic wave (SAW) sensors, with respect to performance metrics such as sensitivity, selectivity, drift stability and cost(Ali et al., 2023; Sun et al., 2025). Besides, Jayan et al. reviewed and discussed the advantages and limitations of several sensor technologies, including MOS sensors, electrochemical sensors, optical sensors, conducting polymer sensors, and sensor arrays(Jayan et al., 2025). Among the studies reviewed, eight employed commercial sensor systems, typically designed for the detection of a single fruit type. In contrast, seven studies developed custom sensor configurations tailored for use across multiple fruit types. Notably, all individual sensors used in these studies were commercially available. Despite these advancements, no widely adopted commercial sensor system currently exists for quality detection across multiple fruit types.

Although E-nose systems can incorporate multiple sensors, they still face several limitations (Ali et al., 2023). Metal oxide-based E-noses, in particular, suffer from issues such as cross-selectivity and reduced sensitivity, especially under dynamic environmental conditions and baseline drift. Additionally, while many studies have explored contact-type E-nose methods, these approaches remain time-consuming and labor-intensive. Another notable limitation is the reliance on controlled, closed environments—such as sample chambers—for testing. In contrast, real-world applications, particularly in large open-field or farm settings, present substantial challenges. The larger spatial volume leads to significantly lower concentrations of volatile compounds, and when fruits are uncovered, ambient odor levels may fall below the sensor's detection threshold. This reduced sensitivity and compromised stability of the E-nose system. To date, no studies have demonstrated the effective deployment of E-nose technologies in large-scale, open-field environments.

4.3. *Limitations of RGB Imaging and slow processing speeds of ML applications*

For computer vision, compared with advanced imaging technologies such as HSI or TI, RGB imaging is less informative in terms of internal or chemical composition analysis. However, its affordability, ease of use, and sufficient performance in external quality detection make it the most widely adopted choice in practical applications. Despite its simplicity and cost-effectiveness, RGB imaging is limited by its narrow spectral range, reducing its capable of detecting internal defects or early spoilage, and its performance is often affected by external conditions.

Table 4
Characteristics of image acquisition in prior studies.

Author/year	Food species	Num of fruits	Spectral measurements	Evaluation	Detection site	Number of Images	Camera types
Juan/2005	Apples	118 Jonagold apples	Visible and near-infrared imaging	Defect detection	Lab	472	A ZEISS MCS501 combined with a ZEISS MCS511 Spectro photometer
Huang/2013	Apples	100 'Fuji' apples, 50 bruised and 50 sound.	Near-infrared Hyperspectral Image	Defect detection	Lab	100	A 1000–2500 nm imaging spectrograph
Huang/2015	Apples	250 ‘Fuji’ apples	Multispectral Imaging	Defect detection	Lab	183	Beamsplitters and filters and prism based 2CCD multispectral progressive area scan cameras with GigE Vision interface.
Zhang/2015	Peach	80 peaches with natural defects and 60 with physical damage.	Hyperspectral imaging	Defect detection	Lab	210	An Andor monochrome liner EMCCD with 1004 1000 pixels, an imaging spectrograph coupled with a standard C-mount zoom lens.
Cen/2016	Cucumbers	130	Hyperspectral imaging	Defect detection	Lab	334	A CCD camera and an imaging spectrograph
Li/2016	Citrus	210 fruits (80 sound fruits and130 infected fruits)	Hyperspectral imaging	Defect detection	Lab	280	A cooled electron multiplying charge-coupled device (EMCCD) camera and an imaging spectrograph
Fan/2017	Blueberry	80	NIR hyperspectral reflectance imaging	Defect detection	Lab	320	An indium gallium arsenide (InGaAs) camera
Chen/2018	Banana	A bunch of bananas weighing about 1.2 kg	RGB image	Ripeness	Lab	105	A digital camera (HERO+, GOPRO Inc., San Mateo, CA, USA)
Li/2018	Peach	200	Hyperspectral imaging	Defect detection	Lab	200	EMCCD camera and a 14-bit LW-NIR charge-coupled device camera
Tan/2018	Apple	40	Hyperspectral imaging	Defect detection	Lab	160	A portable hyperspectral imager (SOC710VP, USA)
Li/2019	Apple	440 sound ‘Fuji’ apples	Hyperspectral reflectance imaging	Defect detection	Lab	1063	EMCCD camera and an imaging spectrograph
Li/2019	Oranges	440 navel oranges	Hyperspectral imaging	Defect detection	Lab	440	A 14-bit monochrome camera
Sun/2019	Peach	600	Structured-illumination reflectance imaging	Defect detection	Lab	37800	An electron-multiplying CCD camera
Yu/2019	Strawberry	2000	RGB image	Ripeness	Nature	1900	A hand-held digital camera
Azarmdel/2020	Mulberries	577	RGB image	Ripeness	Lab	577	A Casio EX-H20G 14.1MP CCD digital camera
Fan/2020	Apples	300 (150 normal and defective)	RGB image	Defect detection	Lab	79200	Two low-cost commercial RGB cameras (<$500) (BFLY-PGE-05S2C-CS, FLIR Integrated Imaging Solutions Inc., Richmond, BC, Canada)
Tian/2020	Citrus	300(132 sound and 168 infected)	Hyperspectral transmittance image	Defect detection	Lab	300	One imaging spectrograph
Tian/2020	Apple	279	Vis/NIR full transmittance spectra	Defect detection	Lab	279	A high sensitivity spectrograph (615–1044 nm)
Zeng/2020	Pear	500 ‘Korla Fragrant’ pears	Thermal images	Ripeness	Lab	4371	A thermographic camera
Zhang/2020	Mandarins	606(456 defective and 150 sound)	Visible and near infrared hyperspectral imaging	Defect detection	Lab	606	An imaging spectrograph (ImSpector V10E, Specim, Finland) and a 12-bit CCD (Charge Coupled Device) camera (Hamamatsu, Japan)
Tian/2021	Citrus	140 “Gannan” navel oranges	Hyperspectral image	Defect detection	Lab	18,273	One 14-bit NIR charge-coupled device camera (Xeva- 2.5–320, Xenics Ltd, Belgium) and one imaging spectrograph within 930–2548 nm
Zhou/2021	Strawberry	NA	UAV imaging and near-ground imaging	Ripeness	Nature	7706	An RGB camera with an image resolution of 3000 × 4000 pixels and a digital camera (Canon EOS 5D Mark III, Canon U.S.A., Inc. Melville, New York)
Cai/2022	Citrus	280	Structured-illumination reflectance image	Defect detection	Lab	280	Monochrome camera.
Chen/2022	Citrus	NA	RGB image	Ripeness	Nature	3336	NIKON D5300 camera
Guo/2022	Strawberry	700 “Chapter Ji” strawberries	Thermal Imaging	Defect detection	Lab	2903	A thermographic camera.
Ismail/2022	Apples and bananas	NA	RGB image	Ripeness and defect detection	Lab	Apple (8791) and bananas (300)	a Google AIY Vision Kit (Raspberry Pi Zero accelerated with vision bonnet for neural network inference and a Pi Camera)
Li/2022	Citrus	204(80 sound and 124 decayed)	Hyperspectral image	Defect detection	Lab	204	Camera (Andor Luca EMCCD DL-604 M, Andor Technology plc., N. Ireland) and imaging spectrograph (ImSpector V10E, Spectral Imaging Ltd, Oulu, Finland)
Luo/2022	Oranges	280 samples (80 sound and 200 rotten)	Hyperspectral image	Defect detection	Lab	707	Imaging spectrograph (ImSpector V10E-QE, Spectral Imaging Ltd., Oulu, Finland)

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Table 4 (*continued*)

Author/year	Food species	Num of fruits	Spectral measurements	Evaluation	Detection site	Number of Images	Camera types
							and an area-array CCD camera (ICL-B1620, Imperx, Boca Raton, FL, USA)
Azadnia/2023	Hawthorn	600	RGB image	Ripeness	Lab	600	A smartphone image-capturing box
Ropelewska/2023	Peach	NA	Visible and near infrared hyperspectral imaging	Ripeness	Lab	NA	Epson Perfection V600 flatbed scanner
Tang/2023	Strawberry	NA	RGB images	Ripeness	Nature	1200	The devices used are MI 8 and MI 12X smart mobile phones
Yang/2023	Strawberries	NA	RGB images	Ripeness	Nature	1089	NA
Unal/2024	Apples	100(50 healthy-undamaged,50 damaged)	RGB and near-infrared camera imaging	Defect detection	Lab	2000	CCD camera and complementary metal oxide semiconductor (CMOS) image detectors
Wang/2024	Strawberry	NA	RGB images	Ripeness	Nature	1187	A smartphone, with a picture resolution of 3024 × 4032
Xu/2024	Apples	120	Thermal Imaging	Defect detection	Lab	7200	DS-2TD2636–1 thermal imaging dual-spectrum network cylindrical camera (Hangzhou Hikvision Digital Technol ogy Co., Ltd., Zhejiang, China)
Zhu/2024	Strawberry	NA	RGB images	Ripeness	Nature	4080	HUAWEI P40 with 50 MP Ultra Vision Camera (Wide Angle, f/1.9 aperture)
Shanthini/2025	Strawberry	314	Hyperspectral image	Defect detection	Lab	6720	Hyperspectral imaging system HySpex-VNIR-1800 camera

Table 5
The relevant preprocessing method used in previous studies.

Author (year)	Fruits species	Methods
Huang (2013), Huang (2015), Li et al. (2018), Sun et al. (2019), Li et al. (2019), Tian et al. (2020), Luo (2022)	Apples, Peach, Citrus, Strawberry, Oranges, Banana	White and Dark Reference Image Correction
Zhang (2015), Chen (2018), Fan et al. (2020), Azadnia (2023), Zhu (2024)	Peach, Apple, Banana, Strawberry, Citrus	Background Removal
Xing et al. (2005), Tian (2020b)	Apple	Multiplicative Scatter Correction (MSC)
Tan (2018), Tian (2020b)	Apple	First Derivative (1D) and Savitzky-Golay (SG) Smoothing
Tan (2018), Tian (2020b)	Apple	Standard Normal Variate (SNV)
Tian (2020a)	Citrus	Image Enhancement (Pseudo-color enhancement)
Ismail (2022)	Apples and Banana	Gaussian Filter for Image Noise Removal
Zhou (2021), Cai et al. (2022), Guo et al. (2022)	Strawberry, Citrus	Image Normalization
Shanthini et al. (2025)	Strawberry	Dark Current Reduction, Sensor Corrections, and Radiometric Calibration

Table 6
Quantitative comparison of performance across imaging modalities and tasks.

Imaging Modality	Task	Accuracy Range (%)
HSI	Defect detection	37.3 – 100
	Ripeness	70 – 100
RGB	Defect detection	74.4 – 90.9
	Ripeness	99.6 – 100
TI	Defect detection	44 – 98
	Ripeness	71.5 – 99.3
MSI	Defect detection	87.3 – 95.8
SIRI	Defect detection	65 – 98.6
UAV	Ripeness	0.80–0.94(precision)

Some studies have explored alternative methods to compensate for these limitations. For example, combining RGB and HSI enables higher-quality image acquisition by integrating surface visual features with internal chemical composition analysis. Aline et al. reviewed various non-destructive spectral measurements for assessing the quality of tropical fruits and vegetables, summarizing their advantages and disadvantages as well as the external quality parameters applied in prior studies(Aline et al., 2023). Although the integration of RGB cameras with spectral measurements, along with the application of deep learning and machine learning technologies, is rapidly advancing to enhance quality control accuracy and address challenges such as spectral variability, spectrometer heterogeneity, environmental fluctuations, and high noise in infrared spectral data, these models often suffer from relatively slow processing speeds due to the computational complexity of deep neural networks(Ma et al., 2024).

4.4. *Integration of pre-preprocessing methods, larger datasets for model training, and modeling evaluation under diverse conditions are needed to ensure practical reliability*

Several studies have demonstrated that integrating pre-processing methods into the ML pipeline can significantly improve model performance compared to using the network alone, as images acquired through various techniques often contain multiple types of noise that degrade overall image quality(Salvi et al., 2021). Our review found that White and Dark Reference Image Correction is widely used in fruit quality analysis. This method significantly enhances image accuracy by normalizing reflectance values, thereby enabling more reliable feature extraction and improved model performance. However, it can be time-consuming and less practical in real-time or field applications. Background removal is also a common pre-processing method that helps isolate the fruit from irrelevant image areas, thereby enhancing feature extraction and improving model focus and accuracy. This method is particularly beneficial when background noise may interfere with classification or detection tasks (Kc et al., 2021). However, its effectiveness can depend on lighting conditions and image complexity, and it may introduce errors if the fruit and background have similar colors or textures(Kc et al., 2021). In addition, other pre-processing methods commonly used in image processing help enhance prediction efficiency by improving image quality and reducing noise, including MSC, 1D-SG Smoothing, and SNV. Compared with general computer vision tasks such as vehicle or face recognition, fruit quality assessment requires

Table 7
Summary of ML methods used to assess different fruits for the quality analysis.

Author/year	Fruit species	Evaluation	ML algorithm	ML Inputs	ML Outputs	Validation	Performance	Accuracy (%)
Juan/2005	Apples	Defect detection	PLS-DA	The reflectance spectra	Healthy and bruised group	Training dataset (75%) and testing (25%).	Accuracy	91.53–94.92
Huang/2013	Apples	Defect detection	PCA	Hyperspectral images	Healthy and bruised group	NA	Accuracy	97
Huang/2015	Apples	Defect detection	PCA	Selected dominant wavelengths	Healthy and bruised group	NA	Accuracy	87.3–95.8
Zhang/2015	Peach	Defect detection	Minimum noise fraction (MNF) transforms and band math method	Discriminant wavelength	Artificial defect, non-artificial defect, and Sound Total	210(160 for training and 50 for testing)	Accuracy	93.3
Cen/2016	Cucumbers	Defect detection	NB, SVM, and KNN	Spectral or image	Two class: Normal or samples with chilling and post-chilling treatments; Three class: Normal, slightly chilling samples, or severely chilling samples	Training dataset (75%) and testing (25%).	Accuracy	76.2–100
Li/2016	Citrus	Defect detection	PCA	Spectra data of ROIs	Healthy and bruised group	Training dataset (66.66%) and testing 33.33%).	Accuracy	98.6
Fan/2017	blueberry	Defect detection	LS-SVM	Every pixel on the surface of the individual fruit	Healthy and bruised group	10-fold cross-validation	Accuracy	77.5–98.0
Chen/2018	Banana	Ripeness	PCA+KNN(K=3), PCA+SVM, LDA+KNN(K=3), LDA+SVM	RGB images	Unripe, half-ripe, fully ripe, and overripe	Leave-one-out cross-validation	Accuracy	86.67–100
Li/2018	Peach	Defect detection	I-WSM	SW-NIR and LW-NIR wavelength	Healthy and bruised group	Training dataset (50%) and testing 50%).	Accuracy	50–97.5
Tan/2018	Apple	Defect detection	GS-SVM	Corrected hyperspectral image	Bruised area, non-bruised area, and bruising degrees	K-fold cross-validation	Accuracy	62.5–95
Li/2019	Apple	Defect detection	WSM	Selected PC	Healthy and bruised group	440 (240 for training, 200 for testing)	Accuracy	62–100
Li/2019	Oranges	Defect detection	WSM	Wavelengths	Healthy and bruised group	Training dataset (50%) and testing 50%).	Accuracy	37.3–100
Sun/2019	Peach	Defect detection	WSM, PLSDA, and CNN	Image or after processing image	Good peaches (Level 0), slightly decayed peaches (Level 1), and severely decayed peaches (Level 2)	Training dataset (66.66%) and testing 33.33%).	Accuracy	65–98.6
Yu/2019	Strawberry	Ripeness	Mask-RCNN	RGB images	Ripe fruits and unripe fruits	Training dataset (80%) and testing 20%).	Detection precision	95.41–95.78
Azarmdel/2020	Mulberries	Ripeness (unripe, ripe, and overripe)	ANN and SVM	The most relevant features from the images.	Unripe, ripe, and overripe for white and red cultivar	65% as training data, 15% as validation, and 20% as test data.	Sensitivity, Specificity, and Accuracy	Accuracy: 98.25–100
Fan/2020	Apples	Defect detection	CNN and SVM	RGB images	Healthy and bruised group	Training dataset (80%) and testing (20%).	Accuracy, recall, and specificity	Accuracy: 83.3–90.9
Tian/2020a	Citrus	Defect detection	PCA	Hyper-spectral transmittance images	Infected and sound group	Training dataset (50%) and testing 50%).	Success rate	93–96
Tian/2020b	Apple	Defect detection	NB, LDA, ELM, and SVM	The average spectra of intact fruit	Healthy and infected apples	Training dataset (66.66%) and testing 33.33%).	Accuracy	82.7–92.7
Zeng/2020	Pear	Ripeness	CNN	Thermal images	Healthy and bruised group	The training set (816 unbruised and 2430 bruised fruit) and test set (288 unbruised and 837 bruised fruit)	Accuracy	71.5–99.3

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Table 7 (*continued*)

Author/year	Fruit species	Evaluation	ML algorithm	ML Inputs	ML Outputs	Validation	Performance	Accuracy (%)
Zhang/2020	Mandarins	Defect detection	PCA	RGB images	Anthracnose, Scarring, Decay, Thrips scarring, and Sound peel	250 for training and 356 for testing	Accuracy	90.57–100
Tian/2021	Citrus	Defect detection	SVM and RF	Decay detection methods in pixel-level: Wavelength; image-level: image	Healthy and bruised group	Training dataset (66.66%) and testing 33.33%).	Accuracy	97.11–99.66
Zhou/2021	Strawberry	Ripeness	YOLOv3	RGB images	UAV images were divided into Flower, Immature Fruit, and Mature Fruit. Near-ground digital camera images: Flower (F), Flower Fruit (FF), Green Fruit (GF), Green White Fruit (GWF), White Red Fruit (WRF), Red Fruit (RF), and Rotted Fruit (ROF).	Training dataset (80%) and testing (20%).	Precision	NA
Cai/2022	Citru	Defect detection	PLS-DA, SVM, LS-SVM, and KNN	Fourteen textural features.	Healthy and bruised group	200 for training and 80 samples for test set	Sensitivity, Specificity, and Accuracy	81.4–97.1
Chen/2022	Citrus	Ripeness (Immature, Semi-mature, and Mature)	LeNet5, VGG16, VGG19, ResNet18, ResNet34, ResNet50, SVM and KNN	RGB images	Immature, Semi-mature, and Mature	Training dataset (80%) and testing (20%).	Accuracy, recall, and precision	74.44–95.07
Guo/2022	Strawberry	Defect detection	CNN	Thermal images	Healthy and bruised group	70% training set and 30% test set	Accuracy, recall, F1 score, and precision	44–98
Ismail/2022	Apples and bananas	Ripeness and defect detection	Res Net, Dense Net, MobileNetV2, NASNet, and Efficient Net	Pixel of the image	Apple: Healthy and bruised group; Banana: unripe, yellow-green, mid-ripe, and overripe	Training, validation, and testing (80%, 10% and 10%).	Sensitivity, Specificity, and Accuracy	96.9–99.2 for apple and 98.2–99.2 for banana
Li/2022	Citrus	Defect detection	PLS-DA and BP-ANN	Corrected hyperspectral image	Healthy and bruised group	The training set to testing set ratio was 3:1	Coefficient (r), RMSE, and accuracy	91.2–96.6
Luo/2022	Oranges	Defect detection	PLS-DA	Corrected hyperspectral image	Two types of citrus tissues (sound tissue and rotten tissue) and three types of citrus tissues (sound tissue and two types of rotten tissues)	220 for training and 60 for testing	Accuracy	85.7–100
Azadnia/2023	Hawthorn	Ripeness	Inception-V3, ResNet-50, and the proposed DL models based on CNN	Corrected image	Unripe, ripe, and overripe	Training dataset (80%) and testing (20%).	Accuracy, precision, sensitivity, specificity, and F1-Score	99.6–100
Ropelewska/2023	Peach	Ripeness	RF and Bayes net algorithms	The slice images	Ripeness classes 0.1, 0.4, and 0.9. For 'Royal Glory', slices belonging to ripening stages 0.1, 0.4, and 1.0 were classified	The 10-fold cross-validation	Accuracy	70–100
Tang/2023	Strawberry	Ripeness	MaskR-CNN	RGB images	White, Breaking, Turning-1, Turning-2, Ripe and Full ripe	Training set (2172) and test set (651)	Accuracy	86.6
Yang/2023	Strawberries	Ripeness	YOLOv8s	RGB images	Ripe and unripe	5-fold cross-validation	Accuracy, recall, F1 score, and precision	93.5–98.7
Unal/2024	Apples	Defect detection	CNN	RGB image and hyperspectral image	Healthy and bruised group	Training, validation, and test sets in the ratios of 70%, 15%, and 15%,	Accuracy, recall, F1 score, and precision	74.66–100
Wang/2024	Strawberry	Ripeness	The YOLOv8 + , YOLOv3, YOLOv4, YOLOv5, YOLOv8n, SSD, and Faster-RCNN	Corrected image	Fully ripe, not fully ripe, and unripe	Training set (949) and testing set (119)	F1score, MAP, and FPS	97.81
Xu/2024	Apples	Defect detection	Passive Thermal Imaging	NA	NA	NA	Precision	NA

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Table 7 (*continued*)

Author/year	Fruit species	Evaluation	ML algorithm	ML Inputs	ML Outputs	Validation	Performance	Accuracy (%)
			Technology: Construction of Damage Detection Models					
Zhu/2024	Strawberry	Ripeness	CNN (ResNet18, ResNet50, and ResNet101)	Corrected hyperspectral image	Unripe, half-ripe, ripe, and rotten	Training dataset (70%) and testing (30%).	Accuracy, sensitivity, specificity, recall, F1 score, and precision	94.02–98.75
Shanthini/ 2025	Strawberry	Defect detection	SVM, KNN, LDA, RF, and DT	Corrected hyperspectral image	Healthy and bruised group	5-fold cross-validation	Accuracy, R2, MSE, and SEP	56.15–100

Note: Partial Least Squares Discriminant Analysis (PLS-DA), Principal Component Analysis (PCA), Naive Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Least Squares Support Vector Machine (LS-SVM), Linear Discriminant Analysis (LDA), Genetic Search Support Vector Machine (GS-SVM), Extreme Learning Machine (ELM), Random Forest (RF), Bayesian Network (Bayes Net), Decision Tree (DT), Mask Region-based Convolutional Neural Network (Mask-RCNN), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), You Only Look Once (YOLO), Single Shot MultiBox Detector (SSD), Faster Region-based Convolutional Neural Network (Faster-RCNN), LeNet5, VGG16, ResNet, DenseNet, MobileNetV2, NASNet, EfficientNet, and Inception-V3, Backpropagation Artificial Neural Network (BP-ANN).

application-specific preprocessing and segmentation methods focused on preserving quality-related spectral or textural information, reflecting its measurement-oriented rather than semantic-object-oriented objectives(Almazroey et al., 2025; Lin et al., 2020).

In our literature review, the top five ML methods used in E-nose studies were PCA, LDA, SVM, KNN, and ANN. For computer vision studies, PCA was most frequently applied, followed by PLS-DA, SVM, and CNN. Our results indicated that deep learning (DL) models have been used only to a limited extent in E-nose studies. Despite only one study using a DL model for fruit quality detection with an electronic nose, it achieved a high accuracy of 96.9%, outperforming most E-nose studies(Ren et al., 2023). DL models have been increasingly and frequently adopted in CV–based fruit quality assessment. Owing to the high dimensionality, complex spatial patterns, and rich texture information contained in images, DL models demonstrate superior representation learning and prediction performance compared with conventional machine learning methods. DL offers significant advantages in fruit quality assessment by automatically extracting features and effectively handling complex, non-linear patterns in high-dimensional data(Akter et al., 2024). Compared to traditional machine learning methods, DL models also demonstrate better generalization under real-world conditions, such as variations in lighting, occluded fruit and environmental factors(Lv et al., 2025). This observation aligns with previous literature; for example, Jia et al. reported that traditional classification methods no longer meet the practical demands of production and daily life(Jia et al., 2024). Therefore, future research should place greater emphasis on applying DL models in this field. In particular, CNNs have recently proven to be effective alternatives for object detection, segmentation, and image analysis tasks, and can be leveraged to improve prediction efficiency in future applications (Akter et al., 2024).

The majority of studies relying on E-nose and computer vision technologies reached high predictive accuracy (more than 80%) for fruit quality classification. This strong performance can be attributed to the E-nose's ability to detect subtle differences in volatile compounds and the capability of computer vision to capture detailed visual features such as color, shape, and texture. In many cases, the combination of various preprocessing techniques and multiple machine learning models led to predictive accuracies surpassing 90%, and in some instances, even reaching 100% (Huang et al., 2015; Zhang et al., 2015; Zhang et al., 2020). These findings suggest that E-nose and computer vision technologies hold substantial promise for effective fruit quality detection (Akter et al., 2024). Although the results are encouraging, the unusually high accuracy reported raises valid concerns about overfitting, particularly in light of the small sample sizes used in many studies(Chen et al., 2018; Huang et al., 2013). Nevertheless, this issue has not been adequately acknowledged in previous research on fruit quality detection. Specifically, our review revealed that 20 computer vision studies used fewer than 1000 images, while the number of fruit samples in E-nose studies ranged from just 15–500. Moreover, most studies relied on internal validation methods, such as the hold-out method (typically using a 66.6%/33.3% training/testing split), K-fold cross-validation, and leave-one-out cross-validation. In the absence of sufficient external validation, the robustness and generalizability of these models in real-world applications remain uncertain. Therefore, further research should emphasize evaluating these models under diverse conditions, incorporating larger datasets, and testing across multiple environments to ensure practical reliability.

4.5. *Integration of E-nose and Computer Vision largely remains unexplored*

E-nose systems are primarily applied under laboratory conditions, achieving accuracies of 45–100% for defect detection, up to 96.9% for freshness evaluation, and 66.7–100% for ripeness assessment. In comparison, computer vision methods are employed in both laboratory and natural environments, showing comparable laboratory performance for defect detection (37.3–100%) and ripeness assessment (70.0–100%), as well as consistently high accuracy for ripeness evaluation under natural conditions (74.4–98.7%). Although both E-nose and computer vision technologies offer notable advantages, they also present inherent limitations. While precise cost data are rarely reported, E-nose systems are generally less expensive and computationally simpler than computer vision systems. E-nose systems are highly sensitive to environmental conditions and sensor sensitivity, while computer vision techniques are susceptible to factors such as lighting variability, spectral noise, spectrometer heterogeneity, and environmental fluctuations, particularly in the case of infrared spectral data. To overcome these challenges, several studies have investigated the integration of both methods. Notably, the combined use of E-nose and computer vision has achieved perfect classification of the four maturity stages of bananas. However, such approaches remain largely unexplored for other fruit types, highlighting the need for further research in this area.

4.6. *Emerging UAV Technology Expands the Application of Computer Vision Beyond Laboratory Settings*

Some studies have investigated fruit quality detection in natural environments using unmanned aerial vehicle (UAV) technology equipped with cameras and spectrographs. These studies reported accuracy exceeding 86%, offering novel insights into assessing fruit quality and assisting decision-makers in determining the optimal maturity stage for harvest. While prior literature reviews on fruit quality have primarily focused on experimental setups, machine vision systems, and classification models(Akter et al., 2024; Aline et al., 2023; Bhargava and Bansal, 2021). Few, if any, have examined the application of these technologies in real-world environments as opposed to controlled laboratory conditions. Our review identified seven studies that employed computer vision to assess fruit ripeness in natural, outdoor settings. Notably, one study combined UAV technology with near-ground imaging and achieved the highest mean average precision of 0.88(Zhou et al., 2021). In recent years, some researchers have adopted UAV technology to predict strawberry yield, monitor and control diseases in strawberries, detect powdery mildew in squash, and identify citrus greening (Zhou et al., 2021). These studies not only demonstrated high accuracy but also showed that UAV-based approaches can be effectively applied in natural environments to support efficient fruit quality detection. Thus, more studies are needed to explore the use of UAV technology across different types of fruit.

4.7. Shelf life, as a key factor in fruit ripeness detection, was overlooked

The shelf life of fruit plays a vital role in fruit transportation, storage, and donation. However, few existing studies have incorporated this aspect in fruit ripeness detection. Our review identified three studies that used E-nose technology to assess fruit ripeness in relation to the timing of each ripeness stage(Chen et al., 2018; Du et al., 2019; Torri et al., 2010). In contrast, only one study considered time as a factor when using computer vision to detect fruit ripeness. Specifically, previous literature reviews on fruit quality detection have largely overlooked the role of shelf life, with most studies focusing exclusively on technological aspects while neglecting practical applications (Al-Dayyeni et al., 2021; Mohamed et al., 2018). The limited consideration of temporal dynamics may restrict the generalizability of current models, especially in real-world scenarios where ripening progresses continuously over time and is influenced by various environmental factors. In practical terms, incorporating temporal information into ripeness detection systems could support more informed decision-making in harvesting, logistics planning, and food donation timing, ultimately helping to reduce postharvest losses.

4.8. Integrating Shelf Life into Life Cycle Assessment to Reduce Environmental Impact and Enhance Health Equity

More than 1.3 billion tons of food are wasted each year across the entire supply chain - from production to consumption - resulting in approximately 3.3 gigatons of CO_2-equivalent emissions annually, or about 6% of total human-generated greenhouse gases(Amicarelli et al., 2021). The present review indicates that research on fruit quality detection has primarily focused on commonly wasted fruits such as apples and bananas, which is reasonable given their high loss rates. However, an analysis of citation patterns within the included studies revealed that few have been referenced by research related to food waste or environmental health. This suggests that most studies in this area remain isolated from broader interdisciplinary contexts and may be limited in their practical application.

After accurately determining fruit ripeness, distribution routes can be optimized to minimize food waste, reduce transportation distances, and lower associated greenhouse gas (GHG) emissions(Jedermann et al., 2014). By accurately estimating the shelf life of fruits, targeted marketing strategies such as dynamic pricing, inventory rotation, and promotional campaigns can be implemented to reduce food waste and increase sales by accelerating product turnover before spoilage occurs (Porat et al., 2018). Most importantly, if the shelf life of fruits is accurately known, food suppliers and retailers can better plan and execute timely food donations, redistributing fresh but near-expiry produce that is still safe and nutritious. This not only significantly reduces post-harvest and retail-level food waste—thereby mitigating greenhouse gas emissions and improving environmental health—but also enhances public health by increasing access to nutritious food among populations experiencing food insecurity. In particular, individuals living below the poverty line often suffer from poor dietary intake due to limited food access. Improved food donation systems enabled by accurate spoilage forecasting can help reduce nutritional disparities and support community-level food resilience.

Life cycle assessment (LCA) frameworks allow for more realistic estimation of food waste-related emissions and environmental burdens when incorporating fruit shelf life, especially for perishable produce(Wu et al., 2025). Optimization models enriched with perishability constraints can guide decisions on transportation, storage, and market allocation to reduce loss and improve sustainability. While previous studies have incorporated the marginal value of time into LCA models to assess the time-sensitive deterioration of perishable goods, the specific role of shelf life in improving fruit donation efficiency and reducing waste has received limited attention (Blackburn and Scudder, 2009). However, there is no published framework that seamlessly integrates LCA with food decay or shelf-life prediction using multimodal sensing and machine learning. Existing studies primarily focus on integrating LCA with food nutrition or applying LCA to evaluate food waste management strategies (Yang et al., 2022). However, a deeper integration of LCA with food decay and shelf life is needed to better understand the dynamic environmental impacts associated with food spoilage and waste generation, and to support more informed decisions regarding food distribution, storage, and preservation.

5. Conclusions and Future Recommendations

Integrating appropriate preprocessing with combined E-nose and computer vision techniques enhances fruit quality classification. However, while many studies focus on ripeness and defect detection, few simultaneously consider shelf life, which is critical for fruit storage and transportation. Based on the overviews above, future studies should focus on these key aspects rather than conducting superficial research or repeating previous work:

(1) Expands fruit quality detection to more fruits, especially oranges, grapes, pineapples, and watermelons.
(2) Expands the application of computer vision and E-nose beyond laboratory settings
(3) Advancement in real-time processing for both computer vision and E-nose.
(4) Multi-Modal Integration of E-nose and Computer Vision:
(5) Developing scalable and cost-effective solutions for large-scale fruit quality detection, particularly in large farms.
(6) Simultaneously assess fruit ripeness or quality along with their estimated shelf life.
(7) Strengthen the integration of fruit quality detection with environmental health considerations.

CRediT authorship contribution statement

Zhongguo Huang: Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Xin Wang:** Writing – review & editing. **Xiaobo Xue Romeiko:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Darvensky M. Eugene:** Writing – review & editing. **Xin Li:** Writing – review & editing.

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.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.clwas.2026.100498.

Data availability

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

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