Available *online* at: http://ajeeet.ft.unand.ac.id/
Andalas Journal of Electrical and Electronic Engineering Technology
ISSN 2777-0079

The Convergence of Artificial Intelligence and Electronic Devices for Rapid Food Quality Measurement: A Systematic Review

Mohammad Alfiza Rayesa[1], Dego Yusa Ali[2], Neza Fadia Rayesa[3], Elsa Lolita Anggraini[1], Togi Siholmarito Simarmata[1]

[1] *Department of Electrical Engineering, Faculty of Science and Technology, Universitas Jambi, Jambi, 36361, Indonesia*
[2] *Department of Food Science and Biotechnology, Faculty of Agricultural Technology, Universitas Brawijaya, Malang, 65145, Indonesia*
[3] *Department of Agricultural Socio-Economic, Faculty of Agriculture, Universitas Brawijaya, Malang, 65145, Indonesia*

ARTICLE INFORMATION

Received: July 23, 2023
Revised: November 06, 2025
Accepted: December 6, 2025
Available online: December 9, 2025

KEYWORDS

Food Quality, Artificial Intelligent, Quality Measuring, Machine Learning, Deep Learning

CORRESPONDENCE

Phone: +62 85159951407
E-mail: m.alfizarayesa@unja.ac.id

A B S T R A C T

Ensuring the quality and safety of food is a critical global challenge intensified by complex supply chains and increasing consumer demand for transparency. Traditional measurement techniques—ranging from microbial plating to sensory panels- are often destructive, time-consuming, labor-intensive, and expensive. Recently, non-invasive electronic sensing technologies, coupled with Artificial Intelligence, have emerged as powerful alternatives for rapid and objective assessment. This review aims to identify, synthesize, and appraise peer-reviewed research published between 2005 and 2025 that incorporates AI into electronic devices: electronic noses, computer vision, and spectroscopy for food quality measurement. A systematic literature search was conducted across ScienceDirect, SpringerLink, and IEEE Xplore. The review followed the PRISMA guidelines by identifying 63 studies that met strict inclusion criteria for integrating sensing, hardware, and machine learning algorithms. Analyses show that Computer Vision Systems (CVS), Hyperspectral Imaging (HSI), and Electronic Noses (e-noses) technologies. Deep Learning, in particular Convolutional Neural Networks (CNNs), has surpassed traditional machine learning techniques, such as SVM and PCA, in performance. Key applications include ripeness grading of fruits, detection of adulteration in powders, and freshness monitoring of vegetables and meat products. Integrating AI with electronic sensors provides a scalable, accurate, and non-destructive path forward for Industry 4.0 in the food sector. However, challenges to the issues of model interpretability, data standardization, and real-world robustness remain.

INTRODUCTION

Paradoxically, in the third decade of the 21st century, the global food system has reached a point where agricultural production has been scaled up to meet the growing needs of an increasingly populous world, while the complexity of ensuring its safety and quality has increased exponentially. Food supply chains are no longer local, but instead traverse continents, introducing numerous points of potential contamination, adulteration, and spoilage. This fact has been highlighted by the WHO in its broad epidemiological study, where it is estimated that unsafe food causes 600 million cases of foodborne diseases annually [1]. This leads to a very high economic burden, especially in the low-to middle-income countries, and a significant morbidity.

Besides the non-negotiable imperative of safety, "quality" encompasses a multidimensional spectrum of attributes that dictate marketability and consumer acceptance. These include organoleptic properties, nutritional integrity, and aesthetic appearance. Even minor deviations in quality can lead to massive financial losses or damage to brand reputation in high-value commodities such as wine, coffee, and export-grade fruits. Besides the non-negotiable imperative of safety, "quality" encompasses a multidimensional spectrum of attributes that dictate marketability and consumer acceptance. These include organoleptic properties, nutritional integrity, and aesthetic appearance. Even minor deviations in quality can lead to substantial financial losses or damage to a brand's reputation in high-value commodities such as wine, coffee, and export-grade fruits.

The food industry has traditionally relied on a suite of "gold standard" conventional assessment methods. Chemical analysis techniques, such as GC-MS and HPLC, provide precise molecular identification of contaminants and flavor compounds. Microbiological assays, such as agar plating and PCR, play a crucial role in identifying pathogens like Salmonella and L. monocytogenes. In the case of sensory attributes, human sensory panels remain the benchmark for evaluating subjective experiences like "mouthfeel" or "aromatic complexity."

https://doi.org/10.25077/ajeeet.v5i2.44

However, a critical review of the literature in this field clearly demonstrates that these traditional techniques are increasingly incompatible with the speed of contemporary industrial production, Hassoun at al [2] argue that though fluorescence spectroscopy and similar lab-bench methods are accurate, they are by their nature destructive. To test a steak for freshness using standard chemical assays often requires homogenizing the sample and thereby rendering it unsellable. Xu et al. [3] in their review on pesticide detection, commented that traditional chromatographic methods are usually very time-consuming, taking up to days for the results. This latency forces manufacturers to use only statistical batch sampling, testing one unit per thousand, instead of a continuous monitoring regime that would leave large gaps in their quality control through which defective products could slip to the consumer. In addition, such methods involve hazardous reagents and highly skilled personnel, which increase the operation costs.

To bridge the chasm between the need for rigorous testing and the demands of high-speed, zero-waste production, the last decade has witnessed a proliferation of rapid, non-invasive electronic sensing technologies. These devices are designed to digitize physical or chemical properties of food into high-dimensional data streams, effectively granting machines the sensory capabilities of sight, smell, and taste, but with superior quantification and endurance.

Computer vision systems (CVS) operates to extract information with many parallels to human visual perception, although in a more objective, quantified manner [4]. Employing RGB, depth, and increasingly thermal cameras, CVS assesses external features of a product. Cubero et al. [5] emphasize that CVS is developing from simple colorimeters that measured the average surface color to complex systems with several cameras capable of reconstructing 3D models. These systems grade fruits and vegetables by morphology, size, and surface defects at speeds far outpacing those of human inspectors, who are prone to fatigue and subjectivity.

While systems based on vision are confined to surface features, spectroscopic techniques allow a view into the internal biochemical state of food. Wu and Sun [6] describe the transformative potential of Hyperspectral Imaging (HSI), which combines conventional imaging with spectroscopy. Unlike a standard camera that captures three bands (Red, Green, Blue), HSI sensors capture hundreds of contiguous spectral bands for every pixel in an image. By analyzing the interaction of light with matter—specifically absorption and reflectance in the Near-Infrared (NIR) region—these technologies can quantify moisture, protein, fat, and sugar content (Brix) without slicing the product open.

Flavor and aroma are chemical signatures. Electronic noses are devices consisting of arrays of gas sensors (commonly Metal Oxide Semiconductors or conducting polymers) that have partial specificity. Karakaya et al. [7] explain that e-noses function by mimicking the mammalian olfactory system: they detect a "fingerprint" of Volatile Organic Compounds (VOCs) rather than identifying individual molecules. Similarly, e-tongues utilize electrochemical sensors to analyze liquid samples, predicting global taste profiles such as sweetness, sourness, bitterness, or umami.

The deployment of these advanced sensors creates a new problem: data deluge. A single hyperspectral image may contain hundreds of thousands of spectral signatures, while one e-nose reading creates complex, nonlinear sensor drift and cross-sensitivity patterns that are unintelligible through simple statistical observation. As Kakani et al. [8] stress, classic univariate statistical methods cannot rise to the challenge presented by these high-dimensional, multicollinear datasets. It is here that Artificial Intelligence becomes the essential catalyst.

The research area has undergone a paradigm shift over the review period, from 2015 to 2025. Researchers first started using dimensionality reduction with Chemometrics and traditional ML algorithms, such as PCA, along with SVMs for classification. However, the limitation on these works was that feature engineering was needed manually, where experts had to choose which wavelengths or shape parameters were important.

This workflow has been revolutionized by the emergence of DL. In their seminal work. Hussain et al. [9], described how deep neural networks, consisting of multiple processing layers, are able to learn multiple levels of abstraction in the representation of data. Considering food, for example, this means a CNN can automatically learn that a certain pattern of texture corresponds to bruising on an apple, without ever having a human define "bruising" mathematically. This technological convergence, as noted by broad industrial reviews from Song et al. [10] and more specifically regarding AI in agriculture by Omotayo [11], forms the cornerstone of the so-called "Food Industry 4.0," wherein automated, intelligent, and predictive quality control systems improve over time with more data processed.

Despite the wealth of individual studies, the literature remains fragmented, often siloed by specific sensor type or food commodity. Shown in Table 1, synthesis is urgently needed if the holistic maturity of AI-driven food quality assessment is to be understood. This systematic review synthesizes findings from 65 pivotal studies published between 2015 and 2025 to address three core research questions:

Table 1. Research Questions (RQs) addressed in this systematic review.

Technological Efficacy	Which electronic sensing modalities are most effective for specific food matrices (e.g., differentiating the needs of meat safety vs. fruit grading)?
Algorithmic Evolution	How have AI methodologies evolved, particularly the transition from shallow learning to deep learning, and what performance gains has this yielded?
Barriers to Adoption	What technical, economic, and practical challenges prevent the widespread industrial deployment of these AI-driven systems beyond the laboratory?

METHODS

Search Strategy and Protocol

A systematic search strategy was carried out to ensure a rigorous, reproducible, and unbiased review, in accordance with the PRISMA guidelines [12]. The search was conducted in November 2025, covering a ten-year window from January 2005 to November 2025. This time span was specifically considered because deep learning applications began to permeate the food science literature around 2016-2017.

The electronic databases searched include ScienceDirect, SpringerLink, and IEEE Xplore. This set of databases is chosen because it represents a balance between the major food science-specific journals and engineering/computer science proceedings. Search strings shown in Table 2, were constructed using Boolean operators to combine terms related to three conceptual blocks, and

Table 2. Search terms and keywords used for the systematic literature search.

Domain	("Food Quality" OR "Food Safety" OR "Food Analysis" OR "Meat Freshness" OR "Fruit Grading")
Technology	("Electronic Nose" OR "Computer Vision" OR "Hyperspectral Imaging" OR "Spectroscopy" OR "Biosensors" OR "Electronic Tongue")
Methodology	("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks" OR "CNN" OR "Chemometrics")

Inclusion and Exclusion Criteria

Eligibility criteria were strict to ensure the relevance and quality of the selected studies during the screening process [13].

Inclusion

Only peer-reviewed original research articles and selected systematic reviews that explicitly integrated a sensor device with an AI/ML model for a food application are included. Food applications focused on major categories, including meat, poultry, seafood, fruits, vegetables, dairy, grains, and beverages, were preferred. Articles had to report quantitative performance metrics such as Classification Accuracy, R^2, and RMSE.

Exclusion

Patents, conference abstracts, and non-English publications were excluded. Importantly, to maintain a strict focus on post-harvest food product quality, studies related to pre-harvest agricultural conditions (such as soil analysis using satellite imagery or crop yield prediction) were excluded. Furthermore, studies that only used sensors without AI, i.e., simple statistical observations, or AI studies without sensor data, such as simulation studies, were also excluded.

Data Extraction and Synthesis

The extracted data from the selected 63 studies was recorded on a standardized form that detailed: 1) Bibliographic details (Author, Year, Country); 2) Food Matrix (e.g., Beef, Apple, Wine); 3) Sensing Technology (Hardware specifics); 4) AI Algorithm (Architecture, Framework); 5) Target Attribute (e.g., ripeness, adulteration, microbial load); and 6) Performance Metrics, the methodology and results of the review process are illustrated in Figure 1. The synthesis of these studies is presented in the next Results section, grouped, as a rule, by the sensing technology employed, since this dictates the type of data and the corresponding AI strategy.

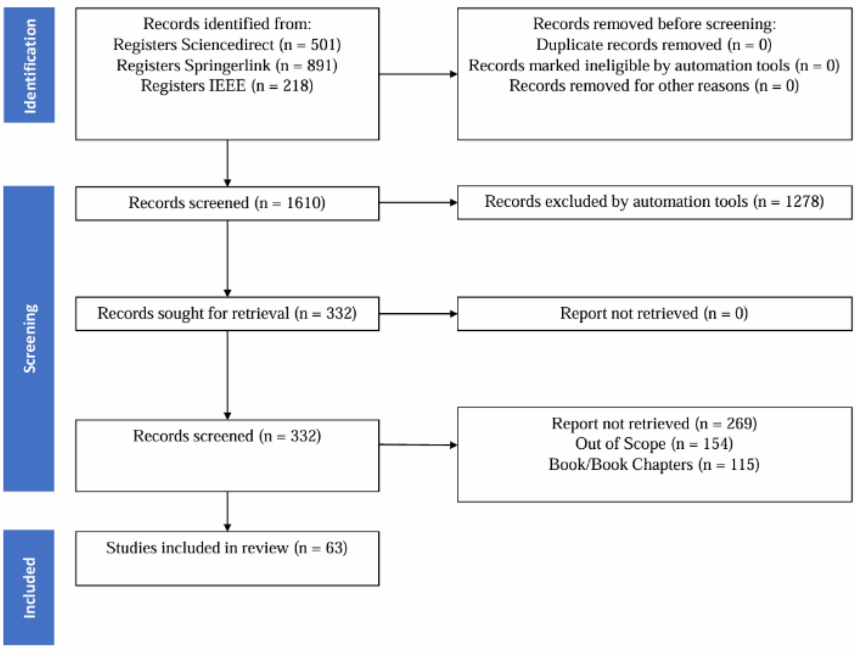

Figure 1. Flowchart outlining the study selection process following the PRISMA 2020 guidelines.

 https://doi.org/10.25077/ajeeet.v5i2.44

RESULTS AND DISCUSSION

Overview of Bibliometric Trends

A clear inflection point in the temporal distribution of the selected 63 studies is observed around the years 2018-2019. Before this, studies were mainly based on traditional machine learning (SVM, k-NN, Random Forest), with several papers focused on dimensionality reduction techniques such as PCA and LDA. Starting from 2019, there is an abrupt rise in the number of publications using Deep Learning, especially Convolutional Neural Networks (CNN). This sudden upsurge coincides with wider availability of GPU computing and open-source libraries like TensorFlow and PyTorch. Indeed, general reviews of AI in food by Zhang et al. [43] and Zhu et al. [26] also confirm that the increasing complexity and volume of food data necessitate deep neural networks capable of nonlinear modeling.

Computer Vision Systems (CVS): From Color to Cognition

Computer vision is perhaps the most mature of the technologies reviewed, having transitioned from simple RGB color thresholding to sophisticated cognitive recognition systems that rival human perception.

Fruit and Vegetable Grading

The most commercially advanced application is the automated grading of fresh produce. Bhargava and Bansal [14] reviewed this field and noted that early systems struggled with variable lighting conditions and complex backgrounds, often requiring controlled "light box" environments. However, recent advances have overcome these robustness issues. As an example, Hussain [9] recently showed how a deep convolutional neural network (VGG-16) could classify varieties of apples at high precision. Their model learned subtle texture and pattern features that differ between, for example, Gala and Fuji apples, which are hard to quantify manually. Similarly, Parvathi and Tamil Selvi [15] employed the model known as Faster R-CNN to detect maturity stages of coconuts, which is challenging because the background of any farm environment would be complex and cluttered; notwithstanding this, the deep learning model was able to achieve remarkably good detection rates, which therefore opens avenues to robotic harvesting.

Defect Detection

Beyond only classification, defect detection is an important means of ensuring minimal food waste while maintaining consumer satisfaction with the finished product. Mureșan and Oltean [16] proposed a deep learning approach to recognizing fruit defects, which achieved new state-of-the-art results on publicly available datasets. They also showed that CNNs are robust with regard to rotation and scale, and therefore fruit does not have to be perfectly oriented on a conveyor belt. Nturambirwe and Opara [17] emphasized in their work that machine learning outperforms human inspection in terms of finding bruised or early-stage rotten spots not directly visible to the human eye but with a specific texture signature. Concretely for industrial uses, the work of Fan et al. [18], implemented an on-line system for defective apple detection using a combined CVS and deep learning approach operating at conveyor belt speeds, while Moya [19] has also proposed mechanized grading systems for tomatoes using computer vision to sort on size and skin integrity; integrating mechanical sorting arms controlled by the AI's decision.

Specialized and Emerging Applications

The versatility of CVS extends to other food groups where visual cues are proxies for quality. Mohebbi et al. [20] applied CV to evaluate moisture content in dried shrimp. By analyzing shrinkage patterns and color changes, they were able to correlate the visual features with chemical moisture content, offering a non-contact drying control method. Yang [21] tackled the difficult problem of detecting the defects of eggs, such as cracks or dirt, using deep learning.

Their system significantly reduced the breakage rates associated with mechanical sorters by identifying weak shells before packaging. Jin et al. [22] further extended vision applications to seed quality assessment, reviewing how deep learning models can predict germination rates based on seed morphology, a critical step for agricultural yield assurance.

Electronic Noses and Tongues: Digitizing Flavor

Electronic noses and tongues handle the "chemical" senses, changing volatile and soluble compounds into digital signals. Thanks to AI's capabilities to correct for hardware weaknesses, including sensor drift, there has been a recent renaissance in these technologies.

Meat and Seafood Freshness

Rapid spoilage detection is thus a key use case, with meat generating distinct volatile amines, such as ammonia and putrescine, as it degrades. Benedetti et al. [23] utilized an e-nose to classify honey quality, but the algorithmic approach (Ensemble Decision Trees) is widely applicable to animal proteins. In the context of meat safety, Bonah et al. [24] developed an e-nose method specifically for detecting Salmonella typhimurium in pork. By training the AI to recognize the specific metabolic volatile profile of Salmonella, they achieved a rapid pathogen screening method.

Ferrier et al. [25] went even further by developing a portable electronic nose system that could monitor the freshness of livestock products in real-time. The work of Ferrier et al. showed that such devices can be miniaturized for field use, pushing quality control from laboratory analysis out onto the loading dock. Yu et al. [26] combined hyperspectral imaging with data fusion techniques for tilapia fillets, but the principles of freshness detection align closely with e-nose capabilities for assessing Total Volatile Basic Nitrogen (TVB-N).

Dairy, Beverage, and Origin Authentication

Food fraud is an important economic problem, especially for high-value liquids. Balivo et al. [27] applied the e-nose, combined with machine learning, to detect the adulteration of milk with added water or other cheaper kinds of milk. Working in the more complex matrix of tea, Zhi et al. [28] illustrated the potential of sensor fusion, combining both electronic nose and electronic tongue data to evaluate tea quality. Their multivariable approach outperformed either sensor type alone, effectively mimicking human flavor perception, which combines retro-nasal smell and taste. A very specific example of this utility was given by Gliszczyńska-Świgło et al. [29] using e-noses to detect coffee's hazelnut adulterations, one of the most common risks of food allergens.

Reviewing the Field

These sensors represent an impact far wider than these industrial applications. Gliszczyńska-Świgło and Chmielewski [29] discussed the use of e-noses for food authenticity, suggesting these devices are essential tools in the fight against food fraud. Vanaraj et al. [30] similarly presented an extensive review of e-tongue applications, with a note on their successful execution in mineral water and wine analysis. Similarly, Wang & Chen et al. [31] and Zia Ul Haq et al. [32] both produced extensive reviews on the industrial applications of e-noses, showing recent interest in "smart" sensors with integrated IoT connectivity.

Ye et al. [33] on the other hand, discussed from the algorithmic point of view recent advances in machine learning specifically for analyzing noisy data, which is typical of e-nose sensors, suggesting that Recurrent Neural Networks (RNNs) are particularly well-suited for time-series sensor data. Alarcón et al. [34] applied e-noses with fuzzy logic classifiers to determine the quality of bananas, correlating the emission of ethylene and esters with ripening stages.

Spectroscopy and Hyperspectral Imaging (HSI): The Internal View

Spectroscopic methods arguably represent the most powerful approaches to quantitative chemical analysis and, not least, offer a non-destructive alternative to wet chemistry.

Internal Quality Assessmen

NIR spectroscopy is now an industry standard for Brix (sweetness) sorting in the packing house. An excellent foundational review on NIR usage for non-destructive fruit and vegetable quality measurement was provided by Nicolaï et al. [35]. More recently, Zeng et al. [36] applied deep learning to NIR data measurement of sugar content in apples. Their deep learning model demonstrated improved robustness against skin thickness variations compared to traditional PLS regression. Sun et al. [37] employed a Vis/NIR spectroscopy coupled deep learning system to detect peach fungal infection. For the first time, their system was able to detect infected tissue that was not yet visible to the naked eye.

Safety and Contaminants

HSI enables the spatial mapping of contaminants, which point spectroscopy cannot do. Liao et al. [38] used HSI and Partial Least Squares Discriminant Analysis (PLS-DA) to detect pesticide residues on fruit surfaces. This theme was also explored by Jiang et al. [39] using Surface-Enhanced Raman Spectroscopy (SERS) combined with machine learning, achieving detection limits comparable to chromatography. W. Li et al. [40] applied HSI and deep learning to a very challenging task: the detection of foreign objects such as plastic or wood pieces present in meat products. These foreign bodies often display colors similar to the meat itself and thus cannot be distinguished by regular cameras but show distinct spectral signatures in the infrared range that can be detected by HSI.

Methodological Advances and Reviews

Most hyperspectral data processing is computationally burdensome due to its "curse of dimensionality." Zhang et al. [26] and Chen et al. [41] independently reviewed deep learning on hyperspectral image classification, mentioning that 3D-CNNs had notable performance since they operate on both spatial and spectral information together. Huang et al. [42] and Wu and Sun [6] emphasized in their reviews that HSI is moving from the lab to the line, though data volume and processing speed remain challenges. Ahmed et al. [43] introduced deep learning-based HSI classification specifically for food quality, proposing lightweight architectures that reduce computational load. Pu et al. [44] focused on the critical step of preprocessing techniques for hyperspectral data (such as scatter correction and derivatives), which is essential for removing noise before AI modeling.

Seafood and Meat

Cheng and Sun [45] and Wu et al. [46] respectively, have reviewed the vast applications of HSI for the quality of fish and meat. This technique is able to map fat and protein distributions, important in grading marbling in beef or freshness in fish. In a further structural analysis, Wellner [47] discussed Fourier Transform Infrared (FTIR), Raman microspectroscopy, and their applications in the characterization of food structure at a microscopic level.

Emerging Technologies and Integrated Systems

Recent research explores the integration of these technologies into broader, interconnected systems. Enériz et al. [48] discussed "in-situ" food quality monitoring using deep learning, moving analysis closer to the point of harvest to prevent spoilage earlier in the chain. Mani et al. [49] reviewed "smart sensors," which include biosensors and IoT-connected devices. Nelis et al. [50] highlighted the democratization of this technology through smartphone-based sensing systems, where the phone's camera and processing power are used for safety checks by consumers or small retailers. Damdam et al. [51] described an IoT-enabled electronic nose, facilitating remote quality monitoring across supply chains.

The Algorithmic Shift: From Shallow to Deep

One of the most significant findings of this review is the dominance of Deep Learning in recent years. As noted by LeCun et al. [52] in their seminal paper on deep learning, these models allow for end-to-end learning. In the specific context of food, Kamilaris and Prenafeta-Boldú [53] and Botero-Valencia et al. [54] explain that DL removes the need for "hand-crafted" features. In traditional machine learning, a scientist had to define that "roundness" or "redness" were the features that mattered. DL models learn the most discriminatory features directly from the raw data. This is echoed in the reviews by Zhou et al. [55] and Nada et al. [56], who observe that DL models consistently outperform traditional chemometrics (like PLS) when datasets are sufficiently large. Lam et al. [57] demonstrated this performance leap in food quality estimation tasks, showing that deep architectures could capture non-linear relationships that linear models missed.

The Challenge of Data and Interpretability

However, the "black box" nature of DL is a significant hurdle for regulatory acceptance. Kharbach et al. [58] discuss the urgent need for "Explainable AI" (XAI) in food quality. If a model rejects a batch of apples or condemns a carcass, the operator and the regulator need to know why (e.g., is it size, color, or a specific pathology?). Gunning and Aha [59] describe the general principles of XAI which are now being applied to food safety to build trust.

Furthermore, Jin et al. [60] highlight the "Big Data" challenge. Deep learning requires massive amounts of labeled data. Unlike the vast datasets available for general object recognition (like ImageNet), labeled datasets for food quality (e.g., "hyperspectral images of Salmonella on chicken") are rare, expensive to create, and often proprietary. Deng et al. [61] identify this data scarcity as a primary bottleneck preventing the democratization of these tools.

Implementation, Hardware, and Industry 4.0

The research aligns with the broader move toward Industry 4.0. Agrawal et al. [62] envision a future where these AI-driven sensors are fully integrated into cyber-physical systems, creating a "digital twin" of the food supply chain. Dodero et al. [63] point to intelligent packaging as the next frontier, where sensors are embedded directly into the wrapper to monitor freshness throughout shelf life, communicating with the consumer's smartphone.

However, Banicod et al. [64] warn that the "road ahead" requires addressing the high cost of hardware (particularly HSI cameras which can cost tens of thousands of dollars) and the need for robust models that can handle the variability of biological products in uncontrolled industrial environments (humidity, temperature fluctuations). Jin et al. [22] also note that for seeds and grains, the speed of processing must match the immense throughput of agricultural sorting machines, requiring optimized, low-latency AI models.

CONCLUSION

This systematic review of 63 studies published between 2015 and 2025 confirms that the convergence of Artificial Intelligence and electronic devices is transforming food quality measurement from a reactive, sample-based discipline into proactive, continuous, and data-driven science. The field has evolved from experimental feasibility studies into robust applications driven by deep learning, capable of real-time operation. Computer Vision has mastered external grading and is headed into internal defect prediction by deep learning. HSI remains the gold standard for non-destructive chemical analysis, enabling "digital dissection" of food, but hardware costs impede ubiquity. Electronic Noses are finding their niche in spoilage detection and authentication with the development of IoT integration and AI's ability to correct sensor drift. Deep Learning remains the de facto standard of data analysis. Offering superior accuracy, deep learning, however, requires large datasets and solutions that will allow for explainability. The agenda for future research should focus on developing low-cost portable sensors, open-access spectral datasets that will reduce the entry barrier for AI training, and explainable AI models able to pass regulatory scrutiny. Convergence of these technologies will provide the nervous system for a safer, more efficient, and transparent global food supply chain.

REFERENCES

[1] WHO, “Food safety,” WHO Press.

[2] A. Hassoun, A. Sahar, L. Lakhal, and A. A\"\it-Kaddour, “Fluorescence spectroscopy as a rapid and non-destructive method for monitoring quality and authenticity of fish and meat products: Impact of different preservation conditions,” *Lebenson. Wiss. Technol.*, vol. 103, pp. 279–292, Apr. 2019.

[3] M.-L. Xu, Y. Gao, X. X. Han, and B. Zhao, “Detection of pesticide residues in food using surface-enhanced Raman spectroscopy: A review,” *J. Agric. Food Chem.*, vol. 65, no. 32, pp. 6719–6726, Aug. 2017.

[4] A. H. Wirasapta, P. Nugroho, and S. B. Wibowo, “Designing QPSK Modulator Using LTspice-Based Discrete Components,” in *2022 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT)*, IEEE, Nov. 2022, pp. 283–288. doi: 10.1109/COMNETSAT56033.2022.9994317.

[5] S. Cubero, N. Aleixos, E. Moltó, J. Gómez-Sanchis, and J. Blasco, “Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables,” *Food Bioproc. Tech.*, vol. 4, no. 4, pp. 487–504, May 2011.

[6] D. Wu and D.-W. Sun, “Advanced applications of hyperspectral imaging technology for food quality and safety analysis and assessment: A review — Part I: Fundamentals,” *Innov. Food Sci. Emerg. Technol.*, vol. 19, pp. 1–14, Jul. 2013.

[7] D. Karakaya, O. Ulucan, and M. Turkan, “Electronic nose and its applications: A survey,” *Int. J. Autom. Comput.*, vol. 17, no. 2, pp. 179–209, Apr. 2020.

[8] V. Kakani, V. H. Nguyen, B. P. Kumar, H. Kim, and V. R. Pasupuleti, “A critical review on computer vision and artificial intelligence in food industry,” *J. Agric. Food Res.*, vol. 2, no. 100033, p. 100033, Dec. 2020.

[9] N. Hussain, G. Zaki, and M. Hassan, “Apple fruits categorizing based on deep convolutional neural network techniques,” *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 13, no. 3, p. 3695, Sep. 2024, doi: 10.11591/ijai.v13.i3.pp3695-3702.

[10] X. Song *et al.*, “AI in food industry automation: applications and challenges,” *Front Sustain Food Syst*, vol. 9, Apr. 2025, doi: 10.3389/fsufs.2025.1575430.

[11] A. O. Omotayo, S. A. Adediran, A. B. Omotoso, K. O. Olagunju, and O. P. Omotayo, “Artificial intelligence in agriculture: ethics, impact possibilities, and pathways for policy,” *Comput Electron Agric*, vol. 239, p. 110927, Dec. 2025, doi: 10.1016/J.COMPAG.2025.110927.

[12] Salisa ’Asyarina Ramadhani, Muhammad Ilhamdi Rusydi, Andrivo Rusydi, Minoru Sasaki, and Luxfy Roya Azmi, “Electroencephalography on Controlling Assistive Device: A Systematic Literature Review,” *Andalas Journal of Electrical and Electronic Engineering Technology*, vol. 4, no. 2, pp. 58–72, Nov. 2024, doi: 10.25077/ajeeet.v4i2.42.

[13] Fitrilina, M. I. Rusydi, R. Kurnia, B. Sunaryo, and S. A. Ramadhani, "A Systematic Review of Noninvasive Blood Glucose Estimation Using Near Infrared," vol. 12, no. 4, pp. 59–76, 2024.

[14] A. Bhargava and A. Bansal, "Fruits and vegetables quality evaluation using computer vision: A review," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 33, no. 3, pp. 243–257, Mar. 2021.

[15] S. Parvathi and S. Tamil Selvi, "Detection of maturity stages of coconuts in complex background using Faster R-CNN model," *Biosyst. Eng.*, vol. 202, pp. 119–132, Feb. 2021.

[16] H. Mureșan and M. Oltean, "Fruit recognition from images using deep learning," *Acta Univ. Sapientiae Inform.*, vol. 10, no. 1, pp. 26–42, Aug. 2018.

[17] J. F. I. Nturambirwe and U. L. Opara, "Machine learning applications to non-destructive defect detection in horticultural products," *Biosyst. Eng.*, vol. 189, pp. 60–83, Jan. 2020.

[18] S. Fan *et al.*, "On line detection of defective apples using computer vision system combined with deep learning methods," *J. Food Eng.*, vol. 286, no. 110102, p. 110102, Dec. 2020.

[19] V. Moya, M. Guerra, K. Pazmiño, F. Abedrabbo, F. A. Chicaiza, and D. Pozo-Espín, "Tomato classification with YOLOv8: Enhancing automated sorting and quality assessment," *Smart Agricultural Technology*, vol. 12, p. 101221, Dec. 2025, doi: 10.1016/J.ATECH.2025.101221.

[20] M. Mohebbi, M. R. Akbarzadeh-T, F. Shahidi, M. Moussavi, and H. B. Ghoddusi, "Computer vision systems (CVS) for moisture content estimation in dehydrated shrimp," *Comput Electron Agric*, vol. 69, no. 2, pp. 128–134, Dec. 2009, doi: 10.1016/J.COMPAG.2009.07.005.

[21] X. Yang, R. B. Bist, S. Subedi, and L. Chai, "A Computer Vision-Based Automatic System for Egg Grading and Defect Detection," *Animals*, vol. 13, no. 14, p. 2354, Jul. 2023, doi: 10.3390/ani13142354.

[22] C. Jin, L. Zhou, Y. Pu, C. Zhang, H. Qi, and Y. Zhao, "Application of deep learning for high-throughput phenotyping of seed: a review," *Artif Intell Rev*, vol. 58, no. 3, p. 76, Jan. 2025, doi: 10.1007/s10462-024-11079-5.

[23] S. Benedetti, S. Mannino, A. G. Sabatini, and G. L. Marcazzan, "Electronic nose and neural network use for the classification of honey," *Apidologie*, vol. 35, no. 4, pp. 397–402, Jul. 2004, doi: 10.1051/apido:2004025.

[24] E. Bonah *et al.*, "Detection of Salmonella Typhimurium contamination levels in fresh pork samples using electronic nose smellprints in tandem with support vector machine regression and metaheuristic optimization algorithms," *J Food Sci Technol*, vol. 58, no. 10, pp. 3861–3870, Oct. 2021, doi: 10.1007/s13197-020-04847-y.

[25] P. Ferrier *et al.*, "Application of a handheld electronic nose for real-time poultry freshness assessment," *Sens Biosensing Res*, vol. 45, p. 100685, Aug. 2024, doi: 10.1016/J.SBSR.2024.100685.

[26] H. D. Yu *et al.*, "Hyperspectral imaging in combination with data fusion for rapid evaluation of tilapia fillet freshness," *Food Chem*, vol. 348, p. 129129, Jun. 2021, doi: 10.1016/J.FOODCHEM.2021.129129.

[27] A. Balivo, S. Cipolletta, R. Tudisco, P. Iommelli, R. Sacchi, and A. Genovese, "Electronic Nose Analysis to Detect Milk Obtained from Pasture-Raised Goats," *Applied Sciences*, vol. 13, no. 2, p. 861, Jan. 2023, doi: 10.3390/app13020861.

[28] R. Zhi, L. Zhao, and D. Zhang, "A Framework for the Multi-Level Fusion of Electronic Nose and Electronic Tongue for Tea Quality Assessment," *Sensors*, vol. 17, no. 5, p. 1007, May 2017, doi: 10.3390/s17051007.

[29] A. Gliszczyńska-Świgło and J. Chmielewski, "Electronic Nose as a Tool for Monitoring the Authenticity of Food. A Review," *Food Anal Methods*, vol. 10, no. 6, pp. 1800–1816, Jun. 2017, doi: 10.1007/s12161-016-0739-4.

[30] R. Vanaraj, B. I.P, G. Mayakrishnan, I. S. Kim, and S.-C. Kim, "A Systematic Review of the Applications of Electronic Nose and Electronic Tongue in Food Quality Assessment and Safety," *Chemosensors*, vol. 13, no. 5, p. 161, May 2025, doi: 10.3390/chemosensors13050161.

[31] M. Wang and Y. Chen, "Electronic nose and its application in the food industry: a review," *European Food Research and Technology*, vol. 250, no. 1, pp. 21–67, Jan. 2024, doi: 10.1007/s00217-023-04381-z.

[32] M. Zia Ul Haq, B. Singh, X. Fuku, A. Barhoum, and F. Tian, "A Systematic Review of the Use of Electronic Nose and Tongue Technologies for Detecting Food Contaminants," *Chemosensors*, vol. 13, no. 7, p. 262, Jul. 2025, doi: 10.3390/chemosensors13070262.

[33] Z. Ye, Y. Liu, and Q. Li, "Recent Progress in Smart Electronic Nose Technologies Enabled with Machine Learning Methods," *Sensors*, vol. 21, no. 22, p. 7620, Nov. 2021, doi: 10.3390/s21227620.

[34] V. A. V. Alarcón *et al.*, "Electronic Nose for Classification of Banana Ripeness by Using MLP, KNN, and SVM Algorithms," 2026, pp. 136–148. doi: 10.1007/978-3-032-02406-0_10.

[35] B. M. Nicola\"\i *et al.*, "Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review," *Postharvest Biol. Technol.*, vol. 46, no. 2, pp. 99–118, Nov. 2007.

[36] Y. Zeng *et al.*, "Non-invasive identification of apple sugar content based on convolutional neural networks," in *Thirteenth International Conference on Information Optics and Photonics (CIOP 2022)*, Y. Yang, Ed., SPIE, Dec. 2022, p. 257. doi: 10.1117/12.2654932.

[37] Y. Sun, K. Wei, Q. Liu, L. Pan, and K. Tu, "Classification and Discrimination of Different Fungal Diseases of Three Infection Levels on Peaches Using Hyperspectral Reflectance Imaging Analysis," *Sensors*, vol. 18, no. 4, p. 1295, Apr. 2018, doi: 10.3390/s18041295.

[38] Y.-H. Liao *et al.*, "Pesticide residue quantification analysis by hyperspectral imaging sensors," B. Huang, C.-I. Chang, C. Lee, Y. Li, and Q. Du, Eds., May 2015, p. 95010B. doi: 10.1117/12.2176800.

[39] L. Jiang, K. Gu, R. Liu, S. Jin, H. Wang, and C. Pan, "Rapid detection of pesticide residues in fruits by surface-enhanced Raman scattering based on modified

QuEChERS pretreatment method with portable Raman instrument," *SN Appl Sci*, vol. 1, no. 6, p. 627, Jun. 2019, doi: 10.1007/s42452-019-0619-9.

[40] W. Li, Y. Wu, L. Du, X. Shang, and J. Shi, "Hyperspectral Imaging for Foreign Matter Detection in Foods: Advances, Challenges, and Future Directions," *Foods*, vol. 14, no. 17, p. 3026, Aug. 2025, doi: 10.3390/foods14173026.

[41] S. Li, W. Song, L. Fang, Y. Chen, P. Ghamisi, and J. A. Benediktsson, "Deep Learning for Hyperspectral Image Classification: An Overview," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 9, pp. 6690–6709, Sep. 2019, doi: 10.1109/TGRS.2019.2907932.

[42] H. Huang, L. Liu, and M. Ngadi, "Recent Developments in Hyperspectral Imaging for Assessment of Food Quality and Safety," *Sensors*, vol. 14, no. 4, pp. 7248–7276, Apr. 2014, doi: 10.3390/s140407248.

[43] M. T. Ahmed, O. Monjur, and M. Kamruzzaman, "Deep learning-based hyperspectral image reconstruction for quality assessment of agro-product," *J Food Eng*, vol. 382, p. 112223, Dec. 2024, doi: 10.1016/J.JFOODENG.2024.112223.

[44] H. Pu, J. Yu, D. W. Sun, Q. Wei, and Z. Wang, "Feature construction methods for processing and analysing spectral images and their applications in food quality inspection," *Trends Food Sci Technol*, vol. 138, pp. 726–737, Aug. 2023, doi: 10.1016/J.TIFS.2023.06.036.

[45] J. H. Cheng and D. W. Sun, "Hyperspectral imaging as an effective tool for quality analysis and control of fish and other seafoods: Current research and potential applications," *Trends Food Sci Technol*, vol. 37, no. 2, pp. 78–91, Jun. 2014, doi: 10.1016/J.TIFS.2014.03.006.

[46] X. Wu, X. Liang, Y. Wang, B. Wu, and J. Sun, "Non-Destructive Techniques for the Analysis and Evaluation of Meat Quality and Safety: A Review," *Foods*, vol. 11, no. 22, p. 3713, Nov. 2022, doi: 10.3390/foods11223713.

[47] N. Wellner, "Fourier transform infrared (FTIR) and Raman microscopy: principles and applications to food microstructures," in *Food Microstructures*, Elsevier, 2013, pp. 163–191. doi: 10.1533/9780857098894.1.163.

[48] D. Enériz, N. Medrano, and B. Calvo, "An FPGA-Based Machine Learning Tool for In-Situ Food Quality Tracking Using Sensor Fusion," *Biosensors (Basel)*, vol. 11, no. 10, p. 366, Sep. 2021, doi: 10.3390/bios11100366.

[49] R. Mani, J. V. Kumar, B. Murugesan, R. Alaguthevar, and J. Rhim, "Smart Sensors in Food Packaging: Sensor Technology for Real-Time Food Safety and Quality Monitoring," *J Food Process Eng*, vol. 48, no. 4, Apr. 2025, doi: 10.1111/jfpe.70120.

[50] J. L. D. Nelis, A. S. Tsagkaris, M. J. Dillon, J. Hajslova, and C. T. Elliott, "Smartphone-based optical assays in the food safety field," *TrAC Trends in Analytical Chemistry*, vol. 129, p. 115934, Aug. 2020, doi: 10.1016/j.trac.2020.115934.

[51] A. N. Damdam, L. O. Ozay, C. K. Ozcan, A. Alzahrani, R. Helabi, and K. N. Salama, "IoT-Enabled Electronic Nose System for Beef Quality Monitoring and Spoilage Detection," *Foods*, vol. 12, no. 11, p. 2227, May 2023, doi: 10.3390/foods12112227.

[52] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.

[53] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Comput. Electron. Agric.*, vol. 147, pp. 70–90, Apr. 2018.

[54] J. Botero-Valencia *et al.*, "Machine Learning in Sustainable Agriculture: Systematic Review and Research Perspectives," *Agriculture*, vol. 15, no. 4, p. 377, Feb. 2025, doi: 10.3390/agriculture15040377.

[55] L. Zhou, C. Zhang, F. Liu, Z. Qiu, and Y. He, "Application of Deep Learning in Food: A Review," *Compr Rev Food Sci Food Saf*, vol. 18, no. 6, pp. 1793–1811, Nov. 2019, doi: 10.1111/1541-4337.12492.

[56] H. Nada, O. Omer, H. Esmaiel, M. Ashour, and A. Arafa, "Deep Learning Networks for Non-Destructive Detection of Food Irradiation," *Revue d'Intelligence Artificielle*, vol. 37, no. 3, pp. 551–556, Jun. 2023, doi: 10.18280/ria.370303.

[57] M. B. Lam, T.-H. Nguyen, and W.-Y. Chung, "Deep Learning-Based Food Quality Estimation Using Radio Frequency-Powered Sensor Mote," *IEEE Access*, vol. 8, pp. 88360–88371, 2020, doi: 10.1109/ACCESS.2020.2993053.

[58] M. Kharbach, "AI-Powered Advances in Data Handling for Enhanced Food Analysis: From Chemometrics to Machine Learning," *Foods*, vol. 14, no. 19, p. 3415, Oct. 2025, doi: 10.3390/foods14193415.

[59] D. Gunning and D. W. Aha, "DARPA's explainable artificial intelligence program," *AI Mag.*, vol. 40, no. 2, pp. 44–58, Jun. 2019.

[60] C. Jin *et al.*, "Big Data in food safety- A review," *Curr Opin Food Sci*, vol. 36, pp. 24–32, Dec. 2020, doi: 10.1016/J.COFS.2020.11.006.

[61] Z. Deng, T. Wang, Y. Zheng, W. Zhang, and Y. H. Yun, "Deep learning in food authenticity: Recent advances and future trends," *Trends Food Sci Technol*, vol. 144, p. 104344, Feb. 2024, doi: 10.1016/J.TIFS.2024.104344.

[62] K. Agrawal, P. Goktas, M. Holtkemper, C. Beecks, and N. Kumar, "AI-driven transformation in food manufacturing: a pathway to sustainable efficiency and quality assurance," *Front Nutr*, vol. 12, Mar. 2025, doi: 10.3389/fnut.2025.1553942.

[63] A. Dodero, A. Escher, S. Bertucci, M. Castellano, and P. Lova, "Intelligent Packaging for Real-Time Monitoring of Food-Quality: Current and Future Developments," *Applied Sciences*, vol. 11, no. 8, p. 3532, Apr. 2021, doi: 10.3390/app11083532.

[64] R. J. S. Banicod, N. Tabassum, D.-M. Jo, A. Javaid, Y.-M. Kim, and F. Khan, "Integration of Artificial Intelligence in Biosensors for Enhanced Detection of Foodborne Pathogens," *Biosensors (Basel)*, vol. 15, no. 10, p. 690, Oct. 2025, doi: 10.3390/bios15100690.

APPENDICES

Appendix 1. Selected Studies on Computer Vision Systems (CVS)

Ref	Author (Year)	Food Matrix	Target Application	AI Methodology	Key Findings / Performance
[8]	Hussain et al. (2024)	Apples	Variety classification (e.g., Gala vs. Fuji)	Deep Learning (CNN); VGG-16	Successfully distinguished visually similar varieties with high precision using texture features.
[12]	Parvathi & Selvi (2021)	Coconuts	Maturity detection in natural environments	Deep Learning; Faster R-CNN	Achieved high detection rates in complex backgrounds, showing potential for robotic harvesting.
[13]	Mureșan & Oltean (2018)	Fruits	Defect recognition	Deep Learning (CNN)	Achieved state-of-the-art results; robust to rotation and scaling.
[15]	Fan et al. (2020)	Apples	On-line defect detection (high-speed)	CVS + Deep Learning	Worked effectively at conveyor speeds, sorting multiple fruits per second.
[16]	Moya (2025)	Tomatoes	Grading (size) and skin integrity	YOLOv8	Integrated AI decisions with a mechanical sorting arm for full automation.
[17]	Mohebbi et al. (2009)	Dried Shrimp	Moisture content estimation	Computer Vision	Enabled non-contact drying control by correlating visual features with chemical moisture content.
[18]	Yang (2023)	Eggs	Shell defect detection	Deep Learning	Reduced breakage rates compared to conventional sorters.

Appendix 2. Selected Studies on Electronic Nose (E-Nose) & E-Tongue

Ref	Author (Year)	Food Matrix	Target Application	AI Methodology	Key Findings / Performance
[20]	Benedetti et al. (2004)	Honey	Quality classification	Ensemble Decision Trees + E-Nose	Viable for volatile-based classification.
[21]	Bonah et al. (2021)	Pork	Salmonella contamination detection	SVM Regression + Metaheuristics	Recognized volatile profiles specific to Salmonella for rapid screening.
[22]	Ferrier et al. (2024)	Poultry Products	Real-time freshness monitoring	Portable E-Nose	Feasible for miniaturized field-use monitoring.
[24]	Balivo et al. (2023)	Milk	Adulteration detection	Machine Learning + E-Nose	Identified dilution and substitution with cheaper milk types.
[25]	Zhi et al. (2017)	Tea	Quality assessment	Sensor Fusion (E-Nose + E-Tongue)	Multimodal system outperformed single sensors; mimicked human perception.
[31]	Alarcón et al. (2026)	Bananas	Maturity stage classification	Fuzzy Logic, MLP, KNN, SVM	Correlated ethylene and ester emissions with ripening stages.

 https://doi.org/10.25077/ajeeet.v5i2.44

Appendix 3. Selected Studies on Spectroscopy & Hyperspectral Imaging (HSI)

Ref	Author (Year)	Food Matrix	Target Application	AI Methodology	Key Findings / Performance
[33]	Zeng et al. (2022)	Apples	Sugar content (Brix) measurement	Deep Learning + NIR Spectroscopy	More robust to skin-thickness variations than PLS regression.
[34]	Sun et al. (2018)	Peaches	Fungal infection detection	Deep Learning + Vis/NIR Spectroscopy	Detected infection pre-symptomatically.
[35]	Liao et al. (2015)	Fruit Surface	Pesticide residue detection	PLS-DA + Hyperspectral Imaging	Enabled spatial contaminant mapping.
[37]	W. Li et al. (2025)	Meat Products	Foreign object detection	Deep Learning + HSI	Detected plastic/wood objects invisible to RGB via spectral signatures.
[36]	Jiang et al. (2019)	Fruits	Pesticide residue detection	Machine Learning + SERS	LOD comparable to chromatography methods.