Rapid Electronic Sensing Technologies for Ensuring Food Safety Against Pesticide Residues: A Comprehensive Review

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Abstract
Pesticide residues in fruits, vegetables, cereals, tea, edible oils and other agricultural commodities remain a major food-safety and environmental concern. Conventional chromatographic methods provide high selectivity and quantitative reliability, but their dependence on laboratory infrastructure, sample preparation, skilled personnel and relatively long analytical workflows limits their use for high-throughput, on-site screening. Recent advances in electronic noses, electrochemical biosensors, optical and spectroscopic sensors, hyperspectral imaging, portable instrumentation and machine learning have created a complementary pathway for rapid, non-destructive or minimally destructive screening. This review synthesizes the technological landscape from 123 references, emphasizing the link between pesticide application, residue-related chemical signatures, sensor transduction, signal processing and data-driven decision making. Particular attention is given to electronic-nose approaches that detect volatile or semi-volatile signatures associated with pesticide contamination, as well as electrochemical and optical systems that provide more chemically specific responses. The review compares sensor modalities, recognition algorithms, reference analytical methods, matrix effects, calibration requirements and deployment barriers. The literature indicates that machine learning can improve discrimination of complex sensor patterns, but generalization remains constrained by sensor drift, humidity and temperature, cultivar and commodity differences, pesticide formulation effects, and limited external validation. A practical deployment framework is proposed in which electronic sensing is positioned primarily as a rapid screening and triage layer, while chromatographic methods remain important for confirmatory quantification and regulatory decisions. Future systems should integrate multimodal sensing, edge AI, standardized datasets, uncertainty estimation, traceability and field calibration to achieve reliable Agriculture 5.0 food-safety monitoring.

Keywords: Pesticide residues, electronic nose, gas sensors, electrochemical biosensors, hyperspectral imaging, machine learning, rapid screening, food safety, Agriculture 4.0, Agriculture 5.0

1. Introduction

Pesticides are an important component of modern crop production because they reduce losses caused by insects, pathogens and weeds. However, pesticide application can introduce residues into food commodities and can also influence soil, water, non-target organisms and environmental quality [7], [9], [22], [23], [25]–[29]. The food-safety problem is therefore not limited to the presence of a single compound: real samples may contain multiple residues, transformation products and matrix components. Recent reviews emphasize the need for rapid, reliable and field-compatible approaches that can complement laboratory-based analytical chemistry [16]–[18], [36], [77].

Liquid chromatography–tandem mass spectrometry (LC–MS/MS) and gas chromatography–mass spectrometry (GC–MS/MS) remain among the most powerful confirmatory approaches because they can provide high sensitivity, selectivity and multi-residue capability [11]–[13], [52]–[59]. Nevertheless, these methods normally require extraction, clean-up, calibrated instrumentation and trained operators. Such requirements are difficult to reproduce at farms, collection centers, wholesale markets and other points where rapid decisions are needed. Consequently, electronic sensing technologies have emerged as a complementary layer for screening, classification and triage.

Electronic noses (e-noses) are particularly attractive because they convert patterns of gas-sensitive responses into information about a sample rather than relying on one highly selective receptor. Recent e-nose reviews describe sensor arrays, signal conditioning, feature extraction and pattern-recognition algorithms as the core components of the system [67], [69], [84]–[91]. Studies specifically addressing pesticide residues have demonstrated the feasibility of detecting or classifying contaminated agricultural products using e-noses, including apples, tea, edible mint and Allium tuberosum [68], [118], [120], [123]. At the same time, electrochemical biosensors, optical spectroscopy, Raman methods, infrared sensing and hyperspectral imaging provide alternative or complementary information channels [47], [60], [66], [73], [78]–[82], [93], [103]–[116].

This review develops an integrated view of these technologies. Rather than treating each sensor family independently, it considers the complete analytical chain: sample and headspace generation, transduction, signal conditioning, machine-learning analysis, validation against reference methods and eventual field deployment. The objective is to identify what electronic sensing can realistically deliver today, what limitations still prevent regulatory-grade substitution of laboratory analysis, and which research directions are most likely to produce robust Agriculture 5.0 food-safety systems.

2. Pesticide Residues And The Need For Rapid Screening

Pesticide residues are affected by application rate, formulation, crop type, environmental conditions, surface characteristics, degradation kinetics and pre-harvest interval. Residue dynamics are consequently heterogeneous across commodities and production systems [23], [38]. Environmental and health impacts have been reviewed extensively, including effects on soil organisms, nutrient cycling, aquatic systems and human exposure [9], [22], [25]–[29]. Biopesticides and other alternatives may reduce dependence on synthetic compounds, but their increasing use does not eliminate the need for residue monitoring [33], [34].

From a food-control perspective, the challenge is multidimensional. A screening method should ideally be fast, inexpensive, portable, sufficiently sensitive around relevant limits, tolerant of commodity variability and able to flag samples requiring confirmatory analysis. Recent analytical developments show the continuing expansion of multi-residue LC–MS/MS and GC–MS/MS methods, including methods targeting hundreds of compounds [53]–[58]. These methods define the reference standard against which emerging electronic systems should be evaluated.

An important distinction is therefore needed between screening and confirmation. A sensor system may successfully distinguish contaminated from uncontaminated samples without identifying or quantifying every chemical species with the selectivity of chromatography. For practical deployment, the electronic device can act as a front-end triage tool: samples classified as suspicious are transferred to an accredited laboratory for confirmatory analysis. This model can increase throughput while reducing unnecessary laboratory workload.

3. Technological Landscape Of Rapid Electronic Sensing

Rapid pesticide-residue sensing can be organized into four broad groups: gas/VOC sensing, electrochemical biosensing, optical/spectroscopic sensing and imaging-based sensing. These modalities differ in the chemical information they capture, sample preparation requirements, portability and susceptibility to matrix effects.

A. Electronic-Nose and VOC Sensing

An e-nose generally combines an array of partially selective gas sensors with pattern-recognition software. Metal-oxide semiconductor sensors are attractive for low-cost systems because their resistance changes in response to interacting gases. The resulting response vector can encode a complex sample signature. However, the same broad sensitivity that makes sensor arrays useful can also create cross-sensitivity to humidity, temperature, background volatiles and packaging materials [67], [86], [90].

Evidence for pesticide applications is increasingly available. Tang et al. reported an e-nose approach for detecting and classifying pesticide residue on apples [118], while Tang et al. developed an electronic-nose method for quantifying pyrethroid contamination in tea [120]. Meng et al. demonstrated qualitative and quantitative residue analysis in Allium tuberosum using an e-nose with multivariate analysis [68]. Other studies have explored low-cost e-nose architectures for food assessment and pesticide detection [91], [119], [121]–[123]. These studies support the concept that residue-related headspace patterns can be measurable even when the target analyte itself is not highly volatile.

B. Electrochemical Biosensors

Electrochemical systems directly measure current, potential, impedance or related electrical responses. Enzyme inhibition, aptamer recognition, antibody-based recognition and nanomaterial-enhanced interfaces can improve selectivity [66], [78]–[82], [98]–[102], [117]. Screen-printed electrodes are especially promising for portable devices because they support compact electronics and low sample volumes [100]. Electrochemical sensors can be more chemically targeted than broadly responsive e-nose arrays, but they may require sample extraction, electrode regeneration or biochemical stabilization.

C. Optical, Spectroscopic and Imaging Approaches

Infrared, Raman, fluorescence, near-infrared and hyperspectral methods provide rich spectral information and can support non-destructive analysis [46], [47], [60], [73], [74], [93]–[95], [103]–[116]. Machine learning is increasingly used to extract subtle residue-related patterns from spectra and images. Hyperspectral imaging is particularly attractive for spatial mapping because it combines spectral and positional information, although instrument cost, calibration and environmental illumination can limit field deployment [70], [73], [75], [93], [94].

D. Multimodal and Integrated Systems

The emerging direction is sensor fusion: combining VOC, electrochemical, optical, image and environmental measurements. Multimodal fusion can reduce dependence on a single weak signal and may improve robustness across matrices [30]. An integrated system can therefore use an e-nose as a rapid broad-spectrum screen and an electrochemical or optical channel for additional specificity. This architecture is consistent with the broader Agriculture 4.0 and Agriculture 5.0 trend toward connected, data-driven sensing and decision systems [1]–[6].

4. Electronic-Nose System Architecture

Figure 2 summarizes a generic electronic sensing architecture. Sampling is the first critical stage. For e-nose applications, the headspace must be generated reproducibly because temperature, equilibration time, sample mass, container geometry and humidity affect VOC concentration. A sensor array then converts chemical interactions into electrical signals. Signal conditioning, baseline correction and normalization are required before machine learning.

Typical features include steady-state resistance, maximum response, response/recovery slopes, area under the response curve and dynamic descriptors. Principal component analysis (PCA), linear discriminant analysis (LDA), support vector machines (SVM), random forests (RF), gradient-boosting methods and artificial neural networks can then be used for classification or regression [67], [85], [90], [97]. Recent reviews emphasize that recognition algorithms are as important as sensor hardware because the information in an e-nose is distributed across the sensor array rather than

concentrated in one channel [86], [90].
Sensor drift is a major engineering challenge. Aging, poisoning, humidity changes and baseline shifts can alter response distributions. A model trained under laboratory conditions may therefore fail when transferred to a different season, farm, commodity or device. Drift correction, periodic calibration, domain adaptation and robust feature representations should be considered part of the sensor design rather than afterthoughts.
Another important issue is interpretability. A classifier that reports 98% accuracy on a randomly split laboratory dataset may not provide equivalent performance on unseen farms. Evaluation should include independent batches, different cultivars, different pesticide formulations, multiple concentrations and realistic environmental variation. Where possible, performance should be reported using sensitivity, specificity, precision, F1 score, calibration error and regression metrics rather than accuracy alone.

5. Machine Learning And Data Analytics

Machine learning converts multivariate sensor responses into decisions. The basic pipeline is: raw signal acquisition → preprocessing → feature extraction → dimensionality reduction or feature selection → model training → validation → prediction. Figure 4 illustrates this workflow.
PCA is useful for visualization and exploratory analysis, but it should not be interpreted as a complete classifier. LDA can provide strong class separation when distributional assumptions are reasonably satisfied. SVM is often effective for small-to-medium datasets with nonlinear boundaries, whereas random forests and gradient boosting can model nonlinear interactions while providing feature-importance measures. Neural networks and one-dimensional convolutional networks can learn representations directly from response curves or spectra when sufficiently large datasets are available [90], [97], [108], [111].
Quantitative prediction is more demanding than qualitative classification. A model that distinguishes treated from untreated samples may still fail to estimate concentration accurately because the signal is influenced by commodity matrix, moisture, temperature and co-occurring chemicals. Therefore, regression models should be trained using concentration ranges relevant to regulatory decisions and evaluated against independent reference measurements.
Data leakage is another risk. Repeated measurements from the same fruit, batch or sampling session should not be randomly distributed between training and test sets. Instead, validation should be grouped by batch, date, farm or production lot. External validation is particularly important for demonstrating generalization. This requirement is consistent with the broader development of machine learning in agriculture, where environmental and operational variability is substantial [1], [5], [6], [97].

6. Comparison With Conventional Analytical Methods

Chromatographic methods provide the benchmark for confirmatory pesticide analysis. Recent LC–MS/MS and GC–MS/MS studies demonstrate the ability to detect dozens to hundreds of residues in complex food matrices [52]–[59], [95]. Their principal advantages are chemical specificity, sensitivity and established quantitative workflows. Their disadvantages include instrumentation cost, laboratory dependence, extraction requirements and lower suitability for immediate field screening.
Electronic sensing occupies a different point in the analytical design space. Its principal value is speed and portability rather than universal chemical identification. E-nose systems can be low-cost and rapid but are affected by cross-sensitivity. Electrochemical biosensors can provide higher selectivity but may require recognition elements and careful surface preparation. Spectroscopic systems are non-destructive and information-rich but can be expensive and sensitive to calibration and matrix effects. Hyperspectral imaging adds spatial information but produces large datasets and requires substantial computation [70], [93], [111], [112].
Accordingly, the most realistic near-term model is hierarchical analysis: rapid electronic screening at the point of production or sale, followed by targeted laboratory confirmation for flagged samples. Such a model also supports traceability and supply-chain monitoring, consistent with Traceability 4.0 concepts [83].

7. Key Challenges For Field Deployment

Despite promising laboratory results, several barriers must be addressed before widespread deployment.
1) Matrix effects: Fruit, vegetables, grains, tea and edible oils have different background chemical profiles. The same sensor response may therefore have different meanings across commodities.
2) Environmental variation: Temperature and relative humidity strongly affect gas-sensor response and headspace chemistry. Field devices need environmental sensing and compensation.
3) Sensor drift and reproducibility: Low-cost arrays can show device-to-device variation. Reference channels, periodic recalibration and drift-aware algorithms are required.
4) Pesticide formulation and degradation: Commercial products contain solvents, surfactants and additives that may contribute to VOC patterns. Residues also degrade and transform after application [19], [38].
5) Detection limits and regulatory relevance: Demonstrating classification is insufficient if the system cannot reliably discriminate samples near maximum residue limits or other decision thresholds.
6) Dataset quality: Many published studies use relatively small laboratory datasets. Larger multi-season, multi-location and multi-variety datasets are required for generalizable AI.
7) Standardization: Sampling protocols, sensor conditioning, calibration, reporting metrics and reference methods should be standardized so that performance can be compared across studies [17], [67], [85].
8) Regulatory positioning: A screening device should clearly state whether its output is a preliminary flag or a legally

defensible quantitative result. For most emerging e-nose systems, the former is the more defensible position.

8. Proposed Deployment Framework For Agriculture 5.0

Figure 5 proposes a translation pathway from laboratory validation to field use. The first stage is controlled calibration against GC–MS/MS or LC–MS/MS. The second stage is prototype development with integrated temperature and humidity sensors, stable sampling chambers and standardized electronics. The third stage is field validation across locations, cultivars, seasons and pesticide formulations. Only after external validation should routine screening be considered.

An Agriculture 5.0 system can connect the sensor to an edge-AI processor, smartphone or gateway. The device can record sample identity, time, location at an appropriate privacy-preserving granularity, environmental conditions, model version and screening result. This creates an auditable data trail while reducing dependence on continuous cloud connectivity. Agriculture 5.0 literature emphasizes human-centered, connected and intelligent technologies, making such architectures technically consistent with the wider digital transformation of agriculture [1]–[6].

The system should also provide uncertainty or confidence information. Instead of returning only 'safe' or 'unsafe', a practical interface could report 'low-risk / model confidence high', 'screening flag / confirmatory analysis recommended', or 'out-of-distribution / repeat measurement required'. Such outputs are safer than forcing a binary decision when the sample differs from the training domain.

Multimodal sensing is a promising next step. A VOC array can provide rapid broad chemical fingerprints, while electrochemical or optical channels can supply additional specificity. Fusion can occur at the feature level or decision level. Edge AI can reduce latency and protect data, while cloud infrastructure can support model updating and fleet-level drift monitoring.

9. Research Gaps And Future Directions

Future research should move from proof-of-concept classification toward standardized, externally validated screening platforms. First, researchers should publish raw or sufficiently detailed sensor-response datasets, metadata and validation protocols. Second, studies should explicitly evaluate environmental robustness and sensor drift. Third, models should be tested on genuinely independent production lots.

Explainable AI is also important. Feature attribution can help determine whether a model is learning chemically meaningful patterns or confounding variables such as container type or temperature. Transfer learning and domain adaptation may reduce the amount of data needed when moving between commodities or sensor units. Federated learning could support collaborative model improvement without centralizing all raw farm data.

Miniaturization is likely to continue through MEMS gas sensors, printed electrodes, smartphone-assisted optical systems and low-power edge processors. The combination of low-cost hardware and modern ML creates a pathway toward distributed screening networks. However, miniaturization should not be pursued at the expense of calibration stability. A slightly larger device with controlled sampling may provide more reliable results than an ultra-small sensor exposed directly to uncontrolled ambient air.

Finally, electronic sensing should be integrated with conventional analytical laboratories rather than viewed as a replacement. The highest-value workflow is likely to be a connected screening-confirmation system in which electronic devices reduce the number of samples requiring expensive analysis while laboratories provide traceable confirmation for regulatory or high-risk cases.

10. Conclusion

Rapid electronic sensing is becoming an important complementary technology for pesticide-residue monitoring. The reviewed literature shows progress across e-noses, electrochemical biosensors, optical and spectroscopic systems, hyperspectral imaging and machine-learning analytics. E-noses are especially attractive for rapid screening because sensor arrays can capture complex VOC-related signatures using compact hardware, while electrochemical and optical approaches can add chemical specificity. Machine learning further enables nonlinear pattern recognition and quantitative prediction.

Nevertheless, laboratory accuracy should not be equated with field readiness. Matrix effects, environmental variability, sensor drift, pesticide formulation, limited datasets and insufficient external validation remain major barriers. The most credible deployment strategy is therefore a hierarchical workflow in which electronic sensing provides rapid screening and triage and LC–MS/MS or GC–MS/MS provides confirmatory analysis. Multimodal sensing, edge AI, standardized datasets, uncertainty estimation and traceability are likely to be central to the next generation of Agriculture 5.0 food-safety systems.

Overall, the field is moving from isolated sensor demonstrations toward integrated cyber-physical analytical platforms. With rigorous validation and appropriate regulatory positioning, electronic sensing can reduce screening time and cost, expand monitoring coverage and strengthen food-safety surveillance across modern agricultural supply chains.

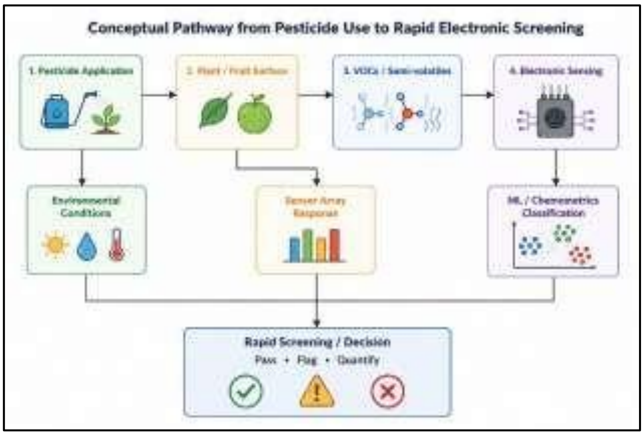

Fig. 1. Conceptual pathway from pesticide application to rapid electronic screening.

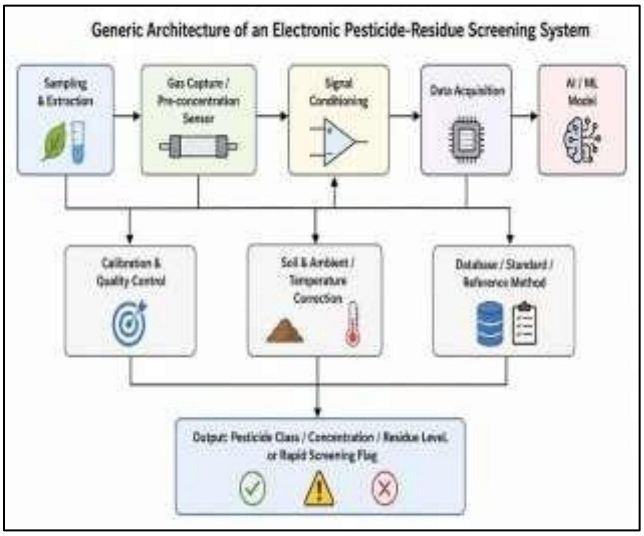

Fig. 2. Generic architecture of an electronic pesticide-residue screening system.

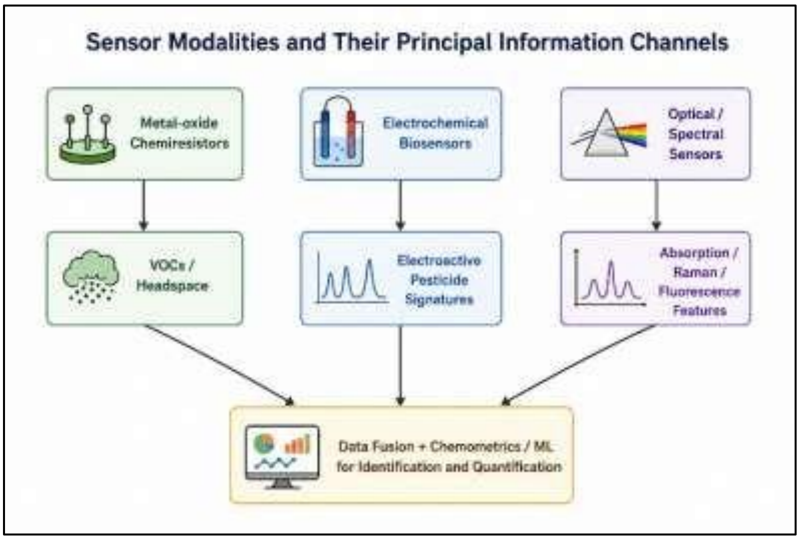

Fig. 3. Sensor modalities and principal information channels.

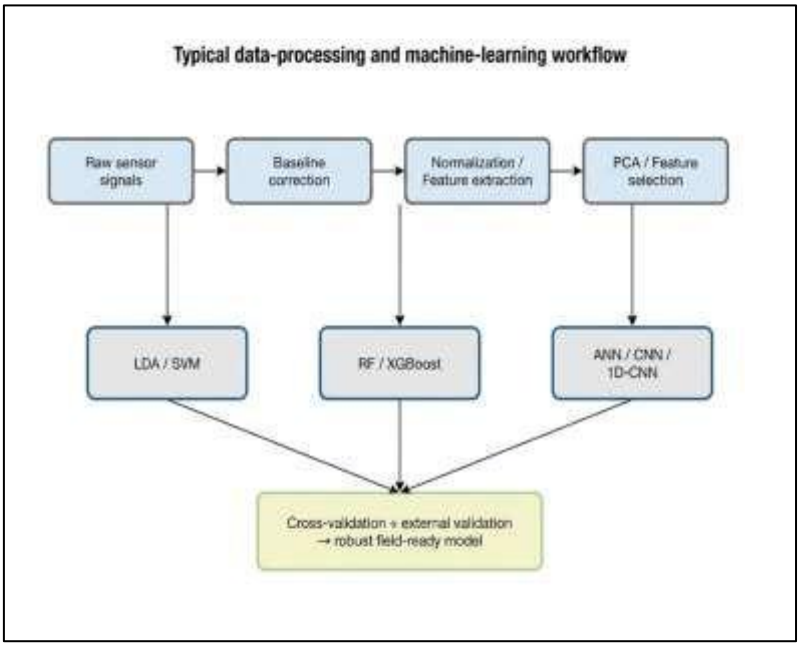

Fig. 4. Typical data-processing and machine-learning workflow.

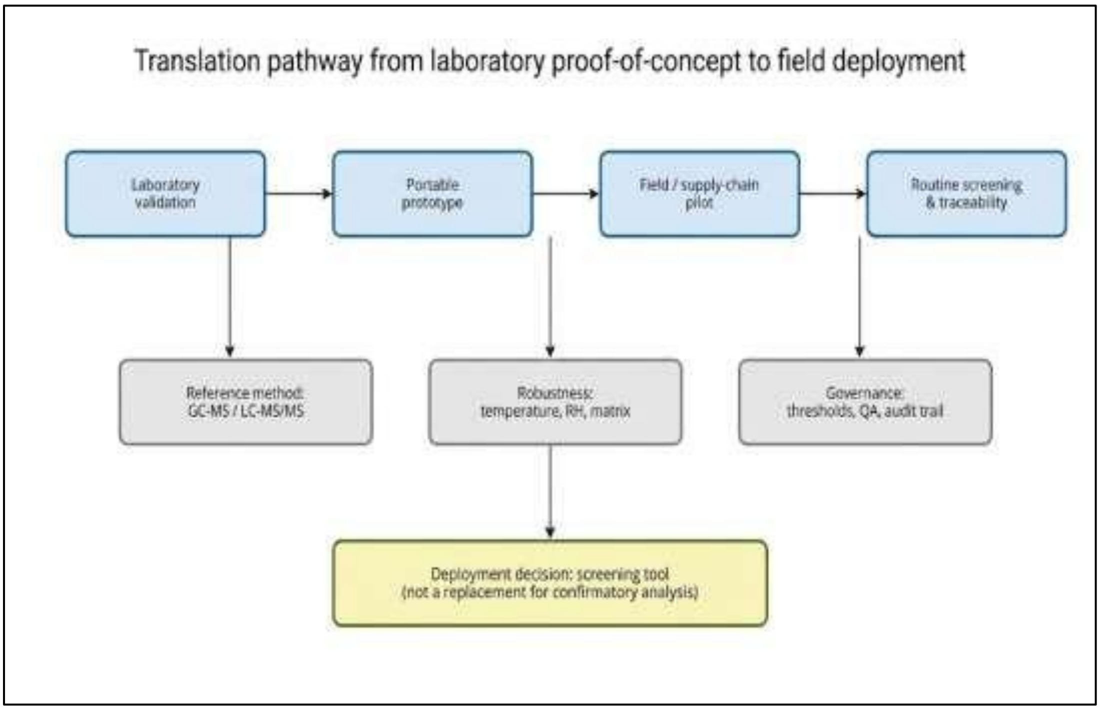

Fig. 5. Translation pathway from laboratory proof-of-concept to field deployment.

Table i: Comparative Characteristics Of Rapid Pesticide-Residue Sensing Modalities

Modality	Main signal	Strengths	Key limitations	Typical role
E-nose / VOC	Gas-sensor response pattern	Fast, compact, low-cost, minimal preparation	Cross-sensitivity, drift, humidity effects	Screening / classification
Electrochemical biosensor	Current, potential, impedance	High sensitivity; selective recognition possible	Electrode fouling, bioreceptor stability, matrix effects	Targeted screening / quantification
NIR / IR / Raman	Spectral response	Non-destructive, information-rich	Calibration and matrix dependence	Screening / quantitative modeling
Hyperspectral imaging	Spatial-spectral cube	Maps spatial variation; non-contact	Cost, data volume, illumination sensitivity	Surface screening / mapping
Chromatography-MS	Separated mass spectra	High specificity; multi-residue	Laboratory infrastructure,	Confirmatory analysis

		confirmation	sample preparation	

Table Ii: Representative Electronic-Sensing Studies For Pesticide Applications

Reference	Commodity / target	Technology	Analytical purpose	Key contribution
[68]	Allium tuberosum	E-nose + multivariate analysis	Qualitative / quantitative	Demonstrated residue analysis from sensor patterns
[118]	Apple	Electronic nose	Detection / classification	Showed feasibility of pesticide-residue discrimination
[120]	Tea / pyrethroids	Electronic nose	Quantification	Applied e-nose response to pyrethroid contamination
[121]	Apple	Low-cost GP-optimized e-nose	Detection	Explored low-cost optimized recognition
[123]	Edible mint	Gas-sensor prototype	Detection	Demonstrated portable gas-sensing concept
[98]	Vegetable oils	AChE electrochemical biosensor	Detection	Examined matrix effects and enzyme inhibition

Table Iii: Reference Methods And Their Complementary Role

Method	Typical advantage	Limitation for field use	Recommended relationship to electronic sensing
LC-MS/MS	High selectivity; multi-residue capability	Cost and laboratory workflow	Primary confirmatory reference
GC-MS/MS	Strong capability for suitable volatile/semi-volatile compounds	Extraction and laboratory requirements	Confirmatory reference
SERS	High molecular sensitivity	Substrate reproducibility and matrix effects	Targeted rapid confirmation / screening
FTIR / NIR	Rapid, non-destructive	Spectral overlap; calibration dependence	Complementary screening
Hyperspectral imaging	Spatial + spectral information	Large datasets; instrument cost	Non-destructive surface screening
E-nose	Rapid fingerprinting	Low chemical specificity	Front-end triage

Table Iv: Machine-Learning Methods For Electronic Sensing

Algorithm	Typical use	Advantages	Main caution
PCA	Exploration / visualization	Compact representation; visualization	Not a standalone classifier
LDA	Classification	Simple and interpretable	Assumption-sensitive
SVM	Classification / regression	Good for small nonlinear datasets	Kernel and parameter tuning
Random forest	Classification / regression	Robust nonlinear modeling; feature importance	Can overfit small correlated datasets
XGBoost / boosting	Classification / regression	Strong tabular performance	Requires careful tuning and validation
ANN / CNN	Classification / regression	Learns complex nonlinear representations	Needs larger datasets; risk of overfitting

Table v: Critical Validation Requirements For Field Deployment

Validation factor	Minimum recommended practice
Commodity diversity	Multiple cultivars / varieties and representative matrices
Pesticide diversity	Multiple active ingredients and realistic formulations
Concentration range	Include concentrations around decision thresholds and below/above them
Environmental robustness	Test across temperature and relative-humidity ranges
Batch independence	Separate train/test by production batch, date or farm

Reference analysis	Compare with validated LC-MS/MS or GC-MS/MS measurements
Model reporting	Sensitivity, specificity, F1, RMSE/MAE, calibration and uncertainty
Drift testing	Repeated measurements over time and across sensor units

Table Vi: Research Priorities Toward Agriculture 5.0 Deployment

Priority	Research direction	Expected impact
1	Standardized multi-season datasets	Improved generalization
2	Multimodal sensor fusion	Higher robustness and specificity
3	Edge AI + uncertainty estimation	Fast, interpretable field decisions
4	Drift compensation / transfer learning	Longer sensor lifetime
5	Reference-linked calibration	Regulatory credibility
6	Traceability and interoperable data	Supply-chain integration

References

[1] M.H. Saleem, J. Potgieter, and K.M. Arif, “Automation in Agriculture by Machine and Deep Learning Techniques: A Review of Recent Developments,” Precis. Agric., vol. 22, pp. 2053–2091, 2021.

[2] V. Martos, A. Ahmad, P. Cartujo, and J. Ordoñez, “Ensuring Agricultural Sustainability through Remote Sensing in the Era of Agriculture 5.0,” Appl. Sci., vol. 11, p. 5911, 2021.

[3] S. Fountas et al., “Agriculture 5.0: Cutting-Edge Technologies, Trends, and Challenges,” IT Prof., vol. 26, pp. 40–47, 2024.

[4] M.A. Dayioğlu and U. Turker, “Digital Transformation for Sustainable Future—Agriculture 4.0: A review,” Tarım Bilim Derg., 2021.

[5] M. Javaid et al., “Enhancing smart farming through the applications of Agriculture 4.0 technologies,” Int. J. Intell. Netw., vol. 3, pp. 150–164, 2022.

[6] Y. Liu et al., “From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges,” IEEE Trans. Ind. Informat., vol. 17, pp. 4322–4334, 2021.

[7] G.M.W. Lengai, J.W. Muthomi, and E.R. Mbega, “Phytochemical activity and role of botanical pesticides in pest management for sustainable agricultural crop production,” Sci. Afr., vol. 7, e00239, 2020.

[8] D.-C. Țopa et al., “Sustainable Practices for Enhancing Soil Health and Crop Quality in Modern Agriculture: A Review,” Agriculture, vol. 15, p. 998, 2025.

[9] I. Mahmood et al., “Effects of Pesticides on Environment,” in Plant, Soil and Microbes. Springer, 2016, pp. 253–269.

[10] Z. Guo et al., “Advances in research on novel technologies for the detection of exogenous contaminants in traditional Chinese medicine,” Front. Pharmacol., vol. 16, p. 1658241, 2025.

[11] F. Jesús et al., “Advancements in multiresidue pesticide analysis in fruits and vegetables using micro-flow liquid chromatography coupled to tandem mass spectrometry,” Anal. Chim. Acta, vol. 1358, p. 344100, 2025.

[12] G.R. Algharibeh and M.S. AlFararjeh, “Pesticide residues in fruits and vegetables in Jordan using liquid chromatography/tandem mass spectrometry,” Food Addit. Contam. B, vol. 12, pp. 65–73, 2019.

[13] H. Pan et al., “Liquid Chromatography Coupled to High-Resolution Mass Spectrometry for High-Throughput Pesticide Residue Detection,” Crit. Rev. Anal. Chem., 2025.

[14] M. Dayoub et al., “Enhancing Animal Production through Smart Agriculture: Possibilities, Hurdles, Resolutions, and Advantages,” Ruminants, vol. 4, pp. 22–46, 2024.

[15] D. Kirubakaran et al., “Smart technologies enhance detection, monitoring, and traceability in global food safety,” Discov. Food, vol. 6, p. 41, 2025.

[16] Y. Han et al., “Advances in Detection Technologies for Pesticide Residues and Heavy Metals in Rice,” Foods, vol. 14, p. 1070, 2025.

[17] S. Mukherjee et al., “A Review on Recent Trends in Advancement of Bio-Sensory Techniques Toward Pesticide Detection,” Food Anal. Methods, vol. 15, pp. 3416–3434, 2022.

[18] L. Xu et al., “Recent Advances in Rapid Detection Techniques for Pesticide Residue: A Review,” J. Agric. Food Chem., vol. 70, pp. 13093–13117, 2022.

[19] D.-C. He et al., “Emission of volatile organic compounds (VOCs) from application of commercial pesticides in China,” J. Environ. Manage., vol. 314, p. 115069, 2022.

[20] S. MacDougall, F. Bayansal, and A. Ahmadi, “Emerging Methods of Monitoring Volatile Organic Compounds for Detection of Plant Pests and Disease,” Biosensors, vol. 12, p. 239, 2022.

[21] A. Alix and E. Capri, “Modern Agriculture in Europe and the Role of Pesticides,” in Advances in Chemical Pollution, Environmental Management and Protection. Elsevier, 2018, pp. 1–22.

[22] S. Datta et al., “Earthworms, pesticides and sustainable agriculture: a review,” Environ. Sci. Pollut. Res., vol. 23, pp. 8227–8243, 2016.

[23] M. Tudi et al., “Agriculture Development, Pesticide Application and Its Impact on the Environment,” Int. J. Environ. Res. Public Health, vol. 18, p. 1112, 2021.

[24] T. Lazarević-Pašti et al., “With or Without You?—A Critical Review on Pesticides in Food,” Foods, vol. 14, p. 1128, 2025.

[25] J.M. Muñoz-Bautista et al., “Environmental and Health Impacts of Pesticides and Nanotechnology as an Alternative in Agriculture,” Agronomy, vol. 15, p. 1878, 2025.
[26] W. Zhou, M. Li, and V. Achal, “A comprehensive review on environmental and human health impacts of chemical pesticide usage,” Emerg. Contam., vol. 11, p. 100410, 2025.
[27] V.M. Pathak et al., “Current status of pesticide effects on environment, human health and it’s eco-friendly management as bioremediation: A comprehensive review,” Front. Microbiol., vol. 13, p. 962619, 2022.
[28] M. Shahid, M. Nadeem, and H.F. Bakhat, “Environmental toxicology and associated human health risks,” Environ. Sci. Pollut. Res., vol. 27, pp. 39671–39675, 2020.
[29] M. Yasir, A. Hossain, and A. Pratap-Singh, “Pesticide Degradation: Impacts on Soil Fertility and Nutrient Cycling,” Environments, vol. 12, p. 272, 2025.
[30] M. Wang et al., “Multimodal Fusion-Driven Pesticide Residue Detection: Principles, Applications, and Emerging Trends,” Nanomaterials, vol. 15, p. 1305, 2025.
[31] S. Kang et al., “Detection and Monitoring of Volatile Organic Compounds (VOCs) via the Use of Engineered Chemical Sensors,” PhytoFrontiers, vol. 6, pp. 5–22, 2026.
[32] R. Li et al., “Volatile Organic Compound Emission Inventory for Pesticide Spraying in an Agricultural City of Northeast China,” Agriculture, vol. 14, p. 1223, 2024.
[33] M.S. Ayilara et al., “Biopesticides as a promising alternative to synthetic pesticides,” Front. Microbiol., vol. 14, p. 1040901, 2023.
[34] C. Damalas and S. Koutroubas, “Current Status and Recent Developments in Biopesticide Use,” Agriculture, vol. 8, p. 13, 2018.
[35] R. Epping and M. Koch, “On-Site Detection of Volatile Organic Compounds (VOCs),” Molecules, vol. 28, p. 1598, 2023.
[36] S. Wahab et al., “Advancement and New Trends in Analysis of Pesticide Residues in Food: A Comprehensive Review,” Plants, vol. 11, p. 1106, 2022.
[37] P. Ravish, S. Chaudhry, and A. Sharma, “Impact of different crop residue burning activities on seasonal variation in ambient air quality,” Discov. Atmos., vol. 3, p. 22, 2025.
[38] B. Kariyanna et al., “Comprehensive insights into pesticide residue dynamics: unraveling impact and management,” Chem. Biol. Technol. Agric., vol. 11, p. 182, 2024.
[39] Z. Zhang et al., “Advanced Applications of Responsive Nanomaterials in Intelligent Food Packaging,” Adv. Funct. Mater., vol. 36, e19324, 2026.
[40] V. Castro-Alves et al., “Liquid and gas-chromatography-mass spectrometry methods for exposome analysis,” J. Chromatogr. A, vol. 1744, p. 465728, 2025.
[41] F. Rahimi et al., “A Review of Portable High-Performance Liquid Chromatography,” Chromatographia, vol. 83, pp. 1165–1195, 2020.
[42] W. Parys, M. Dołowy, and A. Pyka-Pająk, “Current Strategies for Studying the Natural and Synthetic Bioactive Compounds in Food by Chromatographic Separation Techniques,” Processes, vol. 9, p. 1100, 2021.
[43] G. Catarro et al., “Analytical Approaches Using GC-MS for the Detection of Pollutants in Wastewater,” Chemosensors, vol. 13, p. 253, 2025.
[44] D. Tsikas, “Perspectives of Quantitative GC-MS, LC-MS, and ICP-MS in the Clinical Medicine Science,” J. Clin. Med., vol. 13, p. 7276, 2024.
[45] Q. Shen et al., “Revolutionizing food science with mass spectrometry imaging,” Compr. Rev. Food Sci. Food Saf., vol. 23, e13398, 2024.
[46] W. Qi et al., “Research Progress of Applying Infrared Spectroscopy Technology for Detection of Toxic and Harmful Substances in Food,” Foods, vol. 11, p. 930, 2022.
[47] Z. Wang et al., “Recent developments in the spectrometry of fluorescence, ultraviolet visible and surface-enhanced Raman scattering for pesticide residue detection,” Bull. Mater. Sci., vol. 45, p. 202, 2022.
[48] S. Weng et al., “Rapid Detection of Pesticide Residues in Paddy Water Using Surface-Enhanced Raman Spectroscopy,” Sensors, vol. 19, p. 506, 2019.
[49] P.-L. Chang, M.-M. Hsieh, and T.-C. Chiu, “Recent Advances in the Determination of Pesticides in Environmental Samples by Capillary Electrophoresis,” Int. J. Environ. Res. Public Health, vol. 13, p. 409, 2016.
[50] L. Chen et al., “Matrix Interference of Vegetable on Enzyme-Linked Immunosorbent Assay for Parathion Residue Detection,” Foods, vol. 14, p. 3414, 2025.
[51] A.C.G. Foddai and I.R. Grant, “Methods for detection of viable foodborne pathogens: current state-of-art and future prospects,” Appl. Microbiol. Biotechnol., vol. 104, pp. 4281–4288, 2020.
[52] D.-G. Lee et al., “Evaluation of Pencycuron Residue Dynamics in Eggplant Using LC-MS/MS,” Foods, vol. 13, p. 3754, 2024.
[53] M. Erminia Schiano et al., “Monitoring of seven pesticide residues by LC-MS/MS in extra virgin olive oil samples and risk assessment for consumers,” Food Chem., vol. 442, p. 138498, 2024.
[54] S. Santini et al., “Multi-residue method validation of a LC-MS/MS method for quantitative determination of 349 pesticides in tomato,” J. Food Compos. Anal., vol. 128, p. 106049, 2024.
[55] X. Yuan et al., “Validation of a Multi-Residue Analysis Method for 287 Pesticides in Citrus Fruits,” Foods, vol. 11, p. 3522, 2022.
[56] K. Zheng et al., “Establishment of an LC-MS/MS Method for the Determination of 45 Pesticide Residues in Fruits and Vegetables from Fujian, China,” Molecules, vol. 27, p. 8674, 2022.

[57] B.-S. Choi et al., "Simultaneous Screening of 322 Residual Pesticides in Fruits and Vegetables Using GC-MS/MS," Foods, vol. 12, p. 3001, 2023.
[58] Y.-K. Kim et al., "LC-MS/MS and GC-MS/MS Cross-Checking Analysis Method for 426 Pesticide Residues in Agricultural Products," J. Agric. Food Chem., vol. 72, pp. 22814–22821, 2024.
[59] A. Nasiri et al., "A Multi Residue GC-MS Method for Determination of 12 Pesticides in Cucumber," Iran. J. Pharm. Res., vol. 15, 2016.
[60] Z. Chen et al., "SERS detection of triazole pesticide residues on vegetables and fruits using Au decahedral nanoparticles," Food Chem., vol. 439, p. 138110, 2024.
[61] S. Hou et al., "A Broad-Spectrum Monoclonal Antibody-Based Heterologous ic-ELISA for the Detection of Multiple Pyrethroids," Foods, vol. 14, p. 768, 2025.
[62] E. López Dávila et al., "ELISA, a feasible technique to monitor organophosphate, carbamate, and pyrethroid residues," SN Appl. Sci., vol. 2, p. 1487, 2020.
[63] R. Ramadevi et al., "Development of a Multi Residue Method for the Quantification of 45 Pesticides Using GC-MS/MS," Orient. J. Chem., vol. 39, pp. 1145–1155, 2023.
[64] W. Zhang, F. Yang, Y. Zhang, and K. Zhou, "Simultaneous Determination of Seven Carbamate Pesticide Residues in Vegetable by Capillary Electrophoresis," Int. J. Electrochem. Sci., vol. 16, p. 210652, 2021.
[65] S. Wu, L. Huang, and R. Huang, "Review of advances in hyper-spectral imaging-based non-destructive testing methods in food application," J. Food Compos. Anal., vol. 150, p. 108860, 2026.
[66] A. Singh et al., "Recent Advances in Electrochemical Biosensors: Applications, Challenges, and Future Scope," Biosensors, vol. 11, p. 336, 2021.
[67] Z. Zhai et al., "Electronic Noses: From Gas-Sensitive Components and Practical Applications to Data Processing," Sensors, vol. 24, p. 4806, 2024.
[68] F. Meng et al., "Qualitative and quantitative pesticide residue analysis in Allium tuberosum using an electronic nose with multivariate analysis," Food Chem., vol. 492, p. 145661, 2025.
[69] J. Tan and J. Xu, "Applications of electronic nose (e-nose) and electronic tongue (e-tongue) in food quality-related properties determination: A review," Artif. Intell. Agric., vol. 4, pp. 104–115, 2020.
[70] B. Lu et al., "Recent Advances of Hyperspectral Imaging Technology and Applications in Agriculture," Remote Sens., vol. 12, p. 2659, 2020.
[71] S. Martin and T. George, "Applications of hyperspectral image analysis for precision agriculture," in Micro- and Nanotechnology Sensors, Systems, and Applications X, SPIE, 2018, p. 42.
[72] D.A. Pelaez, J.E. Arango, and O.E. Gualdron, "Multispectral Characterization of Pesticide Residues in Strawberries," in 2024 IEEE Colombian Conference on Applications of Computational Intelligence, 2024, pp. 1–6.
[73] W. Ye et al., "Detection of Pesticide Residue Level in Grape Using Hyperspectral Imaging with Machine Learning," Foods, vol. 11, p. 1609, 2022.
[74] J. Xiong et al., "Recent Advances in Fluorescent Detection of Pesticides in Environmental and Food Matrices," J. Agric. Food Chem., vol. 73, pp. 23783–23808, 2025.
[75] J. Wang et al., "UAS-based remote sensing for agricultural Monitoring: Current status and perspectives," Comput. Electron. Agric., vol. 227, p. 109501, 2024.
[76] X. Yang et al., "Advances in UAV Remote Sensing for Monitoring Crop Water and Nutrient Status," Plants, vol. 14, p. 2544, 2025.
[77] A.S. Tsagkaris, J. Pulkrabova, and J. Hajslova, "Optical Screening Methods for Pesticide Residue Detection in Food Matrices," Foods, vol. 10, p. 88, 2021.
[78] T.O. Hara and B. Singh, "Electrochemical Biosensors for Detection of Pesticides and Heavy Metal Toxicants in Water," ACS EST Water, vol. 1, pp. 462–478, 2021.
[79] A. Ejigu, M. Tefera, and A. Guadie, "Electrochemical detection of pesticides: A comprehensive review," Electrochem. Commun., vol. 169, p. 107839, 2024.
[80] A. Li et al., "Application of machine learning to improve the accuracy of electrochemical sensors: A review," TrAC Trends Anal. Chem., vol. 193, p. 118469, 2025.
[81] P. Li et al., "Research Progress of Biosensors in the Detection of Pesticide Residues and Heavy Metals in Tea Leaves," Biosensors, vol. 15, p. 778, 2025.
[82] B. Bucur et al., "Advances in Enzyme-Based Biosensors for Pesticide Detection," Biosensors, vol. 8, p. 27, 2018.
[83] A. Hassoun et al., "Implementation of relevant fourth industrial revolution innovations across the supply chain of fruits and vegetables," Food Chem., vol. 409, p. 135303, 2023.
[84] J. Chilo et al., "E-nose application to food industry production," IEEE Instrum. Meas. Mag., vol. 19, pp. 27–33, 2016.
[85] S. Baruah and D.H. Mazumder, "A Review on Application of Machine Learning Techniques Coupled With E-Nose in Healthcare, Agriculture, and Allied Domains," IEEE Trans. Instrum. Meas., vol. 74, pp. 1–23, 2025.
[86] H. Chen, D. Huo, and J. Zhang, "Gas Recognition in E-Nose System: A Review," IEEE Trans. Biomed. Circuits Syst., vol. 16, pp. 169–184, 2022.
[87] K. Chetna et al., "Electronic nose (e-nose): Principle and advances for seed quality assessment," Food Control, vol. 175, p. 111291, 2025.
[88] A.J. Moshayedi et al., "E-Nose-Driven Advancements in Ammonia Gas Detection," Sustainability, vol. 15, p. 11601, 2023.
[89] P.E.S. Munekata et al., "Applications of Electronic Nose, Electronic Eye and Electronic Tongue in Quality, Safety and Shelf Life of Meat and Meat Products," Sensors, vol. 23, p. 672, 2023.

[90] X. Yang et al., “Recognition Algorithms in E-Nose: A Review,” IEEE Sens. J., vol. 23, pp. 20460–20472, 2023.
[91] K.K. Pulluri and V.N. Kumar, “Development of an Integrated Soft E-Nose for Food Quality Assessment,” IEEE Sens. J., vol. 22, pp. 15111–15122, 2022.
[92] L.S. Leite et al., “Design and implementation of an electronic nose system for real-time detection of marijuana,” Instrum. Sci. Technol., vol. 49, pp. 471–486, 2021.
[93] A. Bhargava et al., “Hyperspectral imaging and its applications: A review,” Heliyon, vol. 10, e33208, 2024.
[94] D. Caballero, R. Calvini, and J.M. Amigo, “Hyperspectral imaging in crop fields: precision agriculture,” in Data Handling in Science and Technology. Elsevier, 2019, pp. 453–473.
[95] O. Golge and B. Kabak, “Determination of 115 pesticide residues in oranges by HPLC–triple-quadrupole mass spectrometry in combination with QuEChERS,” J. Food Compos. Anal., vol. 41, pp. 86–97, 2015.
[96] C. Kassinis et al., “A review on the environment’s influence on coastal marine steel corrosion and in-situ monitoring,” J. Mater. Sci. Mater. Eng., vol. 20, p. 125, 2025.
[97] K.G. Liakos et al., “Machine Learning for Quality Control in the Food Industry: A Review,” Foods, vol. 14, p. 3424, 2025.
[98] D. Tsounidi et al., “AChE-based electrochemical biosensor for pesticide detection in vegetable oils,” Anal. Bioanal. Chem., vol. 415, pp. 615–625, 2023.
[99] R. Umapathi et al., “Portable electrochemical sensing methodologies for on-site detection of pesticide residues in fruits and vegetables,” Coord. Chem. Rev., vol. 453, p. 214305, 2022.
[100] B. Pérez-Fernández et al., “Electrochemical (Bio)Sensors for Pesticides Detection Using Screen-Printed Electrodes,” Biosensors, vol. 10, p. 32, 2020.
[101] T. Gai et al., “Progress of rapid detection of pesticides in fruits and vegetables,” Front. Food Sci. Technol., vol. 3, p. 1253227, 2023.
[102] J. Huang et al., “A novel electrochemical aptasensor based on core–shell nanomaterial labeling for simultaneous detection of acetamiprid and malathion,” Food Chem., vol. 429, p. 136857, 2023.
[103] J. Gao et al., “Detection of Tomato Leaf Pesticide Residues Based on Fluorescence Spectrum and Hyper-Spectrum,” Horticulturae, vol. 11, p. 121, 2025.
[104] G. Lv et al., “Rapid and Nondestructive Detection of Pesticide Residues by Depth-Profiling Fourier Transform Infrared Photoacoustic Spectroscopy,” ACS Omega, vol. 3, pp. 3548–3553, 2018.
[105] G. Lv et al., “In-situ quantitative prediction of pesticide residues on plant surface by ATR-FTIR technique coupled with chemometrics,” Spectrochim. Acta A, vol. 305, p. 123432, 2024.
[106] L. Zhang et al., “Smartphone-based colorimetric paper chip sensor using single-atom nanozyme for the detection of carbofuran pesticide residues in vegetables,” Spectrochim. Acta A, vol. 327, p. 125415, 2025.
[107] H. Sun et al., “Study on Rapid Detection of Pesticide Residues in Shanghaiqing Based on Analyzing Near-Infrared Microscopic Images,” Sensors, vol. 23, p. 983, 2023.
[108] Y. Hu et al., “Detecting different pesticide residues on Hami melon surface using hyperspectral imaging combined with 1D-CNN and information fusion,” Front. Plant Sci., vol. 14, p. 1105601, 2023.
[109] Y.-H. Liao et al., “Pesticide residue quantification analysis by hyperspectral imaging sensors,” presented at SPIE Sensing Technology+Applications, 2015.
[110] Y. Jia et al., “Apple Surface Pesticide Residue Detection Method Based on Hyperspectral Imaging,” in Intelligence Science and Big Data Engineering. Springer, 2018, pp. 539–556.
[111] H. He et al., “Spectroscopic and Imaging Technologies Combined with Machine Learning for Intelligent Perception of Pesticide Residues in Fruits and Vegetables,” Foods, vol. 14, p. 2679, 2025.
[112] R. Jiang et al., “Hyperspectral Detection of Pesticide Residues in Black Vegetable Based on Multi-Classifier Entropy Weight Method,” IEEE Access, vol. 13, pp. 55701–55711, 2025.
[113] F. Rodriguez-Macadaeg et al., “Developing a Multi-Spectral NIR LED-Based Instrument for the Detection of Pesticide Residues Containing Chlorpyrifos-Methyl in Rice,” Sensors, vol. 24, p. 4055, 2024.
[114] A.S. Nazarloo et al., “Evaluation of Different Models for Non-Destructive Detection of Tomato Pesticide Residues Based on Near-Infrared Spectroscopy,” Sensors, vol. 21, p. 3032, 2021.
[115] Q. Chen et al., “A Feasible Approach to Detect Pesticides in Food Samples Using THz-FDS and Chemometrics,” J. Spectrosc., 2020, pp. 1–10.
[116] P. Nie et al., “Trace Identification and Visualization of Multiple Benzimidazole Pesticide Residues on Toona sinensis Leaves Using Terahertz Imaging Combined with Deep Learning,” Int. J. Mol. Sci., vol. 22, p. 3425, 2021.
[117] A. Miglione et al., “An electrochemical biosensor for on-glove application: Organophosphorus pesticide detection directly on fruit peels,” Talanta, vol. 283, p. 127093, 2025.
[118] Y. Tang et al., “A novel electronic nose for the detection and classification of pesticide residue on apples,” RSC Adv., vol. 11, pp. 20874–20883, 2021.
[119] M.J. Oates et al., “Using a Low-Cost Components e-Nose for Basic Detection of Different Foodstuffs,” IEEE Sens. J., vol. 22, pp. 13872–13881, 2022.
[120] X. Tang et al., “An Electronic Nose Technology to Quantify Pyrethroid Pesticide Contamination in Tea,” Chemosensors, vol. 8, p. 30, 2020.
[121] A. Yılmaz and C. Şimşek, “GP-Optimized E-Nose: A Low-Cost Solution for Apple Pesticide Detection,” J. Adv. Res. Nat. Appl. Sci., vol. 11, pp. 276–285, 2025.
[122] B.H. Tozlu, “Electronic Detection of Pesticide Residue on Cherry Fruits,” Int. J. Comput. Exp. Sci. Eng., vol. 10, 2024.