14 Applications of Artificial Intelligence and Machine Learning in Food Quality Control and Safety Assessment

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14.1 INTRODUCTION

Ensuring food quality and safety remains a global priority, especially as international food supply chains expand and food systems become more complex. The global food system is undergoing rapid transformation due to population growth, urbanization, the expansion of international supply chains, and the increasing complexity of food processing and distribution networks (Babaniyi *et al*., 2026). Global food systems have grown in complexity in terms of production, processing, distribution, and retail and now operate at an unprecedented scale across longer supply chains and under higher throughput than ever before (Aransiola *et al*., 2025; Savary *et al*., 2020). This complexity raises new challenges for ensuring consistent food quality and safety, because the points at which contamination, adulteration, or degradation can occur have multiplied across multiple nodes of the value chain. Food-borne diseases continue to impose significant public health and economic burdens, with the World Health Organization (WHO) estimated over 600 million cases of food-borne illness annually (Mallapaty, 2022; Almaary, 2023). Hence, there is a great demand for reliable, rapid, and cost-effective methods of ensuring food quality and safety.

Traditional laboratory-based testing, focused on physical inspection, chemical assays, and microbiological analyses, has served as the backbone of food quality control for decades. However, these methods are often labor-intensive, time-consuming, and limited in their ability to meet the demands of

DOI: 10.1201/9781003727514-16

real-time quality assurance (Ain *et al.,* 2024; Aransiola et al., 2024; Mandal *et al.,* 2025). The methods cannot meet the speed, scale, and continuous monitoring needs of modern supply chains. Consequently, there is a rapidly growing interest in computational, automated methods that integrate sensor technologies, data analytics, and machine learning (ML) to provide continuous, proactive monitoring for real-time food quality control and predictive safety assessment (Chhetri, 2024; Yu *et al.,* 2025).

Artificial intelligence (AI) and ML have emerged as transformative technologies in modern food quality control capable of addressing these challenges. AI-driven systems can process complex datasets, provide tools to extract patterns from high-dimensional, multimodal sensor data (e.g., spectral, visual, and time-series), detect patterns invisible to human inspectors, and predict future states such as spoilage risk or microbial contamination at machine speeds that exceed the speed and accuracy of traditional manual techniques (Kazanskiy *et al.,* 2025; Mandal *et al.,* 2025). AI methods, from classical ML algorithms to advanced deep learning (DL) architectures, now support a wide range of tasks such as food grading, contamination detection, shelf-life prediction, microbial risk profiling, adulteration analysis, and real-time traceability (Chhetri, 2024; Dhal and Kar, 2025). In doing so, these models can automate decision-making on production lines, reduce inspection bottlenecks, lower human error, and trigger timely interventions before food quality deteriorates. Furthermore, by integrating AI with Internet of Things (IoT) sensors and cloud/edge computing, food businesses can move from reactive testing to proactive management, improving both safety outcomes and economic efficiency (Ficili *et al.,* 2025).

AI and ML are increasingly critical in achieving safe, traceable, efficient, and sustainable food supply chains. The food sector generates enormous volumes of data from IoT sensors, industrial cameras, hyperspectral imaging systems, supply-chain logs, and laboratory instruments that traditional statistical approaches cannot fully leverage. ML models can extract value from these datasets, offering continuous monitoring, early warning systems for hazards, and automated decision-support tools (Mu *et al.,* 2024). Liu *et al.* (2023) conducted a bibliometric analysis of AI applications in food safety over a decade, showing steep growth in research and identifying emerging hotspots such as predictive analytics, computer vision, and traceability. These advances highlight an important inflection point that AI is not just a research novelty but a practical tool reshaping food safety frameworks.

This chapter surveys the conceptual foundations of AI and ML applicability in food quality control and safety assessment. It reviews the relevant technologies and data architectures of AI and ML in food safety and presents major applications (e.g., vision-based sorting, shelf-life prediction, pathogen risk modeling, and adulteration detection) and their benefits across dairy, meat, produce, and beverage sectors. It also discusses practical challenges (data quality, deployment, and regulatory and ethical issues) and highlights future directions and opportunities of AI and ML for global food systems.

14.2 OVERVIEW OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

AI refers to computational systems capable of performing tasks that typically require human intelligence, including classification, prediction, reasoning, and pattern recognition. ML, a subset of AI, focuses on algorithms that improve performance with data. It enables systems to learn from data and improve their performance without explicit programming. ML is generally categorized into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, each with unique applications within the food sector (Table 14.1) (Jamali *et al.,* 2025).

Each approach differs in its methodology and analytical power and aligns differently with stages of the food value chain (production, storage, sorting, and distribution) and supports different operational goals (quality classification, predictive maintenance, and anomaly detection) (Chhetri, 2024).

TABLE 14.1 Common ML approaches

ML APPROACH	*EXPLANATION*
Supervised learning	Models are trained on labeled data (e.g., "defect/no defect"and "high/low contamination"). Examples include: CNNs – widely used for image-based inspection of produce, packaging, or defects; SVMs – useful for classification tasks such as defect detection; and Random Forests – robust for handling high-dimensional data in chemical analysis.
Unsupervised learning	Discovering structure in unlabeled data, e.g., anomaly detection in sensor streams. When labels are not available, clustering (e.g., k-means) or dimensionality reduction (PCA) helps discover structure in the data (e.g., grouping similar spoilage profiles).
Semi-supervised learning	Combines a small labeled dataset with a larger unlabeled dataset very useful in food contexts where obtaining labeled contamination examples is expensive or difficult.
Reinforcement learning	Agents learn sequential decision-making policies, such as how a robotic sorter should pick items to minimize damage or maximize yield.

DL, an ML subfield based on artificial neural networks, has rapidly gained attention due to its ability to automatically extract complex, hierarchical features from raw data. DL models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), vision transformers (ViTs), and Generative Models are increasingly used for image-based inspection, infrared spectroscopy analysis, contamination detection, and process optimization in food manufacturing (Trigka and Dritsas, 2025). In food applications, ML tasks typically include classification (e.g., defective vs. acceptable), regression/prediction (e.g., forecasting shelf-life), clustering (e.g., grouping samples with similar contamination profiles), and anomaly detection (e.g., identifying rare adulteration events or unexpected spoilage) (Liu *et al.,* 2023).

DL architectures enable more sophisticated modeling in food inspection. It has enabled breakthroughs in non-destructive testing, hyperspectral imaging, automated grading, and biomarker detection. CNNs outperform classical image-processing methods in defect detection and are widely used for feature extraction from imagery (RGB and hyperspectral), while recurrent networks (RNNs) and temporal architectures (e.g., LSTM) model time-series data (temperature logs and sensor drift) (Yang *et al.,* 2023). Transformer architectures and multimodal models have shown promise in multimodal food quality analysis and are emerging for fusing text (traceability logs), images, and spectra into unified predictions (Rashed *et al.,* 2025). The major AI techniques in food quality applications are summarized in Table 14.2.

TABLE 14.2 Major AI techniques in food quality applications

AI TECHNIQUE	*COMMON APPLICATION*	*ADVANTAGES*	*REFERENCES*
CNN	Visual defect detection	High accuracy in image tasks	Jha and Babiceanu (2023)
Random Forest	Shelf-life prediction	High robustness	Li *et al.* (2024)
SVM	Texture & sensory modeling	Performs well on small datasets	Liu *et al.* (2023)
ANN	Spectral data interpretation	Good nonlinear modeling	Jiang *et al.* (2023)
Transformer models	Multimodal data analysis	Handles complex, high-dimensional data	Rajender and Gopalachari (2024); Rashed *et al.* (2025)

The integration of AI into food systems is driven by three main factors, including growing availability of high-dimensional data (spectral data, imaging, IoT sensors, and microbial sequencing data), advances in computing power, enabling real-time inference, and demand for automation in food processing, driven by labor shortages and regulatory pressures (Wu *et al.,* 2025).

14.2.1 Emerging AI Technologies Relevant to Food Quality and Safety

Recent advances include Explainable AI (XAI) techniques like SHAP (SHapley Additive exPlanations) or LIME allow understanding which features (e.g., spectral bands and pixels) drive a model's decision (Vimbi *et al.,* 2024). This is critical for regulatory transparency and trust. Generative AI (models) like generative adversarial networks (GANs) can simulate adulteration scenarios, sensory attributes, or generate synthetic data for rare events, aiding training when real data are scarce (Gupta *et al.,* 2025). Also, federated learning models can be trained across multiple sites (factories and labs) without centralizing sensitive data, improving privacy and collaboration (e.g., in global food supply networks). Digital twins simulate production lines that mirror real-world factories, enabling "what-if" safety analyses and safety scenario testing without disrupting operations, as well as for virtual simulations of food processing plants (Vidyalakshmi *et al.,* 2025). These technologies mitigate data sharing barriers and improve trust in automated decisions.

14.3 TRADITIONAL APPROACHES TO FOOD QUALITY CONTROL AND SAFETY ASSESSMENT

Food quality and safety assessment has historically relied on a combination of sensory evaluation, chemical analysis, microbiological testing, and visual inspection. Traditional methods form the foundation of food quality control. Physical methods include visual inspection, color measurement, and textural analysis. Classical quality-control tools include sensory panels, plate counts, and other microbiological assays, chromatography and mass spectrometry for chemical contaminants, and physical measurements (e.g., firmness and colorimetry). Chemical assays assess attributes such as acidity, moisture, fat content, and chemical residues, while microbiological tests, including culture-based techniques and biochemical identification, detect pathogens and spoilage organisms (Gillani *et al.,* 2024). Although these methods remain the regulatory gold standard across global food control systems, they face well-documented limitations related to speed, cost, scalability, and human subjectivity. A good understanding of these legacy methods provides essential context for appreciating why AI and ML have gained such unprecedented attention in the last decade.

14.3.1 Sensory and Manual Visual Inspection

For centuries, frontline quality assessment in food processing has depended on human inspectors who rely on sight, smell, and touch to judge attributes such as color uniformity, texture, shape, bruising, ripeness, and the presence of visible defects. In several industries such as fruit grading, fish filleting, and bakery product sorting, manual inspection is still dominant. However, sensory inspection is inherently subjective; judgments vary between inspectors based on experience, fatigue, lighting conditions, and cultural expectations (Ogidi *et al.,* 2025).

Multiple studies highlight the low interobserver reliability associated with manual grading, especially during high-throughput operations where speed compromises precision. For example, fruit packing facilities commonly report misclassification rates of 10–30% when relying solely on human sorting, with quality drift occurring during long shifts (Bollen and Prussia, 2022; Garg *et al*., 2022; Walsh, 2018). These shortcomings have motivated the adoption of optical sorting and computer vision systems as more consistent alternatives.

14.3.2 Microbiological Testing

Microbiological analysis is central to food safety evaluation. Regulatory bodies typically require routine testing for pathogens such as *Salmonella, Listeria monocytogenes, E. coli* O157:H7, *Campylobacter*, and various spoilage organisms. Traditional microbiological methods include culture-based assays requiring selective media incubation (24–72 hours), colony counting used to estimate microbial load, biochemical tests for species differentiation, and PCR-based detection, which shortens diagnostic time but still requires laboratory infrastructure (Ferone *et al.,* 2020).

Although culture methods are accurate and standardized, their slow turnaround times make them poorly suited for real-time decision-making. A batch may sit in storage for days while awaiting microbiological clearance, increasing energy costs and risking unnoticed spoilage. Molecular techniques (e.g., qPCR and multiplex PCR) offer faster detection but remain resource-intensive and require skilled personnel (Kaushik *et al.,* 2025). Moreover, all laboratory sampling methods suffer from a fundamental limitation; only a small portion of a batch is tested, leaving room for heterogeneity and false negatives. These operational constraints are major drivers behind the growing interest in predictive microbiology and AI-based microbial risk modeling.

14.3.3 Chemical and Spectroscopic Analysis

Chemical assays are widely used to evaluate food composition, nutritional attributes, shelf-life indicators, and contaminants. Common analytical methods include: Chromatography (HPLC, GC-MS) for pesticide residues, adulterants, and chemical contaminants; Spectroscopy (FTIR, NIR, Raman, and UV-Vis) for compositional analysis; and Titration and wet chemistry for acidity, moisture, fat, protein, and peroxide values. These techniques are highly accurate and reproducible, forming the backbone of regulatory compliance testing. However, instrumentation is expensive, requiring capital investment and maintenance; skilled technicians are needed to operate analytical equipment, and sample preparation can be time-consuming and labor-intensive (Kumar, 2025). Also, throughput is limited with most methods, only capable of analyzing a few dozen samples per day.

In addition, chemical contaminants in food (e.g., mycotoxins, heavy metals, plasticizers, or industrial adulterants) often occur at trace levels requiring sensitive detection. Mycotoxins have been highlighted by the Food and Agriculture Organization (FAO) and the WHO as critical food safety issues, urging nations to implement strict monitoring and control mechanisms (Adelere *et al.,* 2025). While modern spectroscopic systems can detect such contaminants, AI-driven multivariate pattern recognition is increasingly used because traditional chemometric tools (PCA and PLS-DA) struggle with nonlinear relationships present in complex food matrices (Behmadi *et al.,* 2025).

14.3.4 Packaging Inspection and Physical Contaminant Detection

Traditional packaging inspection typically relies on manual visual checks for sealing defects, label errors, and deformities; X-ray systems for detecting foreign materials (glass and metal), and metal detectors to ensure physical safety compliance. These technologies work well for certain contaminants but cannot reliably detect low-density materials (e.g., plastic fragments, wood pieces, insects). Additionally, X-ray systems require controlled environments and may generate false positives on complex packaging layers (Yahyaei *et al.,* 2025). The industry trend is moving toward AI-driven X-ray and hyperspectral systems capable of detecting subtle density differences or spectral fingerprints, but most conventional factories still use older, rule-based systems.

14.3.5 Limitations of Traditional Approaches

Across all categories – sensory, microbiological, chemical, and physical inspection – traditional methods share several systemic limitations (Chhetri, 2024) (Table 14.3).

TABLE 14.3 Limitations of traditional approaches to food quality control and safety assessment

LIMITATION	*DESCRIPTION*	*EXAMPLES OF IMPACT IN FOOD SYSTEMS*
Slow and Reactive Testing	Traditional microbiological and chemical methods require long processing times (hours to days), causing delays in decision-making.	Batch release delays; products remain in cold storage awaiting results; and increased energy and operational cost.
Labor-Intensive and High Operational Costs	Skilled technicians are required for sample preparation, instrument operation, and interpretation; equipment is expensive.	High testing costs for small producers; limited testing frequency; and challenges scaling testing at high throughput.
Limited Sampling Coverage	Only small subsamples can be tested from large batches, leaving room for undetected heterogeneity or localized contamination.	False negatives in pathogen testing; undetected spoilage pockets in bulk storage; and adulterants missed across large lots.
Lack of Continuous Monitoring	Conventional methods provide periodic results rather than real-time insights, making them unsuitable for dynamic supply chains.	Inability to detect rapid spoilage events; missed temperature excursions during transport; and delayed contamination alerts.
Difficulty with Complex or High-Dimensional Data	Traditional chemometric tools struggle with nonlinear relationships and large datasets (e.g., hyperspectral, multispectral, and genomic data).	Slow or inaccurate interpretation of spectral data and inability to detect subtle adulteration signatures without AI.
Human Subjectivity and Variability	Manual inspections depend heavily on inspector experience, physical conditions, and fatigue levels.	Inconsistent grading of fruits/vegetables; variation in defect detection; and inconsistent assessments during long shifts.

These constraints create a "detection gap" between sampling points that AI-enabled sensors and predictive models can help close. Major drivers for AI-based innovations include stricter regulation, consumer demand for traceability, reduction of food waste through better shelf-life prediction, and the falling cost of sensors and computation. Increased digitalization of supply chains also produces the data necessary for ML, making AI solutions more feasible than a decade ago (Liu *et al.,* 2023). Recent studies emphasize that as sensor technology advances, traditional methods alone cannot handle the data complexity generated by modern imaging, spectroscopy, and IoT systems. AI bridges this gap by enabling deep, fast, and scalable interpretation (Ahmed, 2024; Liu *et al.*, 2023; Sufi, 2025).

14.4 ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FOOD QUALITY ASSESSMENT

AI and ML have emerged as transformative tools in modern food quality assurance. Their capacity to analyze large datasets, detect subtle patterns, automate decision-making, and enhance predictive accuracy positions them as powerful alternatives to traditional food inspection approaches. Unlike manual or laboratory-based analysis, AI systems can rapidly process images, spectral signatures, sensor data, and real-time environmental metrics to provide reliable and scalable assessment of food quality (Liang *et al.,* 2025). Figure 14.1 gives a framework for AI-enabled food quality and safety.

AI-driven automation minimizes human intervention, reduces inspection time, and enhances throughput, especially in large-scale production environments. ML systems integrated with high-speed cameras and robotics can evaluate thousands of items per hour, which is well beyond human capabilities (Waqar *et al.,* 2024). Automated grading systems for fruits, vegetables, grains, and meat products allow producers to maintain uniform quality standards while lowering operational costs.

Traditional methods often struggle with subtle or nonlinear quality indicators. In contrast, AI models, particularly DL, excel at pattern identification, enabling high accuracy even under complex conditions. CNNs, for example, can classify meat freshness, detect mold on cereal grains, or identify bruises on fruits with >95% accuracy in many industrial deployments (Nazir *et al.,* 2025).

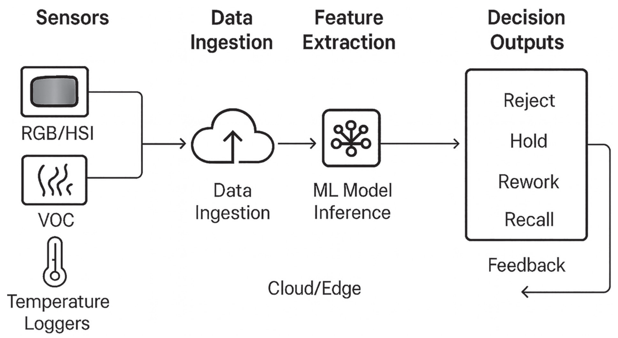

FIGURE 14.1 Conceptual framework for AI-enabled food quality and safety.

One of the most significant contributions of AI lies in predictive modeling for early detection. By analyzing environmental parameters (temperature, humidity, and pH), microbial growth kinetics, or time-series sensor data, ML models can forecast spoilage events before they are visible (Shehzad, 2025). Examples include time-series ML models (predicting bacterial growth in meat packages), gas-sensor-based AI systems (detecting volatile organic compounds (VOCs) associated with spoilage), and AI-enhanced biosensors, which identify trace levels of pathogens such as *E. coli, Salmonella,* or *Listeria* with high sensitivity (Zhao *et al.,* 2025). Predictive analytics support proactive decision-making, allowing producers to adjust storage conditions, modify processing parameters, or remove risky products before they reach consumers.

14.4.1 AI/ML Success in Food Quality Assessment

A CNN-based vision system was employed to detect defects such as rind diseases, pigmentation issues, and bruising in citrus. The AI system increased defect detection accuracy from 78% (manual inspection) to 96% (automated), reduced labor costs by 40%, and improved overall grading consistency (Yu *et al.,* 2025). A meat processor deployed an AI-driven E-nose system to detect spoilage VOCs. The ML model predicted spoilage 24–48 hours before traditional microbiological assays, enabling early removal of compromised batches and saving an estimated $1.2 million annually in waste reduction (Ramadan *et al.,* 2025). Researchers developed a hyperspectral imaging (HSI) + CNN model for detecting subtle adulterants (e.g., melamine and urea) in milk (Aqeel *et al.,* 2024). The model achieved >98% classification accuracy, outperforming FTIR chemical analysis while requiring no chemical reagents.

Dairy plants have applied ML for detecting milk adulteration, predicting spoilage based on fermentation kinetics, and monitoring cheese ripening stages using spectral sensors. Studies show improved early detection of contamination and better consistency in quality grading compared to manual inspection (Agiomavriti *et al.,* 2024; Liakos *et al.,* 2025). ML assists with microbial risk mapping in slaughterhouses, automated bruise and foreign body detection on carcasses, and monitoring cold chain integrity. Predictive models for microbial growth during storage can optimize holding times and freezing strategies, reducing recalls (Tarlak, 2023). Breweries and beverage manufacturers use ML to correlate chemical profiles with sensory outcomes, enabling flavor consistency across batches. Table 14.4 gives AI/ML contributions to food safety.

TABLE 14.4 Benefits of AI/ML in food quality assessment

AI/ML CONTRIBUTION	*BENEFITS*	*FOOD INDUSTRY APPLICATION EXAMPLES*	*REFERENCES*
Automation & Efficiency	High throughput, reduced cost	Sorting fruits/vegetables, automated grading	Tariq *et al.* (2025)
Higher Accuracy	Detects subtle defects/contaminants	Meat freshness, cereal grain defects	Singh *et al.* (2025)
Predictive Modeling	Early spoilage/contamination alerts	VOC-based spoilage prediction	Buwa *et al.* (2026)
Real-Time Monitoring	Continuous sensor-driven tracking	Smart packaging, IoT cold-chain monitoring	Nasrudin *et al.* (2025)
Non-Destructive Testing	Preserves product integrity	Hyperspectral inspection, imaging	Aqeel *et al.* (2024); Xu *et al.* (2024)

14.5 SPECIFIC APPLICATIONS OF AI AND ML IN FOOD SAFETY AND QUALITY CONTROL

AI and ML have become indispensable in addressing modern food safety challenges. They support early detection of hazards, ensure compliance with safety standards, and enhance traceability across supply chains. Unlike traditional inspection methods, which are often slow, reactive, and labor-intensive, AI-driven solutions enable proactive, real-time quality evaluation and risk prediction (Buwa *et al.,* 2026).

Food-borne pathogens such as *Salmonella, L. monocytogenes*, and *Escherichia coli* continue to cause significant global public health concerns. AI and ML enhance detection through rapid pattern recognition, laboratory automation, and interpretation of complex biological signals. A hybrid CNN-SVM model trained on hyperspectral data detected *Salmonella* contamination in poultry carcasses within seconds, outperforming optical inspection technologies and conventional plating (Soni *et al.,* 2022).

Food adulteration, whether economic (e.g., dilution and substitution) or malicious, poses significant safety risks. AI and ML support non-destructive adulteration detection using spectral, chemical, and visual data. Common targets include milk adulteration (e.g., melamine, urea, and water), olive oil dilution with cheaper vegetable oils, and grain and spice adulteration (e.g., Sudan dyes in chili powder). A deep-learning HSI model accurately identified melamine adulteration down to 0.1% concentration in milk, surpassing standard chemical methods (Aqeel *et al.,* 2024).

Furthermore, AI improves agricultural efficiency by optimizing crop management, pest control, and yield prediction. By enabling up to 25% more effective irrigation and lowering fertilizer consumption by 20%–30% through data-driven decision-making, AI-based systems enhance crop management, planting schedules, and resource utilization, all of which boost productivity (Kutyauripo *et al.,* 2023). Ferentinos (2018) noted that AI systems that use image recognition are able to detect diseases with up to 99.5% accuracy in pest control and have contributed to a 30–50% decrease in the use of pesticides. Similarly, You *et al.* (2017) discovered that AI models that use meteorological and remote sensing data to estimate yield have achieved R2 values of up to 0.89, outperforming conventional techniques in predicting accuracy. Table 14.5 presents the major application areas of AI/ML in food quality and safety management.

14.6 CHALLENGES, LIMITATIONS, AND ETHICAL CONSIDERATIONS

Despite the significant breakthroughs made possible by AI and ML, their application in food safety and quality management is not without obstacles. These challenges span technical, economic, infrastructural, regulatory, and ethical dimensions.

Reliable ML depends on representative, labeled datasets (Table 14.6). For many food safety events (e.g., contamination), labeled instances are rare, leading to class imbalance. Standardized, open datasets are scarce, hampering reproducibility and cross-site validation. Federated learning and curated public datasets could help but require governance frameworks (Liu *et al.,* 2023). A study by Ünal *et al.* (2024) showed that apple bruise detection models trained on laboratory images performed poorly when tested under real supply-chain lighting due to data mismatch.

Models trained on a narrow set of products or conditions can perform poorly when exposed to new varieties or geographies. DL methods such as CNNs often operate as "black boxes," making

TABLE 14.5 AI/ML applications in food safety and quality control

APPLICATION AREA	*AI/ML TECHNIQUES USED*	*DATA SOURCES/ INPUTS*	*DETAILED FUNCTIONS*	*EXAMPLES*	*KEY OUTCOMES & BENEFITS*	*REFERENCES*
Detection of Food-borne Pathogens	CNNs, SVM, Random Forests, Deep Neural Networks, ML-integrated biosensors.	Microbial images, biosensor signals, genomic data, hyperspectral signatures.	Identify microbes; classify pathogens; detect contamination; genomic fingerprinting.	CNN-SVM hybrid detected *Salmonella*; ML biosensors detected *E. coli*.	Accuracy >95%; faster than plating/PCR; on-site testing.	Soni *et al.* (2022); Chhetri (2024); Karim *et al.* (2025)
Prediction & Monitoring of Food Spoilage	LSTM, GRU, Time-Series Forecasting, ANN	VOC patterns, temp/humidity, smart packaging sensors.	Predict spoilage timeline; model microbial growth; detect VOCs.	LSTM predicted beef spoilage 48 h early; sensor-ML for fish freshness.	Early alerts; reduced waste; improved cold-chain safety.	Shehzad (2025); Zhao *et al.* (2025); Buwa *et al.* (2026)
Detection of Food Adulteration	CNNs+HSI, SVM, PCA+ML, Random Forests	NIR/FTIR spectra, HSI cubes, chemical fingerprints	Identify adulterants; quantify adulteration; classify purity	HSI-CNN detected melamine at 0.1%; SVM detected olive oil adulteration.	High sensitivity; non-destructive; authenticates foods	Liu *et al.* (2023); Aqeel *et al.* (2024)
Quality Grading of Fresh Produce	Computer Vision, CNNs, Transfer Learning, k-means	RGB, spectral images, 3D scans	Detect defects; color uniformity; size/shape; ripeness	Tomato grading ↑35%; CNN for mango ripeness.	Uniform grading; real-time sorting; reduced human error.	Soltani Firouz and Sardari (2022); Tariq *et al.* (2025)
Hazard Identification & Predictive Risk Modeling	Bayesian Networks, Decision Trees, RF, Gradient Boosting, ML-IoT	Sensor logs, contamination history, environmental data	Predict hazards; assess risks; model environment-biological interactions	ML reduced dairy contamination by 18%	Proactive mitigation; compliance; faster corrective action.	Liu *et al.* (2023); Taiwo *et al.* (2024)

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Optimization of Processing Parameters	Reinforcement Learning, ANN optimization, Genetic Algorithms	Temp, pressure, pH, irradiation dose	Optimize sterilization/ pasteurization; control fermentation	RL improved canned-vegetable safety, less nutrient loss	Safer processing; energy/cost savings; consistent quality	Jafari *et al.* (2025); Jha *et al.* (2026)
Traceability and Supply Chain Integrity	Blockchain+AI, LSTM, anomaly detection	Supply chain logs, RFID, IoT sensors	Detect anomalies; predict cold-chain failure; authenticate origin	Blockchain-AI improved seafood traceability	Better safety; reduced recall time; transparency	Almabrok (2023); Liu *et al.* (2023)
Allergen Detection & Risk Assessment	SVM, Deep Learning, biosensor-AI	Immunoassay signals, optical biosensors, NIR	Detect allergens; quantify levels; predict cross-contamination	AI biosensor detected peanut protein at trace levels	Improved allergen safety; supports sensitive consumers	Taiwo *et al.* (2024); Goumas *et al.* (2025)
Consumer Sensory Analysis	E-nose/E-tongue, PCA-ANN, Deep Learning	Gas/taste sensors, aroma patterns	Analyze aroma/flavor; predict acceptance; consistency control	E-nose+ML predicted coffee flavor >90%	Objective evaluation; faster product development	Ling and Heldman, (2025)
Packaging Integrity & Tamper Detection	CNNs, anomaly detection, sensor ML	X-ray, pressure sensors, vibration data	Detect leaks, punctures, seal failures	ML detected micro-leaks in vacuum-packed meat	Reduced failures; improved shelf stability	Chhetri (2024); Liu *et al.* (2023)

TABLE 14.6 Summary of challenges and limitations of AI/ML in food safety and quality control

CHALLENGE AREA	*DESCRIPTION OF THE LIMITATION*	*IMPLICATIONS*	*TYPICAL EXAMPLES*	*REFERENCES*
Data Quality & Availability Issues	Limited, inconsistent, or poorly annotated datasets hinder effective model training. Class imbalance and proprietary data restrictions further reduce model reliability.	Reduced model accuracy, overfitting, and poor generalization in real production environments.	Poor performance of bruise detection models trained only on lab images and inconsistent microbial datasets.	Deléglise *et al.* (2022); Qin *et al.* (2025)
Low Interpretability & Transparency	Many ML models (especially deep learning) operate as "black boxes," offering limited explainability.	Regulatory compliance difficulties, reduced trust, inability to justify or defend choices in audits.	Difficulty explaining why a batch of milk or meat is rejected by automated inspection systems.	Chhetri (2024); Liakos *et al.* (2025)
Infrastructure Limitations	Limited internet access, low compute power, lack of sensors, and unreliable electricity reduce AI feasibility, especially in low-resource regions.	Interrupted monitoring, unreliable predictions, difficulties scaling real-time inspection systems.	Incomplete cold-chain temperature monitoring due to connectivity issues.	Katende (2025)
High Implementation Costs	High costs for sensors, hyperspectral imaging systems, cloud deployment, and skilled personnel limit adoption among small and medium enterprises.	Slow adoption, financial reluctance, and uneven technological distribution in the food sector.	SMEs unable to afford high-resolution imaging platforms for defect detection.	Katende (2025)
Regulatory and Ethical Challenges	Unclear regulations for AI-driven systems, liability concerns, data governance issues, and risk of algorithmic bias.	Slow certification, safety concerns, legal ambiguity, and consumer mistrust.	In cases of misclassification, it is unclear who is legally responsible – the producer, AI system provider, or model developer.	Levina and Mattern (2023)
Environmental Sustainability Issues	AI models (especially deep learning) consume significant energy, require large computational resources, and increase e-waste.	Increased carbon footprint, sustainability concerns, pressure on producers to justify resource use.	Energy-intensive hyperspectral image processing during model training.	Chhetri (2024); Oise and Konyeha (2025)
Integration Challenges in Real Food Systems	Difficulties integrating AI tools with legacy equipment, seasonal variation, differing real-world conditions, and staff resistance.	Many AI pilot projects fail to scale; models perform well in trials but poorly on actual production lines.	Computer vision sorting systems failing under variable lighting and contamination.	Singh and Adhikari (2023)

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it difficult to understand how they reach decisions. Black-box DL models complicate regulatory acceptance; XAI techniques must be adopted to provide traceable justifications for decisions used in enforcement or recalls (Şahin *et al.*, 2025). As highlighted by Chhetri (2024), low model interpretability poses barriers to certification and adoption in regulated sectors such as meat inspection and allergen detection.

Regulatory authorities are still adapting to AI outputs used for compliance. Questions remain around who is liable for false negatives/positives, how AI models must be validated for food safety decisions, and how to handle model updates. Clear standards for validation, traceability, and audit trails are needed. In addition, models trained on biased datasets may disproportionately misclassify specific product types or production regions (Van Giffen *et al.,* 2022). The European Food Safety Authority Emerging Risks, EFSA(2024) has begun setting global precedents, classifying food safety AI systems as "high-risk," requiring extensive documentation and explanations (Röhrs *et al.,* 2024).

14.6.1 Challenges and Barriers to AI/ML Adoption in Food Safety and Quality Control

AI and ML offer transformative capabilities for food safety, quality control, and supply chain monitoring. However, their adoption across the global and regional food industries, especially in low- and middle-income countries, faces practical, technical, economic, and regulatory constraints. These limitations must be understood to develop strategies that ensure equitable access and effective deployment of AI-driven food safety systems. Figure 14.2 presents the key barriers and challenges that limit the widespread implementation of AI/ML in the food sector.

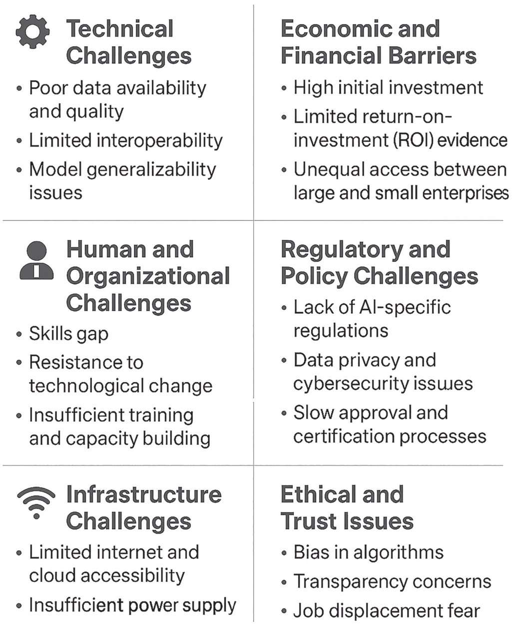

FIGURE 14.2 Challenges and barriers to AI/ML adoption in food safety and quality control.

14.7 FUTURE TRENDS AND OPPORTUNITIES IN AI/ML FOR FOOD SAFETY AND QUALITY CONTROL

The next decade will witness accelerated integration of AI and ML within the global food system. While current applications focus mainly on defect detection, supply-chain monitoring, predictive microbiology, and sensor-based inspection, emerging research signals a shift toward more autonomous, intelligent, and interconnected food-safety ecosystems.

Advances in multimodal models, self-supervised learning, and small-footprint DL (for edge devices) will make robust models easier to deploy. Federated learning will enable cross-company model improvement while preserving privacy, while explainable and certified AI pipelines will be required for regulatory acceptance (Farahani and Monsefi, 2023). These advances will make spectral imaging accessible even to small and medium-scale food producers. Combining data streams from multiple sensors (e.g., NIR + VOC + thermal + acoustic) produces stronger and more robust predictions (Wang *et al.,* 2024). Future AI systems will integrate these multimodal data sources into unified quality scores and automated decision systems. AI and ML will transform food safety through advanced imaging, robotics, blockchain traceability, sensor fusion, and explainable systems. The future will emphasize autonomy, transparency, scalability, and inclusivity, enabling safer, more efficient, and more sustainable food systems worldwide.

There is a strong opportunity for AI to improve food safety in low- and middle-income countries by enabling low-cost sensor deployment and cloud analytics. Partnerships and open datasets are keys to ensuring inclusive benefits and preventing technology concentration in wealthy markets. Figure 14.3 shows the key technological, regulatory, and societal trends shaping the future of AI-driven food quality and safety.

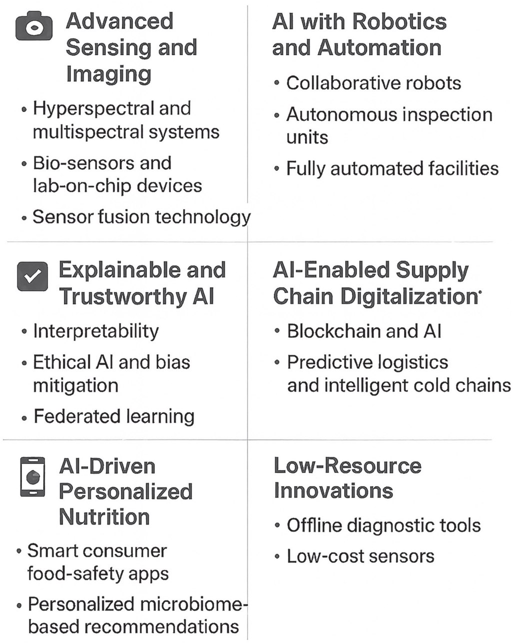

FIGURE 14.3 Future trends and opportunities in AI/ML for food safety and quality control.

14.8 CONCLUSION

AI and ML are increasingly transforming global food safety and quality control. As food systems become more complex and consumers demand higher transparency and reliability, AI-driven tools offer opportunities that far exceed traditional inspection and monitoring methods. These technologies enable rapid data analysis, real-time surveillance, predictive modeling, and automated decision-making across the entire farm-to-fork chain. Current applications, such as computer-vision-based defect detection, hyperspectral imaging, microbial risk prediction, smart packaging, and supply-chain traceability, demonstrate substantial improvements in accuracy, efficiency, and regulatory compliance. Various food sectors confirm that AI not only enhances operational performance but also reduces human error and supports continuous improvement through IoT-enabled smart systems. Despite these benefits, several barriers hinder the widespread adoption of AI and ML. Challenges include poor data quality, interoperability issues, high deployment costs, limited technical expertise, and evolving regulatory frameworks. Overcoming these limitations will require coordinated collaboration among industry stakeholders, researchers, technology developers, and policymakers. Looking ahead, the future of AI in food safety is defined by deeper automation, stronger data ecosystems, and more integrated digital platforms. Advancements in robotics, advanced sensors, and privacy-preserving analytics will expand opportunities, especially in low- and middle-income countries where resource-efficient solutions are vital. Hence, AI and ML represent a central pillar in the modernization of global food safety management. With appropriate policy support, workforce development, and technological integration, these tools will play an increasingly critical role in ensuring food integrity, reducing waste, protecting consumers, and strengthening the resilience and sustainability of food systems worldwide.

REFERENCES

Adelere, I. A., Aboyeji, D. O., Auta, H. S., Barasarathi, J., & Ahmed, A. (2025). Mycotoxins and global food safety. In: Aransiola S. A., Kotun B. M. and Naga R. M. (Eds.). *Biotoxins in Food: Threats and Benefits* (pp. 96–134). Boca Raton, FL: CRC Press.

Agiomavriti, A. A., Nikolopoulou, M. P., Bartzanas, T., Chorianopoulos, N., Demestichas, K., & Gelasakis, A. I. (2024). Spectroscopy-based methods and supervised machine learning applications for milk chemical analysis in dairy ruminants. *Chemosensors*, *12*(12), 263.

Ahmed, R. M. (2024). Integration of wireless sensor networks, internet of things, artificial intelligence, and deep learning in smart agriculture: A comprehensive survey: Integration of wireless sensor networks, internet of things. *Journal of Innovative Intelligent Computing and Emerging Technologies (JIICET)*, *1*(01), 8–19.

Ain, Q. U., Nazir, R., Nawaz, A., Shahbaz, H., Dilshad, A., Mufti, I. U., & Iftikhar, M. (2024). Machine learning approach towards quality assurance, challenges and possible strategies in laboratory medicine. *Journal of Clinical and Translational Pathology*, *4*(2), 76–87.

Almaary, K. S. (2023). Food-borne diseases and their impact on health. *Biosciences Biotechnology Research Asia*, *20*(3), 745–755.

Almabrok, H. A. (2023). Blockchain for supply chain management: To enhance transparency, traceability, and efficiency. *African Journal of Advanced Pure and Applied Sciences (AJAPAS)*, *2*(4), 239–253.

Aqeel, M., Sohaib, A., Iqbal, M., & Ullah, S. S. (2024). Hyperspectral identification of milk adulteration using advance deep learning. *IEEE Access*, *12*, 174965–174982.

Aransiola, S. A., Akinsola, R. O., Abioye, O. P., & Maddela, N. R., (Eds.). (2024). *Emerging Contaminants in Food and Food Products* (1st ed.). Boca Raton, FL, USA: CRC Press. Taylor and Francis Group. https://doi.org/10.1201/9781003438236

Aransiola, S. A., Kotun, B. C., & Maddela, N. R. (Eds.). (2025). *Biotoxins in Food: Threats and Detection*. CRC Press. https://doi.org/10.1201/9781003500605

Babaniyi, G. G., Babaniyi, B. R., Aransiola, S. A., & Sawicka, B. (Eds.). (2026). *Biotechnology of Climate-Smart Agriculture in Food Security and Sustainable Farming*. CRC Press. https://doi.org/10.1201/9781003619284

Behmadi, H., Azarpazhooh, E., Ramaswamy, H. S., & Ahmadauli, K. (2025). Artificial intelligence and machine learning in food analysis. In *Novel Food Analysis: Techniques and Applications* (pp. 391–418). New York, NY: Springer US.

Bollen, A. F., & Prussia, S. E. (2022). Sorting for defects. In *Postharvest Handling* (pp. 377–398). Cambridge, MA: Academic Press.

Buwa, V., Khan, N., Selvaraj, R. C. A., & Nlebedim, V. (2026). Quality control and inspection techniques with AI and ML. In *Artificial Intelligence in Food Science* (pp. 425–445). Cambridge, MA: Academic Press. https://doi.org/10.1016/B978-0-443-26468-9.00029-1

Chhetri, K. B. (2024). Applications of artificial intelligence and machine learning in food quality control and safety assessment. *Food Engineering Reviews*, *16*(1), 1–21.

Deléglise, H., Interdonato, R., Bégué, A., d'Hôtel, E. M., Teisseire, M., & Roche, M. (2022). Food security prediction from heterogeneous data combining machine and deep learning methods. *Expert Systems with Applications*, *190*, 116189.

Dhal, S. B., & & Kar, D. (2025). Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: A comprehensive review. *Discover Applied Sciences*, *7*(1), 75.

European Food Safety Authority Emerging Risks, EFSA (2024). [(accessed on 18 June 2024)]. Available online: https://www.efsa.europa.eu/en/topics/topic/emerging-risks?wtrl=01

Farahani, B., & Monsefi, A. K. (2023). Smart and collaborative industrial IoT: A federated learning and data space approach. *Digital Communications and Networks*, *9*(2), 436–447.

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, *145*, 311–318.

Ferone, M., Gowen, A., Fanning, S., & Scannell, A. G. (2020). Microbial detection and identification methods: Bench top assays to omics approaches. *Comprehensive Reviews in Food Science and Food Safety*, *19*(6), 3106–3129.

Ficili, I., Giacobbe, M., Tricomi, G., & Puliafito, A. (2025). From sensors to data intelligence: Leveraging IoT, cloud, and edge computing with AI. *Sensors*, *25*(6), 1763.

Garg, S., Kolli, V. S., & Shirkole, S. S. (2022). Sorting operations for the classification of agricultural crops. In *Postharvest and Postmortem Processing of Raw Food Materials* (pp. 53–76). Duxford, Cambridge, UK: Woodhead Publishing.

Gillani, S. N., Ahmad, T., Rehman, A., Saba, I., Irshad, S. B. E., Abbas, M., & Ali, K. (2024). The application of chemical analysis techniques in microbiology research: A review of methods, advancements, and implications for food and nutrition. *Applied Chemical Analysis Techniques in Microbiology Research*, *13*(01), 72–81.

Goumas, G., Vlachothanasi, E. N., Fradelos, E. C., & Mouliou, D. S. (2025). Biosensors, artificial intelligence biosensors, false results and novel future perspectives. *Diagnostics*, *15*(8), 1037.

Gupta, R., Tiwari, S., & Chaudhary, P. (2025). Generative AI techniques and models. In *Generative AI: Techniques, Models and Applications* (pp. 45–64). Cham: Springer Nature Switzerland.

Jafari, M., Nazari, R. R., Rezaei, M., Moazzen, M., & Shariatifar, N. (2025). Machine learning for detoxification of aflatoxin M1 by lactococcus lactis probiotic in kashk production. *Food Safety and Risk*, *12*(1), 4.

Jamali, V., Sachithanandhan, V. K., Nambi, E., Loganathan, M., Shanmugasundaram, S., & Chandrasekar, V. (2025). AI and machine learning applications. In *Emerging Non-Destructive Technologies for Food Quality Analysis* (pp. 501–555). Cham: Springer Nature Switzerland.

Jha, A., Kalaiselvi, K., Nandhini, R. S., Raj, A. S., & Karthik, P. (2026). Advancements in computational fluid dynamics-aided artificial intelligence and machine learning in food processing. In *Artificial Intelligence in Food Science* (pp. 359–376). Cambridge, MA: Academic Press.

Jha, S. B., & Babiceanu, R. F. (2023). Deep CNN-based visual defect detection: Survey of current literature. *Computers in Industry*, *148*, 103911.

Jiang, Q., Zhang, M., Mujumdar, A. S., & Wang, D. (2023). Non-destructive quality determination of frozen food using NIR spectroscopy-based machine learning and predictive modelling. *Journal of Food Engineering*, *343*, 111374.

Karim, S. N., Hew, P. S., Anwar, F., Sukor, R., Jambari, N. N., Sanny, M., & Khatib, A. (2025). Innovative technological approaches in the detection and mitigation of food toxicants. *Food Reviews International*, 1–45. https://doi.org/10.1080/87559129.2025.2544980

Katende, R. (2025). Rethinking data-efficient artificial intelligence for low-resource settings. *Machine Learning with Applications*, *25*,100796.

Kaushik, R., Mahajan, S., Dass, G., & Chatli, M. K. (2025). Introduction to molecular diagnostics and viral diseases. In *Molecular Diagnostics for Viral Diseases: Challenges and Emerging Concepts* (pp. 1–28). Singapore: Springer Nature Singapore.

Kazanskiy, N., Khabibullin, R., Nikonorov, A., & Khonina, S. (2025). A comprehensive review of remote sensing and artificial intelligence integration: Advances, applications, and challenges. *Sensors*, *25*(19), 5965.

Kumar, D. (2025). Spectroscopic techniques in chemical analysis: A review of emerging trends. *Indian Journal of Pharmaceutical Chemistry and Analytical Techniques (IJPCAT)*, *1*(3), 55–70.

Kutyauripo, I., Rushambwa, M., & Chiwazi, L. (2023). Artificial intelligence applications in the agrifood sectors. *Journal of Agriculture and Food Research*, *11*, 100502.

Levina, O., & Mattern, S. (2023). Ethical and legal analysis of machine learning based systems: A scenario analysis of a food recommender system. In *Recommender Systems: Legal and Ethical Issues* (pp. 165–185). Cham: Springer International Publishing.

Li, D., Bai, L., Wang, R., & Ying, S. (2024). Research progress of machine learning in extending and regulating the shelf life of fruits and vegetables. *Foods*, *13*(19), 3025.

Liakos, K. G., Athanasiadis, V., Bozinou, E., & Lalas, S. I. (2025). Machine learning for quality control in the food industry: A review. *Foods*, *14*(19), 3424.

Liang, Y., Li, Z., Shi, J., Zhang, N., Qin, Z., Du, L., & Huang, X. (2025). Advances in hyperspectral imaging technology for grain quality and safety detection: A review. *Foods*, *14*(17), 2977.

Ling, J., & Heldman, D. R. (2025). Integration of machine learning technologies in food flavor research: Current applications, challenges, and future perspectives. *International Journal of Agricultural and Biological Engineering*, *18*(3), 1–11.

Liu, M., Liu, M., Bai, L., Shang, W., Ren, R., Zhao, Z., & Sun, Y. (2023). Establishing a berry sensory evaluation model based on machine learning. *Foods*, *12*(18), 3502.

Mallapaty, S. (2022). Why are Pakistan's floods so extreme this year? *Nature*. https://doi.org/10.1038/d41586-022-02813–6

Mandal, S., Kiran, P. R., Mandal, S., & Aradwad, P. (2025). Enhancing food safety and quality assurance through artificial intelligence. *Smart Farming, Smarter Solutions: Revolutionizing Agriculture with Artificial Intelligence* (pp. 239–265). https://doi.org/10.1201/9781003536932-12

Mu, W., Kleter, G. A., Bouzembrak, Y., Dupouy, E., Frewer, L. J., Radwan Al Natour, F. N., & Marvin, H. J. P. (2024). Making food systems more resilient to food safety risks by including artificial intelligence, big data, and internet of things into food safety early warning and emerging risk identification tools. *Comprehensive Reviews in Food Science and Food Safety*, *23*(1), e13296.

Nasrudin, M. W., Ismail, I., Othman, H., Mustafa, W. A., Ali, S. A. S., & Arifin, N. A. M. (2025, August). IoT-driven real-time monitoring and reject analysis in beverage manufacturing: A systematic review. In *2025 9th International Conference on Man-Machine Systems (ICoMMS)* (pp. 453–458). IEEE.

Nazir, A., Hussain, A., & Assad, A. (2025). CNN in food industry: Current. In *Artificial Intelligence in the Food Industry: Enhancing Quality and Safety* (pp. 329–354). https://doi.org/10.1201/9781032633602-17

Ogidi, O. I., Wenapere, C. M., & Chukwunonso, O. A. (2025). Enhancing food safety and quality control with computer vision systems. In *Computer Vision Techniques for Agricultural Advancements* (pp. 51–88). Hershey, PA: IGI Global Scientific Publishing.

Oise, G., & Konyeha, S. (2025). Environmental impacts in e-waste management using deep learning. *Discover Artificial Intelligence*, *5*(1), 1–18.

Qin, K., Dai, X., & Wu, L. (2025). Hybrid sampling and ensemble learning for food safety sampling inspection classification. *Journal of Food Protection*, *88*(12), 100650.

Rajender, N., & Gopalachari, M. V. (2024). An efficient dimensionality reduction based on adaptive-GSM and transformer assisted classification for high dimensional data. *International Journal of Information Technology*, *16*(1), 403–416.

Ramadan, K. M., Bendary, E. S., Khalil, H. B., Ali, S. A., Ahmed, A. R., & Mahmoud, M. A. (2025). Smart detection of food spoilage using microbial volatile compounds: Technologies, challenges, and future outlook. *Journal of Agricultural and Food Chemistry*, *73*(31), 19222–19243.

Rashed, M., Fakhry, S., & Satour, R. (2025). Revolutionizing food quality with machine vision and machine learning techniques. In *Food in the Metaverse and Web 3.0 Era: Intersecting Food, Technology, and Culture* (pp. 71–124). Hershey, PA: IGI Global Scientific Publishing.

Röhrs, S., Rohn, S., & Pfeifer, Y. (2024). Risk classification of food incidents using a risk evaluation matrix for use in artificial intelligence-supported risk identification. *Foods*, *13*(22), 3675.

Şahin, E., Arslan, N. N., & Özdemir, D. (2025). Unlocking the black box: An in-depth review on interpretability, explainability, and reliability in deep learning. *Neural Computing and Applications*, *37*(2), 859–965.

Savary, S., Akter, S., Almekinders, C., Harris, J., Korsten, L., Rötter, R., & Watson, D. (2020). Mapping disruption and resilience mechanisms in food systems. *Food Security*, *12*(4), 695–717.

Shehzad, K. (2025). Predictive AI models for food spoilage and shelf-life estimation. *Global Trends in Science and Technology*, *1*(1), 75–94.

Singh, N., & Adhikari, D. (2023). Challenges and solutions in integrating AI with legacy inventory systems. *International Journal for Research in Applied Science and Engineering Technology*, *11*(12), 609–613.

Singh, T. B., Ghosh, Y., Kundu, R., & Vivek, K. (2025). Multispectral imaging technique: Principles and recent applications in food processing. In *Emerging Non-Destructive Technologies for Food Quality Analysis* (pp. 187–214). Cambridge, UK: Woodhead Publishing.

Soltani Firouz, M., & Sardari, H. (2022). Defect detection in fruit and vegetables by using machine vision systems and image processing. *Food Engineering Reviews*, *14*(3), 353–379.

Soni, A., Dixit, Y., Reis, M. M., & Brightwell, G. (2022). Hyperspectral imaging and machine learning in food microbiology: Developments and challenges in detection of bacterial, fungal, and viral contaminants. *Comprehensive Reviews in Food Science and Food Safety*, *21*(4), 3717–3745.

Sufi, F. (2025). Beyond the sensor: A systematic review of AI's role in next-generation machine health monitoring. *Applied Sciences*, *15*(19), 10494.

Taiwo, O. R., Onyeaka, H., Oladipo, E. K., Oloke, J. K., & Chukwugozie, D. C. (2024). Advancements in predictive microbiology: Integrating new technologies for efficient food safety models. *International Journal of Microbiology*, *2024*(1), 6612162.

Tariq, R., Qureshi, I., Farooq, S., Ayoub, W. S., Akhter, S., Javaid, R., & Sultana, A. (2025). Artificial intelligence in cutting and sorting of fruits and vegetables. In *Artificial Intelligence in the Food Industry* (pp. 134–152). Boca Raton, FL: CRC Press.

Tarlak, F. (2023). The use of predictive microbiology for the prediction of the shelf life of food products. *Foods*, *12*(24), 4461.

Trigka, M., & Dritsas, E. (2025). A comprehensive survey of deep learning approaches in image processing. *Sensors*, *25*(2), 531.

Ünal, Z., Kızıldeniz, T., Özden, M., Aktaş, H., & Karagöz, Ö (2024). Detection of bruises on red apples using deep learning models. *Scientia Horticulturae*, *329*, 113021.

Van Giffen, B., Herhausen, D., & Fahse, T. (2022). Overcoming the pitfalls and perils of algorithms: A classification of machine learning biases and mitigation methods. *Journal of Business Research*, *144*, 93–106.

Vidyalakshmi, G., Gopikrishnan, S., Boulila, W., Koubaa, A., & Srivastava, G. (2025). Digital twins and cyber-physical systems: A new frontier in computer modeling. *Computer Modeling in Engineering & Sciences*, *143*(1), 51.

Vimbi, V., Shaffi, N., & Mahmud, M. (2024). Interpreting artificial intelligence models: A systematic review on the application of LIME and SHAP in Alzheimer's disease detection. *Brain Informatics*, *11*(1), 10.

Walsh, K. B. (2018). Fruit and vegetable packhouse: Technologies for assessing fruit quantity and quality. In *Advances in Agricultural Machinery and Technologies* (pp. 367–395). Boca Raton, FL: CRC Press.

Wang, L., Cheng, Y., Parekh, G., & Naidu, R. (2024). Real-time monitoring and predictive analysis of VOC flux variations in soil vapor: Integrating PID sensing with machine learning for enhanced vapor intrusion forecasts. *Science of the Total Environment*, *924*, 171616.

Waqar, M., Bhatti, I., & Khan, A. H. (2024). Leveraging machine learning algorithms for autonomous robotics in real-time operations. *International Journal of Advanced Engineering Technologies and Innovations*, *4*(1), 1–24.

Wu, K., Ji, Z., Wang, H., Shao, X., Li, H., Zhang, W., & Bao, X. (2025). A comprehensive review of AI methods in Agri-food engineering: Applications, challenges, and future directions. *Electronics*, *14*(20), 3994.

Xu, S., Wang, H., Liang, X., & Lu, H. (2024). Research progress on methods for improving the stability of non-destructive testing of agricultural product quality. *Foods*, *13*(23), 3917.

Yahyaei, K., Khan, M. S. M., Ghosh, S., Roy, A., Craig, P., Varshney, N., & Asadizanjani, N. (2025, April). X-adapt: AI-driven design-based strategy to address x-ray compatibility challenges in advanced packaging metrology. In *Metrology, Inspection, and Process Control XXXIX* (Vol. 13426, pp. 865–875). SPIE.

Yang, R., Singh, S. K., Tavakkoli, M., Karami, M. A., & Rai, R. (2023). Deep learning architecture for computer vision-based structural defect detection. *Applied Intelligence*, *53*(19), 22850–22862.

You, J., Li, X., Low, M., Lobell, D., & Ermon, S. (2017, February). Deep Gaussian process for crop yield prediction based on remote sensing data. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 31, No. 1), pp. 4559–4565.

Yu, K., Zhong, M., Zhu, W., Rashid, A., Han, R., Virk, M. S., & Ren, X. (2025). Advances in computer vision and spectroscopy techniques for non-destructive quality assessment of citrus fruits: A comprehensive review. *Foods*, *14*(3), 386.

Yu, W., Ouyang, Z., Zhang, Y., Lu, Y., Wei, C., Tu, Y., & He, B. (2025). Research progress on the artificial intelligence applications in food safety and quality management. *Trends in Food Science & Technology*, *156*, 104855.

Zhao, Y., Sun, T., Zhang, H., Li, W., Lian, C., Jiang, Y., & Chen, S. (2025). AI-enhanced electrochemical sensing systems: A paradigm shift for intelligent food safety monitoring. *Biosensors*, *15*(9), 565.