

APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN FOOD QUALITY AND SAFETY ASSURANCE - A REVIEW

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DOI: 10.37550/tdmu.EJS/2026.02.719

Article Info

Volume: 8

Issue: 2

June: 2026

Received: Mar. 28th, 2026

Accepted: May. 25th, 2026

Page No: 124-133

Abstract

Artificial intelligence (AI) has been increasingly explored in the food industry, particularly in enhancing food safety and quality assurance systems. This study provides a comprehensive synthesis of current AI applications across the food supply chain, from raw material monitoring to post-processing quality control. Machine learning (ML), deep learning (DL), computer vision, and spectroscopy-integrated AI systems are increasingly utilized to detect pathogens, identify contaminants, predict spoilage, and monitor environmental conditions in real time. Additionally, AI-driven predictive models support risk assessment and proactive decision-making, thereby minimizing foodborne hazards and improving operational efficiency.

In food quality assurance, AI technologies enable objective and rapid evaluation of sensory attributes, replacing traditional subjective methods. Advanced techniques such as convolutional neural networks (CNNs) and near-infrared spectroscopy combined with ML have demonstrated high accuracy in grading, classification, and compositional analysis of food products. Furthermore, AI applications extend to supply chain transparency, fraud detection, allergen identification, and predictive maintenance of processing equipment.

Despite these advancements, challenges remain in data integration, model generalization, and infrastructure requirements. Future studies are expected to further explore the integration of AI with Internet of Things (IoT) systems and big data platforms, which may contribute to more automated and adaptive food safety management systems. Overall, AI represents a critical enabler for achieving safer, more efficient, and sustainable food systems in the context of global food security challenges.

Keywords: artificial intelligence, deep learning, food quality assurance, food safety, machine learning.

1. Introduction

Ensuring food safety and quality has become increasingly complex due to the globalization of supply chains, rising consumer expectations, and stricter regulatory requirements. Traditional approaches to food safety monitoring and quality assessment

often rely on manual inspection, laboratory-based analyses, and experience-driven decision-making. These methods are typically time-consuming, labor-intensive, and subject to variability, which limits their effectiveness in modern large-scale food systems.

Recent advances in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), have created new opportunities to overcome these limitations. AI technologies enable automated, data-driven analysis of large and complex datasets, supporting rapid detection of hazards, real-time monitoring, and predictive decision-making (Zhang et al., 2020). The integration of AI with advanced sensing technologies such as hyperspectral imaging (HSI), spectroscopy, and Internet of Things (IoT) devices further enhances its capability to detect contaminants, assess food quality, and monitor environmental conditions throughout the supply chain (Meyers et al., 2015).

In addition, AI is increasingly applied to address critical challenges such as food fraud detection, allergen identification, and supply chain traceability, thereby improving transparency and consumer trust (Ponce et al., 2019; Adedeji et al., 2024). AI-driven predictive models also support risk assessment by anticipating spoilage events and contamination risks based on historical and environmental data, enabling proactive interventions (Ni et al., 2019; Kumar et al., 2024). In the domain of food safety, AI-based microbial assessment has shown potential to improve contaminant detection practices. Conventional microbiological methods are often labor-intensive and time-consuming, whereas AI approaches allow rapid processing and interpretation of large datasets, thereby enhancing both speed and accuracy in pathogen detection (Qian et al., 2023). These capabilities contribute to more efficient food safety management and reduced public health risks.

Despite these advancements, challenges remain in data integration, model generalization, and infrastructure requirements. Moreover, existing studies are often fragmented, focusing on specific applications rather than providing a comprehensive synthesis across the food system. Therefore, this study aims to synthesize current applications of artificial intelligence in food safety and quality assurance, highlight key technological approaches, and evaluate their implications for improving efficiency, reliability, and sustainability in modern food systems.

2. Research Methods

This study employed a structured narrative review approach to examine current applications of artificial intelligence (AI) in food safety and quality assurance. To improve transparency and methodological rigor, the literature identification and screening processes were informed by selected principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. A systematic literature search was conducted using major scientific databases, including Scopus, Web of Science, ScienceDirect, and Google Scholar, covering publications from 2010 to 2025.

A comprehensive search strategy was developed using combinations of keywords and Boolean operators. The primary search terms included: “artificial intelligence”, “machine learning”, “deep learning”, “food safety”, “food quality”, “contaminant detection”, “pathogen detection”, “predictive modeling”, and “food supply chain”. These terms were combined using operators such as AND/OR to refine the search (e.g., “artificial intelligence AND food safety”, “machine learning AND food quality assurance”).

The study applied a structured article screening process to improve transparency in study selection. A total of 122 records were initially identified through database searching. After removing 20 duplicate records, 102 articles remained for screening. Titles and abstracts were reviewed, resulting in the exclusion of 60 records due to lack of relevance to AI applications in food systems. The remaining 42 articles were assessed for full-text eligibility. Of these, 14 articles were excluded because they lacked sufficient methodological rigor, did not present empirical evidence, or were not directly related to food safety and quality assurance. Finally, 28 studies were included in the qualitative synthesis.

The inclusion criteria were defined as follows: (i) studies focusing on applications of artificial intelligence in food safety, food quality assessment, or food supply chain management; (ii) research employing AI techniques such as machine learning, deep learning, computer vision, spectroscopy, or predictive analytics; and (iii) studies providing empirical results, experimental validation, or case-based evidence. Exclusion criteria included: (i) studies not related to food systems; (ii) articles lacking methodological transparency; and (iii) non-peer-reviewed or non-English publications.

Data extraction was conducted systematically to collect information on study objectives, AI techniques, application domains, datasets, and key findings. The selected studies were analyzed using qualitative content analysis to identify key themes, technological trends, and research gaps in AI applications for food safety and quality assurance.

3. Results and Discussion

3.1. Artificial Intelligence in Food Safety

Artificial intelligence (AI) has rapidly emerged as a transformative tool in the food safety domain, enabling more efficient detection, monitoring, and prevention of foodborne risks. Its integration into food systems supports the identification of pathogens, contaminants, and other safety hazards through advanced analytical and predictive capabilities. One of the most significant applications of AI lies in pathogen detection. In parallel, the integration of AI with hyperspectral imaging (HSI) has enabled the detection of contaminants and adulterants in food products. By analyzing spectral signatures, AI models can identify trace-level impurities that are otherwise invisible, making this approach particularly valuable in high-risk sectors such as meat processing (Sun, 2010).

AI also plays a critical role in predictive food safety management. By leveraging historical datasets and environmental variables, ML algorithms can estimate the likelihood of spoilage or contamination events. This predictive capacity allows manufacturers to implement preventive measures, thereby minimizing economic losses and reducing the risk of foodborne illnesses (Zhang et al., 2020). The development of intelligent packaging systems further enhances food safety monitoring. Embedded sensors can track changes in temperature, humidity, and gas composition, while AI algorithms analyze these data in real time to estimate shelf life and detect early signs of spoilage. Such technologies are particularly relevant for perishable commodities, including dairy and fresh produce (Meyers et al., 2015).



Figure 1. Application of AI in ensuring food safety and quality

Source: Wang, 2025

Figure 1 (Wang, 2025) illustrates the comprehensive role of artificial intelligence across the food safety and quality assurance system, spanning from raw material monitoring to processing, storage, and distribution stages. The figure highlights how AI integrates data from multiple sources, including sensors, imaging systems, and environmental monitoring platforms, to enable real-time detection of contaminants, quality deviations, and potential hazards. This integrated framework reflects a shift from conventional reactive approaches toward predictive and preventive food safety management. As reported by Wang (2025), AI-driven systems can significantly enhance the efficiency and accuracy of quality control processes by automating detection tasks and supporting data-driven decision-making. The figure therefore provides a systems-level perspective on how AI technologies contribute to improving traceability, risk management, and overall food system reliability.

Beyond production, AI contributes to supply chain transparency and risk management. By integrating data from multiple digital sources, AI systems can identify critical control points where contamination risks may arise during transportation or storage. This enables rapid intervention and improves traceability across the supply chain (Ni et al., 2019). Similarly, AI-driven approaches are increasingly used to combat food fraud, where ML and natural language processing (NLP) techniques analyze product labels and documentation to detect inconsistencies indicative of adulteration or mislabeling (Ponce et al., 2019). In addition, AI has demonstrated strong potential in allergen detection and chemical hazard identification. By analyzing molecular composition data, AI models can accurately detect allergens, supporting the development of safer, allergen-free products (Adedeji et al., 2024). Spectroscopic analysis combined with AI also enables the detection of chemical contaminants such as pesticide residues, heavy metals, and antibiotic traces, ensuring compliance with food safety standards (Teklemariam, 2024).

Automation represents another major advancement, particularly in quality inspection and contamination control. AI-powered robotic systems equipped with computer vision can perform high-speed visual inspections to identify defects or contamination, thereby improving both accuracy and operational efficiency (Chen and Yu, 2021). Similarly, AI supports regulatory compliance monitoring by analyzing inspection reports and regulatory data to identify potential violations and recommend corrective actions (Esteki et al., 2018).

AI applications also extend upstream into agriculture, where crop health monitoring systems utilize data from drones, sensors, and satellite imagery to detect early signs of disease or pest infestation. This enables timely interventions, reducing the risk of contaminated raw materials entering the food chain (Susheel and Rajkumar, 2023). Furthermore, AI enhances food safety through predictive maintenance in processing systems. By analyzing sensor data from equipment, ML models can predict potential failures that may lead to contamination, allowing preventive maintenance to be conducted in advance (Kharbach et al., 2023). In specialized areas such as mycotoxin detection, AI models have been explored for processing biosensor and assay data to support contamination identification (Inglis et al., 2024).

AI is also applied in optimizing thermal processing conditions, ensuring that heating parameters are sufficient to eliminate pathogens while preserving product quality (Chidinma-Mary Agbai, 2020). Environmental monitoring using AI further supports food safety by predicting harmful algal blooms, which are associated with shellfish poisoning risks (Mu et al., 2024). In addition, AI-based systems are used to monitor water quality in food production environments, detecting contaminants and ensuring safe processing conditions (Czyczula Rudjord et al., 2022). Sector-specific applications continue to expand. In the dairy industry, AI models using spectroscopic data can detect adulterants such as water or starch in milk (Mhapsekar et al., 2022). Similarly, AI is employed in the detection of antibiotic residues in meat products, ensuring compliance with safety regulations prior to market distribution (Cheng and Sun, 2015). In packaging systems, AI-based inspection tools can identify micro-defects and leakage, thereby preventing contamination risks (Wang et al., 2018). Overall, the growing adoption of AI technologies across global food systems, including initiatives reported by companies such as Nestlé, highlights the potential role of technological innovation in supporting food safety and quality assurance practices.

3.2. AI-based Approaches for Food Quality Assessment

AI technologies have become central to modern food quality assurance, enabling more objective, efficient, and scalable evaluation processes. By integrating machine learning, deep learning, and computer vision, AI systems reduce reliance on subjective human assessment while improving consistency and accuracy. Traditionally, food quality evaluation has relied heavily on human sensory analysis, which is often time-consuming and prone to variability. AI-based models trained on large datasets of sensory attributes can overcome these limitations by providing more reliable predictions. For instance, ML models incorporating image processing and sensory-related variables have demonstrated improved accuracy in predicting yogurt quality (Hany et al., 2023). Similarly, convolutional neural networks (CNNs) have been successfully applied to classify chili quality based on attributes such as color, aroma, and texture (Adam and Niswar, 2023).

AI also enables non-destructive quality assessment, which is a significant advancement over traditional destructive testing methods. Techniques combining AI with compositional analysis allow accurate prediction of parameters such as moisture and starch content, achieving high levels of precision (Yoon et al., 2023). In food processing, AI systems facilitate real-time quality monitoring and control. By analyzing data from sensors and production systems, ML models can predict sensory outcomes and adjust processing parameters accordingly. For example, in the wine industry, AI has been used to optimize production conditions based on chemical composition, thereby enhancing product quality (Armstrong et al., 2023).

Computer vision further enhances quality assurance by automating inspection processes. Advanced learning approaches, including active and semi-supervised learning, have been shown to significantly reduce data labeling requirements while maintaining high classification accuracy (Fisher et al., 2023). This leads to more efficient and scalable quality control systems. AI also enables the development of novel quality assessment methodologies. For example, the integration of near-infrared spectroscopy with ML models has been successfully used to predict sensory characteristics of dry-cured meat products, offering a viable alternative to traditional sensory panels (Vasconcelos et al., 2023).

Beyond quality evaluation, AI supports risk management and decision-making within food systems. Predictive models can identify potential risks along the supply chain, allowing companies to implement preventive measures and improve overall product quality (Abass et al., 2024). In industrial applications, AI-driven systems are increasingly embedded in processing equipment, enabling automated quality checks and improving operational efficiency. Technologies adopted by companies such as Tetra Pak illustrate how AI is setting new standards in food quality assurance and safety.

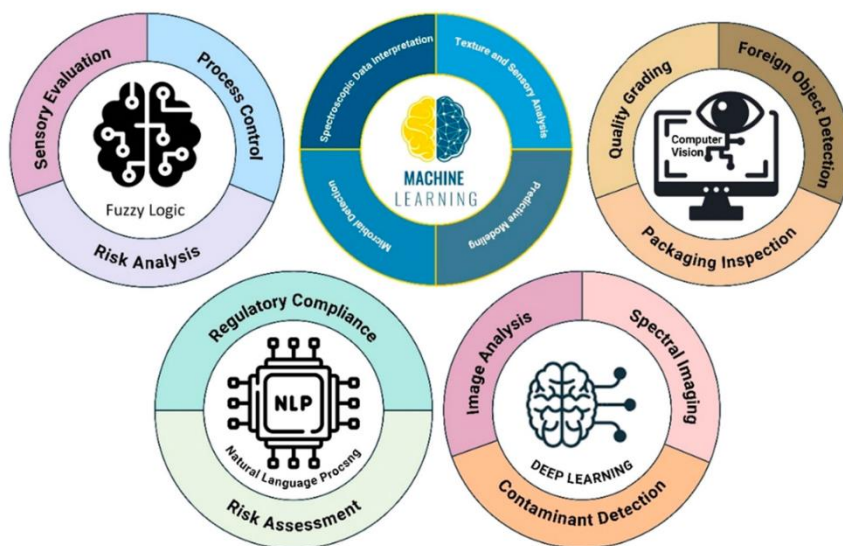


Figure 2. Types of AI used for food analysis and food safety

Source: Ammar et al., 2025

Figure 2 presents the classification of artificial intelligence techniques applied in food analysis and safety, including machine learning, deep learning, computer vision, and

spectroscopic-AI integration. The figure emphasizes the functional differentiation among these approaches, where machine learning is primarily used for predictive modeling and pattern recognition, while deep learning—particularly convolutional neural networks—enables high-precision image-based analysis. In addition, the integration of AI with spectroscopic techniques supports rapid, non-destructive detection of chemical contaminants and compositional attributes. As highlighted by Ammar et al. (2025), these AI-based approaches significantly improve analytical accuracy and processing speed compared to traditional methods. The figure thus serves as a conceptual framework linking AI methodologies with their specific applications in food safety and quality assurance, demonstrating the technological foundation underlying modern intelligent food systems.

Despite the rapid advancement and promising applications of artificial intelligence (AI) in food safety and quality assurance, several critical limitations must be carefully considered. First, the reliability of AI models is highly dependent on the quality, representativeness, and scale of training datasets. Many existing models are developed using controlled laboratory data, which may not adequately capture the variability and complexity of real-world food systems. As a result, model performance can degrade significantly when deployed in industrial or field conditions. Second, the issue of model interpretability remains a major challenge, particularly for deep learning approaches. While these models often achieve high predictive accuracy, their “black-box” nature limits transparency and hinders trust among stakeholders, including regulators and industry practitioners. This lack of explainability can be problematic in high-stakes contexts such as food safety decision-making, where accountability and traceability are essential. Third, the integration of AI into existing food systems requires substantial infrastructure, including high-performance computing, sensor networks, and data management platforms. Such requirements may create disparities between developed and developing regions, potentially limiting the widespread adoption of AI technologies. Furthermore, data standardization and interoperability issues pose additional barriers to effective system integration across the food supply chain. Finally, ethical and regulatory considerations must be addressed to ensure responsible use of AI in food systems. Issues related to data privacy, algorithmic bias, and compliance with food safety standards require the development of robust governance frameworks. Without clear regulatory guidelines, the implementation of AI technologies may face resistance or unintended risks. Taken together, these challenges highlight the need for a more holistic approach that combines technological innovation with robust validation, interdisciplinary collaboration, and adaptive regulatory frameworks. Future research should prioritize the development of explainable AI models, standardized datasets, and scalable solutions that can be effectively translated from laboratory settings to real-world applications.

4. Conclusion

Artificial intelligence is reshaping the landscape of food safety and quality assurance by enabling more precise, efficient, and data-driven approaches across the entire food supply chain. This study synthesizes current applications of AI, demonstrating its capacity to enhance pathogen detection, contaminant identification, predictive risk assessment, and real-time monitoring systems. In parallel, AI-driven tools have significantly improved the objectivity and consistency of food quality evaluation, reducing reliance on subjective and labor-intensive traditional methods.

A key insight emerging from this analysis is that AI does not merely optimize existing processes but fundamentally transforms how food safety and quality are managed—shifting from reactive control toward predictive and preventive systems. The integration of AI with advanced sensing technologies and big data platforms enables a more holistic understanding of food systems, allowing stakeholders to anticipate risks, minimize losses, and improve overall product integrity.

However, the full potential of AI can only be realized through addressing critical challenges related to data quality, model interpretability, infrastructure, and regulatory frameworks. Bridging the gap between technological development and real-world implementation remains essential to ensure scalability and inclusiveness across different contexts.

Looking forward, the convergence of AI with Internet of Things (IoT), cloud computing, and digital traceability systems is expected to drive the development of intelligent, autonomous food safety ecosystems. Such advancements will play a crucial role in ensuring sustainable, transparent, and resilient food systems capable of meeting the growing global demand for safe and high-quality food.

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