Review Paper

Machine Learning for Enhanced Sustainability in Food Quality and Safety: A Big Data Classification Perspective

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Abstract: This paper explores the pivotal role of machine learning (ML) models and algorithms in classifying and managing big data to enhance food safety and sustainability across the modern food supply chain. The increasing complexity of global food systems and the vast, heterogeneous data generated from various sources necessitate advanced analytical tools beyond traditional methods. This review examines the application of supervised and unsupervised ML techniques, including decision trees, support vector machines, random forests, artificial neural networks, convolutional neural networks, and recurrent neural networks, in critical areas such as contamination detection, hazard classification, predictive maintenance, and quality assurance. Advanced studies highlight the superior performance of ML over conventional methods in domains like aflatoxin detection, food fraud monitoring, and risk prediction in livestock. The integration of Industry 4.0 and 5.0 technologies, such as AI, IoT, blockchain, and cloud/edge computing, is also discussed as a driver for improved efficiency and traceability. Despite the significant progress, the paper addresses key challenges including data imbalance, the scarcity of labeled datasets, the interpretability of complex models, and the integration of these advanced systems with existing regulatory frameworks. By providing a comprehensive overview of current applications and outlining future opportunities and barriers, this paper aims to bridge the gap between research and practical implementation, guiding future innovations in digital food safety management.

Keywords: Big Data, Machine Learning, Smart Tools, Cloud Computing, Blockchain, Food Safety and Sustainability

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1. Introduction

Ensuring food safety in the face of growing global food demand, environmental concerns, and complex supply chains has become a pressing public health and sustainability challenge. Foodborne diseases continue to affect millions annually, and the globalization of food systems has introduced new risks and increased the difficulty of real-time contamination detection and risk assessment (Grace, 2023; Mu et al., 2024). Traditional analytical tools are often inadequate in processing the vast, dynamic, and heterogeneous data generated across modern food production environments—from farms and factories to packaging and distribution (Ding et al., 2023; Mu et al., 2024). Recent advances in big data (BD) technologies and machine learning (ML) have opened new possibilities for transforming food safety monitoring and sustainability strategies. The integration of sensor data, smart packaging, blockchain records, and consumer feedback generates large-scale datasets, which are often unstructured and require advanced computational tools for analysis (Siddique et al., 2025; Brous et al., 2020). ML techniques are particularly well-suited for classifying, predicting, and detecting anomalies within such complex data streams (Deng et al., 2021; Liu et al., 2023; Onyeaka et al., 2024). Growing role of machine learning models in classifying and managing big data for food safety applications getting more important. This paper focuses on the implementation of supervised and unsupervised learning techniques—including decision trees (DT), support vector machines (SVM), random forests (RF), artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN)—and their application in contamination detection, hazard classification, predictive maintenance, and quality assurance (Kausik et al., 2025; Kumar et al., 2015; Revelou et al., 2025). Case studies demonstrate ML's ability to outperform traditional methods in terms of speed, accuracy, and scalability across domains such as aflatoxin detection (Deshmukh et al., 2025), food fraud monitoring (Revelou et al., 2025), and risk prediction in livestock and poultry farms (Golden et al., 2019).

The increasing adoption of Industry 4.0 and 5.0 technologies—including artificial intelligence (AI), smart sensors, Internet of Things (IoT), blockchain (BCT), and cloud/edge computing—is reshaping the food industry, improving efficiency, sustainability, and traceability throughout the supply chain (Hassoun et al., 2023a; 2024a; Ait-Kaddour et al., 2024; Nath et al., 2024; Meemken et al., 2024). These digital solutions support circular economy principles, waste reduction, and predictive modeling in both agricultural and seafood sectors (Agnusdei & Krstic, 2023; Elgarahy et al., 2025; Yang et al., 2025; Leal et al., 2025). Despite promising progress, key challenges remain in the widespread implementation of ML-based food safety systems. These include data imbalance, lack of labeled training datasets, interpretability of black-box models, and integration with existing regulatory infrastructure (Waqas et al., 2025; Konfo et al., 2023). Furthermore, environmental variability and technical limitations continue to constrain the practical use of AI in sustainable agri-food applications (Barbedo, 2025). To address these gaps, this paper provides a comprehensive review of ML classification models and their application in food safety and sustainability. It includes the architectural landscape of big data in the food industry, assesses real-world ML deployments, and outlines the most significant opportunities and barriers to implementation (Mu et al., 2024; Siddique et al., 2025; Xiong et al., 2024). By doing so, it aims to bridge the divide between academic research and operational practice, and guide future innovations in digital food safety management (Siddique et al., 2025). This paper explains how ML models and big data analysis are revolutionizing food safety and sustainability by enabling advanced classification, prediction, and anomaly detection across the food supply chain, while also addressing existing challenges for wider adoption.

2. Big Data, Data Analysis and Machine Learning in Food Safety and Sustainability

Food safety remains a critical global public health concern, with millions affected annually by foodborne illnesses and contamination (Grace, 2023). The globalization of food supply chains and the intensification of food production have increased the complexity of monitoring and managing food safety risks (Mu et al., 2024). Traditional methods, while valuable, are insufficient for handling the vast volumes of heterogeneous data generated in modern food systems. This includes data from sensors, smart packaging, processing machinery, laboratory test results, and consumer feedback (Ding et al., 2023; Mu et al., 2024).

The emergence of big data (BD) technologies has revolutionized how food safety is addressed, enabling the collection, integration, and analysis of large-scale unstructured or semi-structured data.

Machine learning (ML), a branch of artificial intelligence (AI), offers powerful tools for classification, anomaly detection, and predictive analytics in food safety applications (Deng et al., 2021; Liu et al., 2023; Onyeaka et al., 2024). Commonly used ML algorithms for classification tasks include decision trees (DT), support vector machines (SVM), random forests (RF), and artificial neural networks (ANN) (Kausik et al., 2025; Kumar et al., 2015). In more complex scenarios, deep learning methods such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are employed, particularly for image and time-series data analysis in inspection and HACCP monitoring systems (Revelou et al., 2025). Despite these advances, several barriers persist. These include data imbalance, missing values, limited labeled datasets, model interpretability, and challenges related to integration with existing infrastructures (Waqas et al., 2025). Moreover, Barbedo (2025) emphasizes that while AI has shown promise in sustainable agri-food systems, environmental variability and data scarcity remain persistent issues, necessitating continued research and cross-sector collaboration. Addressing these challenges is essential for bridging the gap between academic development and real-world applications (Mu et al., 2024; Siddique et al., 2025).

The analysis of keywords from recent scientific articles related to Big Data, identified through OpenAI GPT-4o, was conducted using Mentimeter. This aimed to determine which specific areas within Big Data are the most frequent research topics of scientific publications in food science. Figure1 created from dataset of the most common words used in scientific studies related to artificial intelligence in food science by OpenAI GPT-4o's Big Data and Mentimeter frequency analysis.

Figure1. The most common words used in scientific studies related to AI in food science by OpenAI GPT-4o's Big Data and Mentimeter frequency analysis

3. Artificial Intellegence Building a Smart and Sustainable Food System

Modern food systems are undergoing rapid transformation under the influence of Industry 4.0 and 5.0 technologies, where AI, IoT, smart sensors, and blockchain (BCT) play central roles (Hassoun et al., 2023b; 2024a; 2024b; Ait-Kaddour et al., 2024). These cyber-physical systems and data-centric solutions enhance sustainability by improving resource efficiency, predictive maintenance, waste reduction, and quality control across the entire production line (Nath et al., 2024; Meemken et al., 2024). AI-driven tools have been applied in areas such as circular economy implementation and biological waste optimization, including anaerobic digestion and pyrolysis, yielding enhanced environmental outcomes and energy efficiency (Agnusdei & Krstic, 2023; Elgarahy et al., 2025). The integration of cloud computing and IoT has enabled real-time data acquisition and adaptive decision-making for food processing facilities (Rashvand et al., 2025). Nevertheless, barriers to large-scale AI adoption persist. These include high implementation costs, shortages of trained personnel, privacy concerns, and algorithmic bias (Konfo et al., 2023). Furthermore, the adaptation of AI to legacy infrastructures remains a significant hurdle in digital transformation processes.

4. Big Data Ecosystem in Food Supply Chains and the Blue Economy

The digitization of agriculture and food production has resulted in massive and diverse data generation—from soil sensors and drones to consumer feedback and smart logistics (Hassoun et al., 2025). These datasets, collected across farming, processing, packaging, logistics, and retail stages, represent the "3Vs" of big data: volume, variety, and velocity. Effective integration and analysis of such data are crucial for achieving traceability, safety, and sustainability (Ding et al., 2023). In primary production, sensors collect data on irrigation, soil conditions, and pest control, which are crucial for predictive modeling of contamination risks (Barbedo, 2025; Kuppusamy et al., 2024; Wang et al., 2021).

Post-harvest, machine vision systems and smart inspection technologies generate image and video data for automated quality control (Dhanush et al., 2023). Blockchain systems offer immutable records of product history, improving traceability and enabling swift recalls when integrated with big data analytics (Duan et al., 2024; Ellahi et al., 2023). Furthermore, consumer reviews, complaints, and social media posts are increasingly used to identify emerging food safety threats via text mining and natural language processing (Xiong et al., 2024; Dhal and Kar, 2025). Despite these advances, significant integration and standardization challenges remain—particularly for small and medium-sized enterprises (SMEs) with limited digital capacity (Brous et al., 2020).

Cloud and edge computing infrastructures have emerged to support distributed ML processing, with edge devices now capable of running embedded models that trigger automated safety interventions (Jouini et al., 2024; Mu et al., 2024). These systems have become essential tools in aquaculture, fisheries, and seafood traceability, enabling real-time water quality monitoring and genetic optimization (Yang et al., 2025; Leal et al., 2025; Alwi et al., 2024). As Liu et al. (2025) and Gladju et al. (2022) emphasize, multidisciplinary collaboration is essential for developing secure and scalable data ecosystems in the blue economy.

5. Machine Learning Based Classification Models in Food Safety Applications

ML-based classification has revolutionized food safety by offering rapid, accurate, and scalable solutions for contamination detection, food fraud identification, spoilage prediction, and allergen risk assessment (Lin et al., 2022; Revelou et al., 2025; Kehinde et al., 2025). Emerging hazards due to process-induced contaminants—such as acrylamide (AA), heterocyclic aromatic amines (HAAs), polycyclic aromatic hydrocarbons (PAHs), and glycidyl esters (GE)—necessitate new monitoring techniques (Zahir et al., 2025). Spectroscopic methods such as

NIR, FTIR, and Raman spectroscopy generate high-dimensional datasets ideal for ML applications (Abdul et al., 2024; Su and Sun, 2017).

Deshmukh et al. (2025) demonstrated the use of ML in aflatoxin detection via spectral, imaging, and behavioral data. Kabir et al. (2025) highlighted the integration of hyperspectral imaging (HSI) with ML for mycotoxin detection in grains and nuts, noting its industrial relevance and future promise. AI has also been effectively used in computer vision for food inspection. Gorji et al. (2022) developed a deep learning system combining EfficientNet-B0 and U-Net to detect and segment fecal contamination on meat carcasses, achieving 97.32% classification accuracy and 89.34% segmentation IoU. Similarly, Golden et al. (2019) employed random forest and gradient boosting models with weather data to predict Listeria contamination risks in poultry farms. Additionally, Chen et al. (2024) introduced a novel approach using LC-HRMS and ANN to classify unknown chemical contaminants by MS2 spectral patterns, achieving over 80% accuracy and under 0.2% false positives. Soni et al. (2022) reviewed two decades of advancements in HSI and ML for microbial and chemical contaminant detection, underscoring ML's critical role in addressing complex food matrix challenges. As Kuppusamy et al. (2024) noted, the integration of multimodal data and adaptive algorithms allows modern ML models to support food safety systems with unprecedented precision and scalability. Table 1 explains that machine learning (ML) techniques have been widely applied across various domains of food safety, ranging from contamination detection and traceability to predictive maintenance and consumer feedback analysis. These applications utilize diverse algorithms—including decision trees, support vector machines, deep learning models, and natural language processing (NLP)—and are supported by big data sources such as IoT sensor outputs, hyperspectral images, blockchain records, and social media text. As illustrated, each implementation addresses specific challenges in the food supply chain, highlighting the transformative potential of ML in achieving food safety and sustainability.

Table 1. Machine Learning and Big Data Applications in Food Safety and Sustainability

Application Area	ML/AI Technique(s)	Use Case - Description	References
Contamination Detection	Random Forest, Gradient Boosting	Predicting Listeria risk in chicken farms using weather data	Golden et al., 2019
Fecal Contamination Detection	EfficientNet-B0, U-Net (Deep Learning)	Image classification and segmentation of meat carcass contamination	Gorji et al., 2022
Mycotoxin Detection	Hyperspectral Imaging (HSI) + ML	Non-destructive classification and quantification in grains and nuts	Kabir et al., 2025
Aflatoxin Detection	Spectral, Imaging, Behavioral Data + AI	Enhanced prediction through multimodal data analysis	Deshmukh et al., 2025
Chemical Contaminant Classification	ANN + LC-HRMS	Classification of unknown compounds in pork/seafoods using mass spectral data	Chen et al., 2024
Consumer Feedback Risk Analysis	NLP, Text Mining	Analysis of reviews, complaints, and social media for emerging risks	Xiong et al., 2024; Dhal & Kar, 2025
Food Safety Infrastructure Optimization	Embedded ML on Edge Devices	Real-time hazard detection and system shutdowns in processing plants	Jouini et al., 2024; Mu et al., 2024
Traceability & Supply Chain	Blockchain + Big Data	Track product movement, support recalls, improve accountability	Duan et al., 2024; Ellahi et al., 2023
Spoilage and Quality Prediction	CNN, RNN	Detecting spoilage or anomalies from image and time-series sensor data	Kausik et al., 2025; Revelou et al., 2025
HACCP Monitoring (Animal Source Foods)	ML Models (e.g., DT, RF, SVM)	Monitoring hazards in critical control points in animal food production	Kausik et al., 2025; Revelou et al., 2025
Sustainable Agri-food Prediction	AI + Remote Sensing	Wheat quality prediction under environmental variability	Barbedo, 2025
Chemical Process-Induced Contaminants	Spectroscopy + ML	Detection of AA, HAAs, PAHs, AGEs, GE, etc. formed during thermal/microbial processes	Zahir et al., 2025
Risk-Based Food Classification	Decision Tree, SVM, ANN, RF	Classification of microbial, chemical, physical risks in food samples	Liu et al., 2023; Onyeaka et al., 2024

Application Area	ML/AI Technique(s)	Use Case - Description	References
Big Data Infrastructure for SMEs	Cloud & Edge Computing	Scalable, real-time analytics architecture for small and medium enterprises	Brous et al., 2020; Ding et al., 2023
Genetic Optimization in Aquaculture	Data Mining + ML	Enhancing fish farming efficiency via water quality and gene selection data	Yang et al., 2025; Leal et al., 2025

6. Discussion and Future Directions

The application of ML to big data offers a transformative approach to enhancing food safety and sustainability, moving beyond traditional methods that struggle with the volume and complexity of modern food systems. As outlined in this review, ML techniques are being effectively employed across various critical areas of the food supply chain.

6.1 Key Applications and Benefits:

- Enhanced Detection and Classification: ML algorithms have demonstrated superior capabilities in the detection of contaminants, including aflatoxins (Deshmukh et al., 2025) and mycotoxins (Kabir et al., 2025), and in the classification of chemical contaminants (Chen et al., 2024). Deep learning models, such as CNNs, have also improved the accuracy of fecal contamination detection (Gorji et al., 2022).
- Risk Prediction and Prevention: ML facilitates the prediction of food safety risks, such as Listeria contamination in poultry farms, by leveraging diverse data sources like weather patterns (Golden et al., 2019). This predictive capability enables proactive interventions, reducing the likelihood of foodborne illness outbreaks.
- Improved Traceability and Transparency: The integration of blockchain technology with big data analytics, enhanced by ML, offers the potential for more robust traceability systems. This integration can track product movement, support efficient recalls, and improve accountability throughout the supply chain (Duan et al., 2024; Ellahi et al., 2023).
- Addressing Emerging Challenges: ML is also being used to address emerging challenges, such as food fraud and the analysis of consumer feedback to identify potential risks (Xiong et al., 2024; Dhal & Kar, 2025).

7. Challenges and Future Directions:

Despite these advancements, several challenges need to be addressed to fully realize the potential of ML in food safety and sustainability:

- Data Quality and Availability: A significant challenge is the availability of high-quality, labeled data. Issues such as data imbalance, missing values, and heterogeneity can affect the performance of ML models (Waqas et al., 2025). Future research should focus on developing strategies for data augmentation, transfer learning, and active learning to mitigate these limitations.

- Model Interpretability: The "black-box" nature of some ML models, particularly deep learning models, poses a challenge for their adoption in food safety applications, where transparency and explainability are crucial. Future research should prioritize the development of explainable AI (XAI) techniques to enhance model interpretability and build trust among stakeholders.

- Integration and Scalability: Integrating ML solutions with existing food industry infrastructure, especially for small and medium-sized enterprises (SMEs), remains a challenge (Brous et al., 2020; Ding et al., 2023). Future efforts should focus on developing scalable and cost-effective solutions, possibly through cloud computing and edge computing, to facilitate wider adoption.

- Regulatory and Ethical Considerations: The use of ML in food safety raises important regulatory and ethical considerations, including data privacy, algorithmic bias, and the need for standardized validation and certification procedures. Future research and policy development should address these issues to ensure the responsible and ethical deployment of ML in the food sector (Levina and Mattern, 2023; Manning et al., 2022).

- Emerging Technologies and Applications: The continued advancement of emerging technologies, such as advanced sensing technologies, IoT, and improved computing power, will create new opportunities for ML in food safety. Future research should explore the integration of these technologies to develop more sophisticated and real-time food safety monitoring systems. There is also a growing interest in using ML to predict the impact of climate change on food safety and to optimize food production for enhanced sustainability (Barbedo, 2025).

While ML offers powerful tools to advance food safety and sustainability, overcoming the identified challenges through focused research and collaboration is essential. Future research should aim to develop robust, interpretable, and scalable ML solutions and promote their responsible and ethical application in the food industry.

8. Conclusion

The application of machine learning to big data is fundamentally reshaping food safety and sustainability paradigms, enabling a transition towards more proactive and data-driven strategies across the food supply chain. This integration offers enhanced capabilities to address critical challenges, including: the rapid and accurate detection of contaminants, the effective prevention of food fraud, the optimization of resource utilization for greater sustainability, and the establishment of more robust traceability systems. The ongoing integration of Industry 4.0 and 5.0 technologies, characterized by advancements in artificial intelligence, the Internet of Things, and interconnected digital platforms, is further accelerating the development of smart and sustainable food systems. However, the realization of the full transformative potential of these technologies necessitates concerted interdisciplinary efforts to overcome several key barriers. These include: addressing inherent issues in data quality and availability (such as heterogeneity, incompleteness, and bias), improving the interpretability of complex ML models (particularly within the realm of deep learning), ensuring seamless integration with existing food industry infrastructures, and navigating the complex landscape of regulatory and ethical considerations surrounding data usage and algorithmic decision-making. By diligently addressing these challenges, researchers can effectively translate academic research advancements into industrial, scalable solutions that significantly enhance the long-term resilience, efficiency, sustainability and safety of the global food system.

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