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Advancing Food Safety Through Artificial Intelligence: A Detailed Review of Monitoring and Detection Technologies

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ABSTRACT

This review paper provides a comprehensive overview of how artificial intelligence (AI) is transforming food safety, particularly in detection and surveillance technologies. It highlights AI approaches such as machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision, emphasizing their role in detecting physical, chemical, and microbial contaminants, ensuring quality control, and predicting outbreaks. This paper also examines real-world applications and recent case studies while addressing challenges such as data privacy, technical barriers, and regulatory acceptance. Furthermore, it proposes future research directions, including AI–IoT integration, blockchain-enabled traceability, and quantum computing applications. By synthesizing recent developments (2021–2024), this review aims to guide researchers, policymakers, and industry stakeholders toward leveraging AI for a safer and more resilient food supply chain.

1 | Introduction

Ensuring food safety is a vital aspect of public health, involving proper handling, preparation, and storage practices aimed at preventing foodborne illnesses and contamination. However, the globalization of the food supply chain has made maintaining strict safety standards increasingly complex. Modern supply chains span multiple regions and involve diverse stakeholders—farmers, processors, distributors, retailers, and consumers—creating numerous points of potential contamination and complicating traceability and accountability.

As food products often cross several national borders before reaching consumers, the risks multiply. At each stage, contamination can arise from biological agents such as bacteria, viruses, and parasites, or from chemical hazards such as pesticides, heavy metals, and industrial pollutants (Burch and Lawrence 2005). Longer transportation times also increase spoilage risks, whereas the demand for year-round product availability has led to greater reliance on preservation techniques and additives, raising new safety concerns. Furthermore, inconsistencies in food safety standards and regulations between countries create enforcement gaps (Henson and Caswell 1999).

The consequences of unsafe food are profound. Globally, foodborne illnesses remain a major public health burden. The World Health Organization (WHO) estimates that about 600 million people fall ill from contaminated food annually, resulting in 420,000 deaths (WHO 2020). Pathogens such as *Salmonella*, *E. coli*, and *Listeria* can trigger severe gastrointestinal diseases, sometimes leading to long-term health issues or fatalities. In addition, chemical contaminants—including heavy metals such as lead and mercury and persistent pollutants such as dioxins—pose chronic risks, with prolonged exposure linked to cancer, neurological disorders, and reproductive problems (Järup 2003).

Beyond health implications, food safety breaches carry significant economic and social costs. Outbreaks of foodborne illness drive up health care expenses and cause productivity losses. For businesses, safety lapses result in expensive recalls, legal liabilities, and reputational harm (Scharff 2012). Consumers lose trust in food systems and regulatory bodies, which alters purchasing behavior and weakens confidence in the market. On a larger scale, disruptions to food safety undermine international trade and global market stability.

Traditional approaches to food safety—relying on periodic inspections, manual interventions, and reactive measures—are no longer adequate to address the challenges of a globalized food system. In this context, artificial intelligence (AI) emerges as a transformative solution. AI, broadly understood as the capacity of machines to perform tasks requiring human intelligence, encompasses fields such as machine learning, deep learning, computer vision, and natural language processing. These technologies enable systems to analyze data, recognize patterns, and generate predictions.

Within food safety, AI is particularly valuable for its ability to rapidly detect contaminants, automate inspection processes, and support predictive risk management across the supply chain. AI-driven tools can process vast amounts of complex data in real time, enabling proactive rather than reactive responses. By improving monitoring, early detection, and traceability, AI can enhance consistency in food safety practices worldwide, reduce human error, and increase the overall reliability of food systems.

1.1 | The Role of Technology in Food Safety

Advances in technology play a pivotal role in improving food safety by enhancing detection, prevention, and response strategies. Technologies such as blockchain, the Internet of Things (IoT), and biosensors are increasingly integrated into food safety systems to provide better traceability, real-time monitoring, and rapid detection of contaminants (Kumar et al. 2020). Blockchain technology, for instance, provides a decentralized and immutable ledger that can trace the journey of food products from farm to table, ensuring transparency and accountability throughout the supply chain (Tian 2017). IoT devices allow for continuous monitoring of critical environmental conditions, such as temperature and humidity, to prevent spoilage and contamination (Verdouw et al. 2016).

Biosensors, on the other hand, enable rapid and sensitive detection of microbial and chemical contaminants. These sensors can be applied at various stages of the food production process, helping to swiftly identify and address contamination risks, thereby reducing the occurrence of foodborne illnesses (Velusamy et al. 2010). However, although these technologies offer critical improvements, they often operate in isolation, creating a need for systems that can integrate and synthesize information across different platforms—this is where AI's ability to analyze vast and diverse data sources becomes invaluable.

1.2 | Importance and Potential of AI in Food Safety

Artificial intelligence (AI) is increasingly recognized for its potential to revolutionize food safety practices. AI technologies, such as machine learning and predictive analytics, can process enormous datasets to identify patterns, detect anomalies, and predict potential food safety risks before they occur (Birgand et al. 2020). This proactive approach enables the industry to implement more effective prevention and mitigation strategies, moving from a reactive to a predictive model.

AI also enhances the accuracy and efficiency of food safety inspections by automating the detection of contaminants and noncompliance issues. For example, AI-powered image recognition systems can analyze images of food products to detect defects or contamination that human inspectors might miss (Liakos et al. 2018). Additionally, AI-driven predictive models can forecast potential food safety breaches by analyzing historical data on foodborne illnesses, environmental conditions, and supply chain operations. These models help to identify critical control points and optimize food safety interventions (Marucheck et al. 2011). Moreover, AI systems can streamline regulatory compliance by automating documentation and reporting processes, thus reducing the administrative burden on food safety authorities and enabling them to focus on critical inspection and enforcement activities (Jung et al. 2020).

AI's ability to synthesize large volumes of real-time data from diverse sources, including sensors, IoT devices, and blockchain systems, makes it uniquely suited to address the multifaceted challenges of food safety. By predicting potential risks, automating routine tasks, and providing insights for rapid decision-making, AI can transform food safety practices and provide a more resilient and efficient system.

1.3 | Evolution of AI Technologies in Food Safety

Artificial intelligence (AI) has seen rapid development since the mid-20th century, transforming various industries, including food safety. Early AI applications focused on automating routine tasks and data management. In the 1980s, expert systems began to be used in food safety to replicate decision-making processes of human experts (Nilsson 2010).

With advancements in machine learning and data analytics, AI applications in food safety have expanded significantly (Figure 1). Machine learning algorithms can now analyze vast amounts of data from various sources, including environmental sensors, genomic data, and supply chain information, to detect patterns and predict potential food safety issues (Zhu et al. 2020). AI technologies, such as computer vision and natural language processing, have also been employed for tasks such as food inspection and monitoring compliance with safety regulations.

Recent developments in deep learning have further enhanced the capabilities of AI in food safety. Deep learning models can

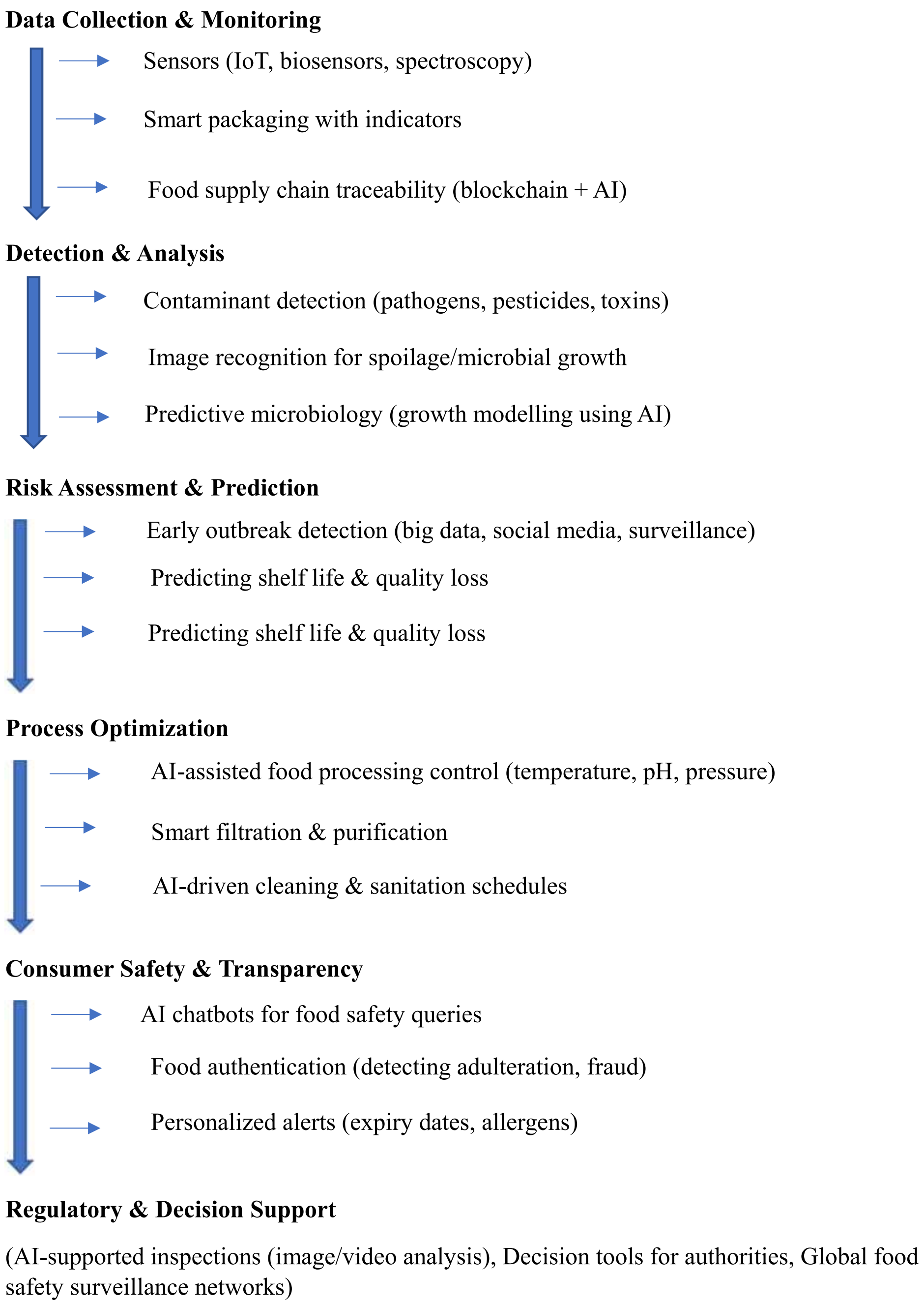

FIGURE 1 | AI techniques and their applications in food safety.

process complex and high-dimensional data, making them suitable for tasks such as detecting contaminants in food products through image analysis or predicting spoilage based on environmental conditions (Z. Zhang et al. 2021).

1.4 | Key Studies and Findings in AI-Enabled Food Safety

Numerous studies have highlighted the potential of AI in enhancing food safety through improved detection and surveillance technologies. For example, a study by Feng et al. (2019) demonstrated the use of machine learning algorithms to predict foodborne pathogen outbreaks by analyzing environmental and epidemiological data. Their model achieved high accuracy in predicting outbreaks, showcasing the potential of AI in proactive food safety management.

Another key study by Huang et al. (2020) explored the use of deep learning for the detection of food contaminants. The researchers developed a convolutional neural network (CNN) model that could accurately identify contaminants in food images, outperforming traditional image processing techniques. This study highlights the effectiveness of AI in improving the accuracy and efficiency of food inspection processes.

Additionally, AI has been applied in the development of smart sensors for real-time monitoring of food quality. A study by Wang et al. (2021) presented an AI-enabled sensor system that could detect spoilage indicators in perishable foods, such as changes in pH and gas composition. This system provided real-time alerts, enabling timely intervention to prevent foodborne illnesses.

Furthermore, AI has been used to enhance traceability in the food supply chain. Blockchain technology, combined with AI, has been employed to create transparent and immutable records of food production and distribution. This integration helps in quickly tracing the source of contamination during foodborne illness outbreaks, thereby reducing response times and improving consumer safety (Kamath 2018).

1.5 | AI Techniques in Food Safety

The food industry is increasingly leveraging artificial intelligence (AI) to enhance food safety, quality control, and regulatory compliance. Three primary AI techniques (Table 1) include machine learning (ML) and deep learning (DL) models, computer vision applications, and natural language processing (NLP) for food safety data analysis. These technologies are revolutionizing the way food safety is managed, ensuring better detection of contaminants, efficient data handling, and improved decision-making processes.

1.6 | Machine Learning (ML) and Deep Learning (DL) Models in Food Safety

Machine learning and deep learning are subsets of AI that use statistical methods to enable machines to improve their performance on a task with experience. In food safety, these models are used for predicting contamination risks, identifying foodborne pathogens, and monitoring supply chain integrity. ML models are employed to predict the likelihood of contamination in food products based on historical data and environmental conditions. For instance, logistic regression and decision trees can forecast the probability of microbial growth under certain conditions (Y. Zhang et al. 2023). DL models, such as convolutional neural networks (CNNs), have shown high accuracy in detecting pathogens in food samples through image analysis and spectral data interpretation. These models can be trained to identify specific bacterial strains or contaminants from microscopic images or sensor data (Kaviani et al. 2022). ML algorithms are used to track and predict potential hazards along the food supply chain, from production to consumption. This includes monitoring temperature variations, humidity levels, and transportation conditions to prevent spoilage and contamination (Y. Zhang et al. 2023).

1.7 | Computer Vision Applications in Food Safety

Computer vision, a field of AI that trains computers to interpret and make decisions based on visual data, is widely used in food safety for quality control and contamination detection. Automated inspection systems using computer vision can detect defects in food products, such as bruises on fruits, irregularities in shape and size, and packaging flaws. High-resolution cameras and image processing algorithms enable real-time monitoring of production lines, ensuring consistent quality standards (A. Chen et al. 2021; Q. Chen et al. 2021). Advanced imaging techniques, including hyperspectral imaging and infrared thermography, are employed to identify contaminants and foreign objects in food products. These methods provide a nondestructive means of inspecting food items, enhancing safety without compromising product integrity (Siche et al. 2016). Computer vision systems integrated with blockchain technology can track food items through the supply chain, providing detailed records of each stage of the process. This ensures transparency and accountability, crucial for maintaining food safety standards (Galvez et al. 2018).

TABLE 1 | AI techniques and their applications in food safety.

AI technique	Application in food safety	Examples
Machine learning (ML)	Prediction of contamination risks, outbreak forecasting, hazard modeling	Feng et al. (2019)—outbreak prediction; Y. Zhang et al. (2023)—hazard forecasting in supply chain
Deep learning (DL)	Image/spectral analysis for pathogen and contaminant detection	Huang et al. (2020)—CNN for contaminant detection; Sahu et al. (2020)—pesticide detection in vegetables
Computer vision	Automated inspection, defect detection, nondestructive quality control	A. Chen et al. 2021, Q. Chen et al. 2021—food inspection; G. Liu et al. (2025)—automated defect detection
NLP (text mining)	Analysis of reports, regulatory compliance, consumer sentiment	Van Erp et al. (2021)—nutrition/sustainability text mining; Nguyen et al. (2021)—sentiment analysis
AI + IoT sensors	Real-time monitoring of food storage/transport conditions	Wang et al. (2021)—AI-enabled smart sensors; Abdel-Basset et al. (2021)—IoT-AI applications
AI + blockchain	Traceability, contamination tracking, fraud prevention	Kamath (2018)—Walmart pilot

1.8 | Natural Language Processing (NLP) for Food Safety Data Analysis

NLP, a branch of AI that deals with the interaction between computers and human language, is increasingly utilized to analyze large volumes of textual data related to food safety. NLP tools can parse and analyze regulatory documents, inspection reports, and compliance records to ensure that food companies adhere to safety standards. These tools can automatically extract relevant information, identify noncompliance issues, and suggest corrective actions (Van Erp et al. 2021). By analyzing social media posts, customer reviews, and online forums, NLP algorithms can gauge public sentiment regarding food safety incidents. This helps companies respond promptly to potential safety issues and manage their reputation effectively (Nguyen et al. 2021). NLP techniques can sift through scientific literature, news articles, and incident reports to identify emerging risks in food safety. This proactive approach allows stakeholders to anticipate and mitigate potential hazards before they become widespread problems (Alvito et al. 2021).

The integration of AI techniques, such as ML, DL, computer vision, and NLP, in food safety is transforming the industry by providing more accurate, efficient, and proactive methods of ensuring food quality and safety. These technologies not only enhance the detection and prevention of contamination but also streamline compliance with regulatory standards and improve overall supply chain management.

2 | Detection Technologies

2.1 | AI-Based Contamination Detection

AI-driven technologies have transformed the way food contaminants are detected, significantly improving overall food safety. Recent research highlights their practical potential in real-world applications. For instance, Z. Zhang et al. (2024) utilized a hybrid deep learning model combined with hyperspectral imaging to identify pesticide residues in leafy vegetables with an accuracy exceeding 95%. Similarly, Z. Liu et al. (2023) designed an AI-powered portable biosensor capable of detecting *Salmonella* in poultry products in real time, cutting detection time to less than 30 min. More recently, A. Chen et al. (2021a) and Q. Chen et al. (2021b) demonstrated the integration of AI with blockchain to monitor and trace aflatoxin contamination in nuts, enabling both rapid detection and transparent supply chain tracking.

Bacterial contaminants: AI techniques, particularly machine learning algorithms, are employed to identify bacterial pathogens. Methods such as deep learning and computer vision are used to analyze images and sensor data to detect pathogens such as *Salmonella*, *E. coli*, and *Listeria* with high accuracy (Sharif et al. 2021).

Chemical contaminants: AI models are trained to detect chemical residues such as pesticides, heavy metals, and allergens. Techniques such as hyperspectral imaging and mass spectrometry, combined with AI, provide rapid and precise detection (Kang et al. 2021).

Physical contaminants: AI-driven image processing systems are used to detect physical contaminants such as glass, plastic, and metal fragments in food products. These systems can be integrated into production lines for continuous monitoring (Kang et al. 2021).

2.2 | Real-Time Monitoring Systems

Real-time monitoring systems are transforming food safety management by leveraging advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and blockchain. These systems offer continuous and immediate monitoring of food safety parameters, ensuring prompt detection and mitigation of potential hazards.

The integration of IoT, blockchain, and AI in food safety represents a significant advancement in the industry, providing robust solutions for monitoring, traceability, and risk management. IoT-based monitoring systems employ sensors to continuously track critical parameters such as temperature, humidity, and pathogen levels throughout the food supply chain, ensuring immediate detection of potential hazards. Blockchain technology enhances traceability by creating a secure, immutable ledger of transactions and data, which ensures transparency and accountability from farm to fork. Meanwhile, AI-driven data analytics and predictive models analyze the vast amounts of data collected by IoT devices, identifying patterns and anomalies that indicate potential safety issues before they become critical. Together, these technologies form a comprehensive, real-time monitoring framework that not only improves food safety but also boosts consumer confidence by ensuring the integrity and quality of food products (Eruaga 2024).

2.3 | Quality Control in Food Processing

2.3.1 | AI Enhances Quality Control in Food Processing Through Automation and Precision

Automated inspection: AI-powered vision systems are used for automated inspection of food products, ensuring they meet quality standards. These systems detect defects, inconsistencies, and contamination with greater accuracy and speed than manual inspections (Saha et al. 2025).

Predictive maintenance: AI models predict equipment failures and maintenance needs, reducing downtime and ensuring continuous, contamination-free production. This predictive approach enhances overall operational efficiency and food safety (Belaud et al. 2019).

3 | Challenges and Limitations

3.1 | Technical Challenges in Implementing AI in Food Safety

Implementing AI in food safety presents several technical challenges. One major issue is the integration of AI systems with existing food safety infrastructure. Many traditional food safety systems are not designed to handle the vast amounts of data required for AI analysis, necessitating significant upgrades or replacements. Additionally, there is the challenge of ensuring data quality and consistency, as AI models rely heavily on accurate and comprehensive datasets to function effectively (Z. Liu et al. 2023).

Another technical challenge is the interpretability of AI models. Food safety regulations often require clear explanations for decision-making processes, but many AI models, particularly deep learning ones, operate as "black boxes" with decision pathways that are not easily understood. This lack of transparency can hinder regulatory approval and acceptance by stakeholders (Marvin et al. 2022).

Furthermore, the development and deployment of AI in food safety require specialized knowledge and skills that are not always available within the food industry. Training personnel to effectively use and maintain AI systems is a significant hurdle, as is the ongoing need for technical support and updates to the AI models and systems (Z. Liu et al. 2023).

3.2 | Data Privacy and Security

Data privacy and security are critical concerns in the implementation of AI in food safety. The collection and analysis of large datasets can expose sensitive information about supply chains, production processes, and consumer behavior. Ensuring that these data are protected from unauthorized access and breaches is paramount.

AI systems often require extensive data sharing across various stakeholders, including producers, suppliers, and regulators. This increases the risk of data breaches and unauthorized access. Implementing robust cybersecurity measures and ensuring compliance with data protection regulations, such as GDPR in Europe, are essential steps to mitigate these risks (Kudashkina et al. 2022).

Moreover, there is the issue of data ownership and consent. Companies must navigate the legal and ethical complexities of collecting and using data, particularly when they involve personal information about consumers. Ensuring that data collection practices are transparent and that consumers have given informed consent is crucial for maintaining trust and compliance with legal standards (Z. Liu et al. 2023).

3.3 | Ethical Considerations and Regulatory Hurdles

The integration of AI into food safety processes represents a significant advancement in ensuring the safety and quality of food products. AI technologies, including machine learning, predictive analytics, and IoT, enable real-time monitoring, data analysis, and decision support, thereby enhancing the overall efficiency and effectiveness of food safety systems. However, the adoption of AI is not without its drawbacks. This review examines both the advantages and disadvantages of AI in food safety, highlighting the need for a comprehensive and ethical approach to its implementation.

3.4 | The Pros and Cons of AI in Food Safety

Artificial intelligence (AI) is rapidly transforming the food safety landscape by offering various benefits while also posing significant challenges. This article synthesizes findings from two comprehensive studies to present a balanced view of AI's role in food safety.

3.5 | Advantages of AI in Food Safety

Enhanced monitoring and detection: AI technologies, such as machine learning algorithms and computer vision, significantly improve the monitoring and detection of foodborne pathogens. These technologies can analyze vast amounts of data from multiple sources to predict and identify potential contamination issues earlier than traditional methods. This leads to quicker responses and reduced incidences of foodborne illnesses (Dara et al. 2022; Charlebois et al. 2022).

Predictive analytics: AI's ability to predict food safety risks through predictive analytics is transformative. By analyzing historical data and current trends, AI systems can forecast outbreaks of foodborne diseases and other safety hazards, allowing for proactive measures rather than reactive ones. This predictive capability is particularly valuable in managing supply chains and ensuring the timely recall of contaminated products (Charlebois et al. 2022).

Efficiency and accuracy: The integration of AI in food safety protocols increases efficiency and accuracy. Automated systems reduce human error, streamline inspection processes, and ensure consistent compliance with safety standards. This efficiency not only enhances safety but also reduces operational costs for food producers and regulators (Dara et al. 2022).

Supply chain transparency: AI enhances transparency in the food supply chain by providing detailed tracking and traceability of food products from farm to table. This transparency helps in pinpointing the source of contamination swiftly and accurately, thus mitigating the spread of foodborne diseases and bolstering consumer trust in food safety measures (Charlebois et al. 2022).

3.6 | Challenges and Ethical Considerations

Data privacy and security: One of the primary concerns with AI in food safety is data privacy and security. The extensive data collection required for AI systems includes sensitive information that could be vulnerable to breaches. Ensuring robust data protection measures is crucial to maintaining public trust and compliance with regulations such as the General Data Protection Regulation (GDPR) (Dara et al. 2022).

Bias and transparency: AI systems, particularly those using machine learning, can inherit biases present in their training data. This can lead to unequal outcomes and reduced trust in AI-driven decisions. Moreover, the "black box" nature of some AI algorithms, where the decision-making process is not transparent, poses significant challenges in accountability and auditability (Dara et al. 2022).

Ethical implications: The deployment of AI in food safety raises several ethical questions. These include the equitable distribution of AI benefits, the potential for job displacement due to automation, and the broader impact on society. Ethical frameworks need to be developed to guide the responsible use of AI, ensuring that its implementation does not lead to unintended negative consequences (Dara et al. 2022; Charlebois et al. 2022).

Regulatory challenges: The rapid pace of AI development often outstrips the ability of regulatory bodies to keep up. Establishing comprehensive regulations that address the unique challenges posed by AI in food safety is necessary. These regulations must balance innovation with safety and ethical considerations to foster a sustainable integration of AI in the food industry (Dara et al. 2022).

4 | Future Directions and Opportunities

4.1 | Emerging AI Technologies and Their Potential Applications

The landscape of artificial intelligence (AI) is continually evolving, presenting new opportunities for enhancing food safety. One emerging technology is the use of advanced neural networks, such as generative adversarial networks (GANs) and reinforcement learning (RL). GANs can generate synthetic data to augment training datasets, improving the accuracy of machine learning models for detecting food contaminants and predicting spoilage (Goodfellow et al. 2014). RL can optimize food processing and handling protocols by learning optimal strategies through trial and error, thus minimizing contamination risks (Li 2017).

Another promising technology is the integration of AI with Internet of Things (IoT) devices. IoT sensors can continuously monitor environmental conditions such as temperature and humidity in real time, whereas AI algorithms analyze these data to detect deviations that might indicate food safety risks. For example, an AI-IoT-integrated system can predict and alert about potential microbial growth in perishable food items, thereby preventing foodborne illnesses (Abdel-Basset et al. 2021).

AI-powered blockchain solutions are also gaining traction. Blockchain provides a transparent and immutable record of the food supply chain, and AI can enhance this by identifying anomalies and ensuring data integrity. This integration is crucial for traceability and rapid response during food safety incidents, as demonstrated by initiatives such as IBM Food Trust (Kamath 2018).

4.2 | Future Research Areas and Technological Advancements

Future research in AI-enabled food safety is likely to focus on several key areas. First, the development of more sophisticated predictive models for foodborne disease outbreaks is essential. These models could leverage diverse data sources, including climate data, social media trends, and global trade patterns, to predict outbreaks with greater accuracy (Zhu et al. 2020).

Advancements in AI for food safety will also involve improving the interpretability of machine learning models. Current models, particularly deep learning algorithms, are often seen as "black boxes" with limited transparency in decision-making processes. Enhancing model interpretability will increase trust and adoption in the food industry, ensuring that stakeholders can understand and validate AI-driven decisions (Rudin 2019).

Furthermore, research should explore the potential of quantum computing in food safety. Quantum algorithms can process vast amounts of data at unprecedented speeds, offering new possibilities for real-time food safety monitoring and rapid detection of contaminants (Biamonte et al. 2017).

4.3 | Policy and Industry Implications

The integration of AI in food safety has significant policy and industry implications. Policymakers need to establish clear regulatory frameworks that address the ethical and safety considerations of AI applications. This includes ensuring data privacy, preventing algorithmic biases, and setting standards for AI transparency and accountability (European Commission 2020).

For the food industry, adopting AI technologies requires a paradigm shift in operations and culture. Companies must invest in AI infrastructure and workforce training to harness the full potential of these technologies. Collaboration between industry players, technology providers, and regulatory bodies will be essential to develop best practices and standards for AI implementation in food safety (Sharma et al. 2020).

Moreover, public–private partnerships can drive innovation and facilitate the adoption of AI in food safety. Governments can provide funding and support for research initiatives, whereas industry stakeholders can offer practical insights and applications. Such collaborations will accelerate technological advancements and ensure that AI solutions are effectively integrated into the food safety ecosystem (World Economic Forum 2018).

5 | Conclusion

In summary, artificial intelligence (AI) is proving to be a transformative force in food safety, offering proactive detection, real-time monitoring, and improved traceability across the supply chain. Through the integration of machine learning

(ML), deep learning (DL), and computer vision, AI has the potential to minimize contamination risks and strengthen consumer protection. Although challenges persist—such as ensuring data quality, improving model interpretability, and achieving regulatory acceptance—the advantages of AI far outweigh these limitations.

AI-powered systems further enhance food safety surveillance by enabling continuous monitoring and predictive risk assessment. Advanced models can forecast potential hazards using historical data and emerging patterns, whereas data analytics can consolidate information from multiple sources to provide a holistic understanding of food safety risks. To fully realize this potential, however, critical issues must be addressed, including data accessibility, algorithm transparency, interdisciplinary collaboration, and the seamless integration of AI tools into existing food safety frameworks. Continuous validation of these technologies is equally essential to ensure their reliability and acceptance.

Future research should emphasize the development of interpretable and adaptable AI models, foster improved data-sharing practices, and explore ethical considerations in the use of AI for food safety. Combining AI with complementary technologies such as the Internet of Things (IoT) and blockchain will be key to building transparent, robust, and resilient food safety systems.

Overall, AI represents a powerful opportunity to advance modern food safety practices. As these technologies continue to evolve, their role in protecting public health and ensuring food quality will only expand, making them central to addressing the complex challenges of globalized food systems.

Author Contributions

Anju Kanicheril Ambikalekshmi: conceptualization, methodology, supervision, writing – review and editing, writing – original draft, visualization, resources. **Poojitha Pushparaj:** writing – review and editing, supervision, formal analysis, resources, methodology. **Elsa Cherian:** investigation, writing – review and editing, formal analysis, supervision. **Rosamma Rajan:** project administration, supervision, formal analysis. **Lakshmi Mohan:** resources, data curation, formal analysis.

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Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

No new data were generated or analyzed in this study. Data sharing is not applicable to this article.

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