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Food safety – the transition to artificial intelligence (AI) modus operandi

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ABSTRACT

Background: The integration of artificial intelligence (AI) represents a revolutionary advancement in the global food safety paradigm, particularly in the transition from historically reactive measures to predictive and preventive methodologies. In the past, laws concerning food safety were created mainly to address emergencies and prevent both adulteration and obvious contamination. However, recent AI developments have made it possible to handle pathogen detection, assess risks and monitor the supply chain more quickly, accurately and efficiently.
Scope and approach: This critical review analyses significant historical milestones, from ancient practices through medieval regulations to transformative discoveries of the industrial era, and ultimately towards contemporary technological integration.
Key findings and conclusions: AI can indeed be a valuable tool in enhancing the efficiency of food safety regulations, and it is a natural progression in the historical transition toward increased acceptance of AI by public sector institutions. Convolutional neural networks, hyperspectral imaging, and blockchain-based traceability demonstrate how AI has enhanced food safety management by detecting and preventing issues early on. This review highlights the significant challenges that remain, including data availability, the opacity of algorithms (the "black box" problem), substantial implementation costs, and specialized skill requirements. We outline the progression from reactive, historically driven food safety regulations to proactive AI-powered predictive and preventive strategies, examining the associated strengths, limitations, opportunities, and threats. Lastly, the review provides policymakers, those in the food sector, and academics with the knowledge and guidance they need to adopt and effectively apply AI technologies to enhance food safety.

1. Introduction

To understand how artificial intelligence (AI) can help us deliver food deemed safe for human consumption, we first need to recognise that AI is not only a tool that needs to be enforced, but is also a natural, historical transition based on established concepts. For example, the United Kingdom government has taken significant steps to promote the adoption of artificial intelligence (AI) in the public sector through some key initiatives. First, the Department for Science, Innovation and Technology (DSIT) has published an "Artificial Intelligence Playbook" to guide the safe, responsible, and effective use of AI in government organisations. Secondly, a new government Digital Service was established in January 2025 to unite efforts in grasping the opportunities of technology and AI under DSIT. These two institutions, the Cabinet Office and DSIT, will ultimately work together to develop a clear strategy and strong leadership for AI adoption in the public sector. The implementation of AI, especially in food safety management, can enhance our understanding of how public health can be better protected and how this can be more effectively translated into policy when considering a historical perspective.

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Hence, historical documents highlight that food is an essential item, provided by governments to keep people alive and ensure their survival at any cost, as declared by the British Government during the famine in Ireland in 1846 (Mokyr, 2025). This documented historical evidence indicates that food safety was, until the second half of the 19th century, primarily viewed as a food supply issue without any consideration of its implications on human health. However, without a genuine intention to provide food that is also safe for consumption, the government also issued instructions to Soup Kitchens to follow precise recipes, which include the thermal treatment of vegetables for soup preparations (Miller, 2012). The earliest documented food regulations date back to the Babylonian period (1700 B.C.) and were written in the Code of Hammurabi, with later references in Mesopotamian texts (Gallagher & McKevitt, 2019, pp. 239–271; Lásztity et al., 2004). The Book of Leviticus, written around 1400 B.C., through the Old Testament, made it forbidden to eat animals that died naturally while establishing proper slaughter techniques for hygiene purposes to limit carcass contamination (C. Griffith, 2006; Lásztity et al., 2004). Fermentation was used by ancient Egyptians, as well as the Mosaic law, to produce bread and beer, as these processes provided essential nutrition while protecting against contaminated water consumption (Gallagher & McKevitt, 2019, pp. 239–271). The laws enacted provisions to prevent the ingestion of unsafe meat (Lásztity et al., 2004). Records show that food contamination has frequently endangered lives – Alexander the Great might have succumbed to typhoid fever from *Salmonella*-infected food or water in 323 B.C., according to scholarly analysis (Lásztity et al., 2004). During their military campaigns and sea expeditions, Greeks and Romans sustained their food supplies through salting and smoking techniques to protect meat and fish. Observational experience led to the creation of preservation techniques, which later provided the foundation for microbiological discoveries.

Convolutional neural networks, currently used to understand the role of AI in food safety, can also serve as a model to describe food safety measures implemented over the past centuries worldwide. Across the ancient world (Fig. 1), food quality laws aimed to curb adulteration and spoilage. In ancient India, over 2000 years ago, regulations prohibited tampering with grains and fats (Lásztity et al., 2004). Chinese writings and Hindu texts also allude to concerns about food purity (Lásztity et al., 2004). The use of spices, such as pepper, cloves, and cinnamon, became widespread not only for their flavour but also for their preservative properties (Van der Veen & Morales, 2015).

These spices were believed to have antimicrobial properties, which helped prolong the shelf life of food and prevent spoilage. The origins of food safety can be traced back to ancient times, with early practices such as inspecting meat in Roman markets to remove rancid products. The Roman Empire developed an impressively organised state food control system; records indicate that the Romans enforced standards to protect consumers from fraudulent or substandard produce (Fortin, 2023; Organization, 2018). Under Roman law, rules governing the sale of food became as detailed as some modern legislation (Lásztity et al., 2004). For instance, the Roman writer Pliny the Elder, in the 1st century A.D., documented merchants using poisonous additives to improve wine's taste, warning that "many poisons are used to adapt wine to our tastes" and cautioning that such tampered wine is not healthy (Maestro et al., 2022). Notably, most ancient food laws were intended to prevent deceit, such as diluting wine or selling spoiled goods, but this had the side effect of protecting public health. The integration of all the measures presented in Fig. 1 can currently be achieved by AI and described through the principle of convolutional neural networks (CNNs). This review aims to provide a historical perspective and facilitate an understanding of the need for AI implementation in food safety. Moreover, we strive to outline the benefits of using AI in managing and delivering food safety, as well as to understand the challenges posed by the sector and its stakeholders. Through various consultations, we understood that the best way to explore the value of AI integration is to introduce AI as a natural transition with a historic perspective (Fig. 2).

2. Food safety approach during the medieval period and its likely impact on present-day AI implementation

A successful AI application in food safety regulatory institutions is based on our ability to collect sufficient and high-quality data for network implementation. These types of data have and will always include information from microbiological controls, transportation,

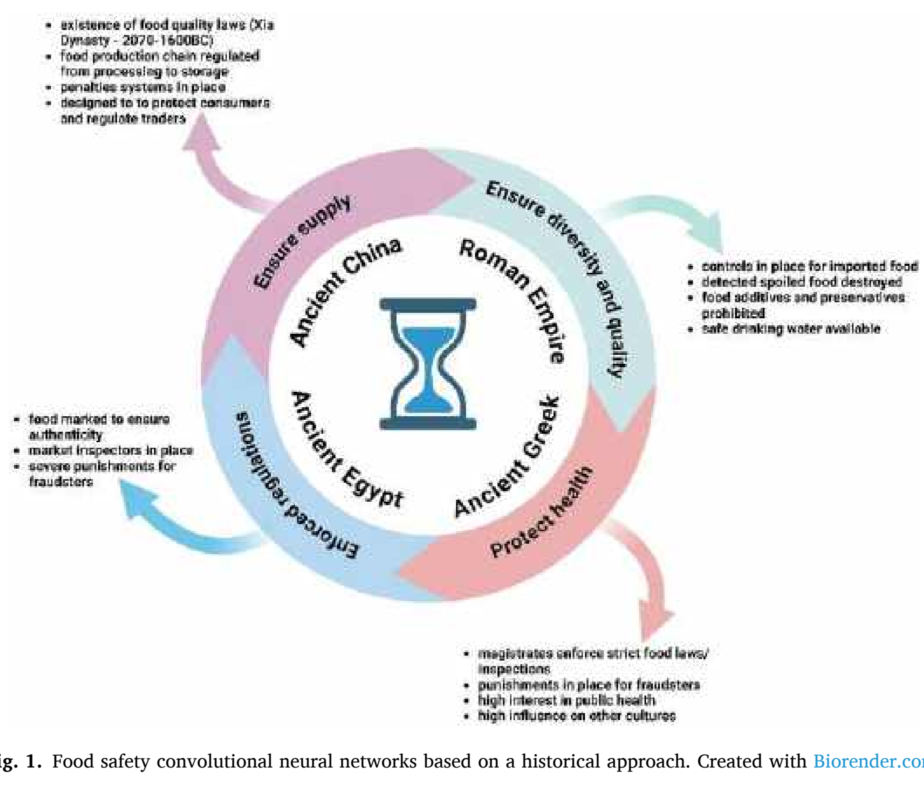

Fig. 1. Food safety convolutional neural networks based on a historical approach. Created with Biorender.com.

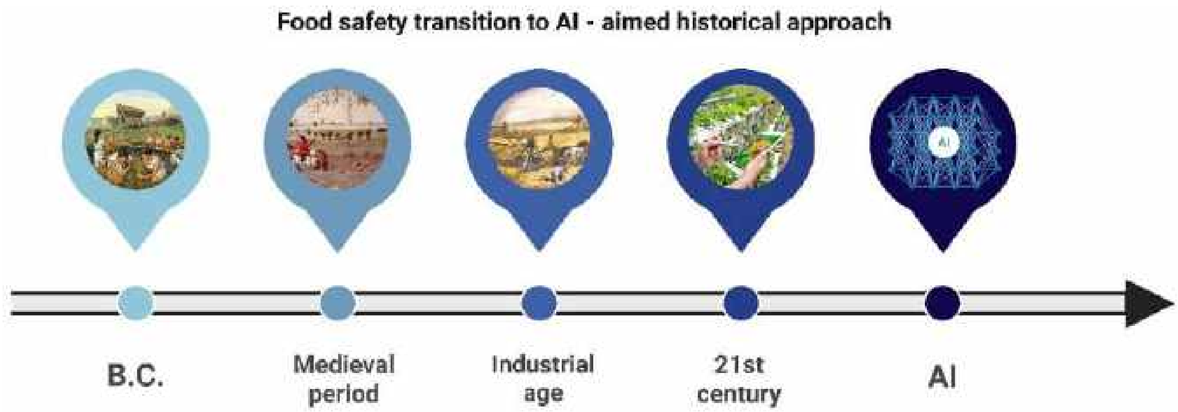

Fig. 2. The proposed aim of the review is to examine the historical transition to AI in food safety (B.C. – Before Christ; AI – Artificial Intelligence). Created with Biorender.com.

ingredient quality, chemical safety, and other relevant factors. Food safety regulations were first developed in the medieval period by European local authorities, who initiated basic controls to prevent food vendors from selling spoiled or adulterated products (Gallagher & McKevitt, 2019, pp. 239–271). During this period, various food regulations, along with market inspection systems, were also introduced to ensure food safety in public food markets.

The European guilds took responsibility for food safety by developing specific rules that butchers, fishmongers, and bakers needed to follow to ensure the safety of their products. The early forms of food regulations evolved into the modern food safety regulations that exist today (Knežević et al., 2021). City authorities, along with monarchs, created standardised versions of previously unwritten rules, one of the first ways of creating and transmitting information. The Assize of Bread, enacted by King John in 1202, established that bakers could not add peas or beans to their dough while setting mandatory weight standards for wheat-based bread (Mahajan & Gupta, 2010). The first English food regulation established under King John during the Middle Ages aimed to standardise bread measures and protect customers from exposure to poor-quality ingredients that threatened their safety. The first food law was introduced during the reign of Henry III in 1266, primarily concerning the weight and price of bread and beer. Much later, between 1730 and 1776, the Tea Acts were introduced, which prohibited the adulteration of tea. These acts also banned the use of sloe, liquorice, or previously used tea in new products. The records demonstrate that European laws from the medieval period enforced standards for beer and wine quality and banned spoiled meat or fish, along with market cleanliness rules (Organization, 2018). Medieval towns punished people who sold "corrupt" or days-old meat through fines or banished them to the town square, as the population recognised that spoiled meat would threaten their health, despite a lack of microbiological understanding. The 1516 German beer purity law, known as Reinheitsgebot, allowed only barley, hops, and water in brewing beer to protect beer quality from dangerous additives – an early food safety law acknowledged for preventing toxic herbs and spoiled grains in beer production (Dornbusch, 1998; Yates, 2023).

Apart from Europe, food regulations during this period incorporated both religious mandates and cultural restrictions. During the medieval caliphates, Islamic law and the Hisba (market inspector) system enforced fair food trading practices by inspecting markets to prevent merchants from adulterating food products by Qur'anic anti-fraud rules. Religious dietary laws of Judaism and Islam implemented both hygienic procedures during slaughter. They banned certain foods that decreased foodborne threats, such as pork, to prevent trichinosis and the spoilage of rotten meat(C. Griffith, 2006). Various modes of regulation were implemented across Middle Age territories to control food safety standards. By modern standards, these laws remained preliminary, primarily targeting obvious threats from rot, filth, and fraud. This shift represents the beginning of a process that eventually led to the formalisation of food safety regulations during the industrial era (C. Griffith, 2006). Indeed, the actual implementation of all this data during medieval times was by no means based on coordinated storage and usage of data; however, it likely improved consumer safety and reduced mortality rates. Highlights, however, that presently AI can harvest the abundance of food safety sectoral data and provide immense benefits to public food safety and health.

3. Industrial age impact on the transition to the present day AI

Nowadays, the implementation of AI can be successfully applied in food safety domains mainly because the data available is not only based on observational conclusions, as in medieval times, but is further enriched through technological and regulatory developments. So, what are the industrial age revolutionary discoveries and policy regulations that make today's AI implementation possible? The microbiological aspect of food safety became a palpable issue since the invention of the microscope by Antonie van Leeuwenhoek (1632–1723), which facilitated the visualization and confirmation of bacteria in rainwater. During the 19th century, as industrialisation and urbanisation swept through society, it immediately necessitated new food safety legislation. The combination of manufacturing at scale and cross-country food distribution created numerous pathways through which contamination and fraudulent practices could occur, ultimately leading to severe consequences, including deadly outcomes.

As a consequence, many governments, both in Europe and worldwide, established multiple food laws in the late 1800s to combat public health emergencies (Lásztity et al., 2004). The development of food hygiene regulatory frameworks primarily emerged due to an increase in human fatalities related to foodborne pathogens. For example, the widespread infection of Trichinellosis (trichina worm infection) through undercooked pork meat impacted 19th-century Germany to such an extent that the country documented more than 12,500 cases, which claimed 5 % of the patients recorded between 1861 and 1890 (Hinz, 1991). As a consequence, it was not until the 19th century, with the development of commercial heat processing by Nicolas Appert and Louis Pasteur, that food microbiology made significant progress(C. J. Griffith, 2006).

Adulteration scandals also prompted reform. Unlike today, when AI can access information widely available through various databases, profiteers in the industrial sector routinely employed deleterious methods during food modification, presenting safety risks to consumers. The Sale of Food and Drugs Act of 1875 strengthened previous food safety regulations from 1860, following public anger after twenty people died during the 1858 Bradford poisonings caused by arsenic-tainted candy in England (London, 2014). Public food inspectors working within these chemical contamination regulation frameworks played an additional role in reducing microbial food spoilage, as they penalised food products that appeared unwholesome under defined purity standards. Journalism, referred to as muckraking journalism, revealed deplorable work conditions in American food manufacturing industries during this period.

AI can currently process disease, food microbiological, or chemical composition data due to the revolutionary discoveries made during the Industrial Revolution, which made this linkage possible. The Theory of disease, proposed by Louis Pasteur and Robert Koch, established the scientific principle linking microbial agents to the development of sickness through their co-discovery. Later, William Mansfield Clark and Harold Lubs significantly contributed to the developed microbiology and food safety by creating the methyl red and Voges-Proskauer tests in 1915 (McDevitt, 2009). These tests brought advanced weapon systems to Enterobacteriaceae family bacterial identity investigations. The Clark and Lubs buffers are a set of solutions created by these scientists to stabilise pH levels in multiple biochemical and microbiological experiments across a broad pH spectrum(Bower & Bates, 1955). Food safety regulations in the United States experienced their initial federal enactment during the late 19th century, as citizens demanded protection from contaminated and adulterated food products. Upton Sinclair's novel "The Jungle" inspired the passage of the Pure Food and Drug Act of 1906, a foundational law that aimed to prevent the manufacturing and distribution of contaminated or mislabelled food and drugs (Drew & Clydesdale, 2015).

Public health protection took a significant step forward with the establishment of food safety legislation. These food safety regulations prohibited the purchase of spoiled food, required accurate labelling of products, and enforced sanitary standards during federal inspections of slaughterhouses. The Meat Inspection Act established its sanitary processing requirements to prevent the contamination of meat by microorganisms, such as *Salmonella* and *Mycobacterium tuberculosis*. However, the term "microbe" did not appear in the actual legislation. Different regions, including the European Union, the Middle East, Africa, China, Southeast Asia, and Latin America, integrate food safety regulations with the World Trade Organisation. The ageing diseases that spread through milk produced a breakthrough in sanitary practice, which was another significant advance. Raw milk transmission of tuberculosis combined with "milk sickness" resulted in thousands of deaths, targeting primarily children during the 1800s (Bryan, 1983). Cities became more responsive toward public health solutions in the first decade of the 1900s. The city of Chicago established the first mandatory raw milk pasteurisation rule in 1908 because typhoid and multiple other milk-borne diseases ravaged the population (Bryan, 1983). Milk and dairy products underwent pasteurisation processing first for spoilage prevention in the early 1900s, before the practice successfully expanded to other food products, thus decreasing the incidence of diseases such as brucellosis, scarlet fever, and tuberculosis disease incidence (Havelaar et al., 2010; Helvig, 1959). During the mid-20th century, pasteurised milk became responsible for safeguarding and saving countless lives. The development of milk pasteurisation led to its adoption as a standard food safety practice before governments established pasteurisation as a legal requirement, as microorganisms shaped foundational regulations. Cost-effective regulation techniques for foodborne pathogens emerged as a key component of food safety laws. The Industrial Revolution introduced massive food production methods that created new obstacles to food safety. Standardised food microorganism testing procedures emerged because of rising complications within food supply systems.

The early focus of food safety initiatives centred on detecting visible cases of food adulteration and spoilage problems. The 20th century began with a transformative change because bacteriology developed, allowing scientists to understand microbial contamination better alongside its effects on public health. Bacteria received recognition as agents of foodborne illness, marking one of the first significant developments in microbiological food safety. The term "food poisoning" emerged during this time to depict how microbes transform food into unsafe products (HARDY, 1999). Research investigators actively supported the creation of food bacteriological standards for microorganisms because the public's understanding of microbial food dangers was increasing, and scientists required official methods for quality control through random sample collections. Louis Pasteur's study of fermentation and pasteurisation techniques established the first scientific understanding of the microbial processes involved in food preservation. The pasteurisation process serves as an important example demonstrating how microbiological research has driven changes in food safety laws. The transition from traditional practices to a more scientific approach via the food heating process known as pasteurisation, which bears Louis Pasteur's name, involves specific temperature and time combinations to eliminate dangerous microorganisms while preserving taste and essential nutritional elements (Hasell & Salter, 2003; Todd, 2004). In food adulteration, AI is becoming a powerful tool, revolutionising food safety through its ability to identify small variations and anomalies that may indicate contamination or substitution.

The practice of naming pathogens throughout history dates back to 1855 when Theobald Smith first isolated *Salmonella*, which earned its name in honour of David Elmer Salmon (Dolman, 1982; Schultz, 2008). The second half of the 20th century introduced modern risk evaluation and management practices for *Listeria* and *Salmonella* spp., focusing on pathogen management. These strategies used qualitative and quantitative data, incorporating global and local research to develop risk models (Hasell & Salter, 2003; Stringer, 2005). Microbiological criteria for ready-to-eat foods determine their acceptable foodborne pathogen limits, an example of scientific research used to implement health protection standards (Gorris, 2005). The ISO laboratory methods for *Salmonella* isolation were essential in supporting standardised food safety practices worldwide (Ramsingh, 2014). Through this standardisation process, foodborne risk management improved globally by establishing consistent, effective food safety measures worldwide. These industrial age discoveries provide a tremendous advantage nowadays to the implementation of AI in infectious disease control, allowing us to more rapidly develop diagnostic tools and drugs (Cesaro et al., 2025).

We understand now the importance of AI in food safety risk management, and we will discuss this in more detail during the review; however, history has taught us that food safety regulation has adopted proactive risk-based approaches and global standards over the latter part of the 20th and 21st centuries. Advances in microbiology and epidemiology have led regulators to shift their focus from outbreak response to creating systematic controls that prevent future outbreaks. These efforts paved the way for the emergence of the Hazard Analysis and Critical Control Points (HACCP), a pivotal concept that was introduced during this era. During the 1960s, the HACCP system originated within the NASA US space program to guarantee astronaut food safety through its development. Since then, the system has evolved and now serves many domains in food industry operations (Murano et al., 2018).

AI implementation is also based on the current understanding of food safety investigation of all factors that connect pathogens in foods to environmental factors and human influences. In the absence of databases and properly structured information, many nations have utilised modernisation in their food legislation during the last several decades to enhance their preventive control measures. In 1938, the United States established the Food Safety Modernisation Act (FSMA) in 2011 as its most extensive reform of food regulations. The law emerged as a direct response to lethal *E. coli* outbreaks in spinach and fatal *Salmonella* incidents in peanut butter during the 2000s, alongside increasing global food imports (Strauss, 2011). The United States started to approach the One Health approach for implementing the FSMA as an example of a comprehensive food safety strategy (Garcia et al., 2020). During its 2011 introduction, the FSMA delivered major changes to U.S. food safety laws by establishing both preventive controls and science-based safety planning requirements. Policies must overcome hurdles in achieving their full potential; hence, scientists may continue to research the intricate dynamics (Garcia et al., 2020). After the 2008 melamine adulteration mistake, China fully redesigned its food safety legislation and, together with the UK and EU, continuously developed their regulations to address new outbreaks by taking specific actions such as enhancing poultry egg regulation after *Salmonella* outbreaks and strengthening produce safety after *E. coli* incidents (Evershed & Temple, 2016). Food safety regulatory systems in China suffered major public health consequences after melamine-contaminated dairy products in 2008, thus affecting about 300,000 infants (Hellberg et al., 2020). At the international level, the World Trade Organisation (WTO) and Codex Alimentarius standards have guided developed and developing countries in raising their food safety legislation to meet international standards.

Overall, food safety standards have evolved significantly due to scientific microbiological advancements. Throughout history, scientists have continued to provide both regulatory frameworks with updated bacteriological findings and present-day preventive procedures through modern risk assessments. The introduction of ancient meat spoilage restrictions has evolved into contemporary pathogen laboratory testing and genomic-based tracking protocols, demonstrating a rising scientific focus on preventative measures. Throughout history, major regulatory advancements have emerged because disease outbreaks and scandals (driven by disease) exposed weaknesses in contemporary regulatory systems. Today's regulatory frameworks ensure a high level of safety protection, to the extent that pathologies such as trichinosis, milk-borne typhoid, and botulism-causing canned goods are nearly non-existent (Tauxe, 2001).

These developments have not only enhanced the safety of food products but also underscored the importance of a science-based approach in protecting public health. The ongoing interplay between microbiology and food safety legislation continues to drive progress in this critical field, ensuring that food systems remain safe and resilient in the face of emerging challenges. The long arc of food microbiological safety regulation shows through the long-term process that enforced standards and proactive policies successfully save lives, validating the statement "the law was written in reaction to illness, so that fewer must fall ill in the future". As a result, there is huge potential for AI to help us transition from historical concepts and approaches related to food safety implementation to more efficient and AI-based technologies.

4. Neural networks and SWOT analysis

Building upon the extensive historical progression of microbiological food safety from ancient civilisations through the medieval period and the transformative influences of the industrial age, the modern technological innovations, particularly the integration of Artificial Intelligence (AI), now promise revolutionary enhancements in ensuring food safety and security worldwide (Zatsu et al., 2024). Its key areas of impact will include optimisation of production methods, improving supply chain management, advancing quality assurance, and strengthening consumer safety. These can be achieved by utilising AI-powered systems, which automate tasks, enhance efficiency, and ensure consistent product quality. Regarding food safety, AI algorithms will be able to detect contaminants and analyse food composition (e.g. potential hazards), leading to safer food products. Moreover, AI can help optimise the supply chain by predicting demand, managing inventory, and ultimately leading to more efficient and cost-effective distribution. In recent years, AI has emerged as a transformative tool in the context of food safety. AI and big data technologies—often referred to as the "fourth industrial revolution"—are already making a significant impact in the food industry by improving production efficiency, quality, and reducing waste (Ding et al., 2023; Liu et al., 2023). However, the "fourth industrial revolution" extends beyond food safety and technologies (e.g., biotechnology), assessing their impact on society, economies, and the way we live, while also providing a historical perspective. Beyond production, AI-driven approaches are being integrated across the entire farm-to-fork continuum to enhance food safety and security (De Cock et al., 2025a). Indeed, modern food safety systems are turning to data-intensive, AI-powered methods to protect consumers from food-borne illness and companies from costly recalls and reputational damage (Liu et al., 2023).

The enhanced early detection and additional predictive capabilities will allow AI-driven analytical techniques to significantly improve detection accuracy, speed, and reliability in identifying pathogens, toxins, chemical contaminants and food adulteration (Taiwo et al., 2024; Yu et al., 2025; Zatsu et al., 2024). However, these studies have shown that applying predictive models in food microbiology can have limitations, especially when considering complex microbial interactions. Their efficiency has been significantly improved following the integration of new technologies, including whole-genome sequencing (WGS), metagenomics, artificial intelligence, machine learning, robotics, the Internet of Things, and time-temperature indicators. Their integration into the general framework will enable the involvement of these technologies through knowledge and computational approaches, allowing for proactive rather than reactive interventions to enhance overall food safety (Dakhia et al., 2025). For example, CNNs (Fig. 3) can predict the freshness of fruits and vegetables with high accuracy (over 99 %) by analysing data gathered from colour uniformity, image resizing, augmentation, and labelling through an extremely fast computational system of 8 ms until the final classification result (Amin et al., 2023).

To support the detailed review of AI applications in food safety and security, a strategic SWOT analysis (Fig. 4) has been carried out to systematically study the strengths, weaknesses, opportunities and threats connected to AI integration, allowing for a planned assessment of its feasibility and lasting effects.

Digging further into the highlights presented in Fig. 4 becomes clear that the machine learning algorithms can provide standardised evaluations (Bhat et al., 2025) and that automation of inspection and sorting processes using AI reduces human labour dependency (Femimol & Joseph, 2025). These analytical capabilities, including also the convolutional neural networks (CNNs significantly improved detection accuracy, speed, and reliability in identifying pathogens, toxins, chemical contaminants and food adulteration (Taiwo et al., 2024; Yu et al., 2025; Zatsu et al., 2024). These advanced analytical methodologies will

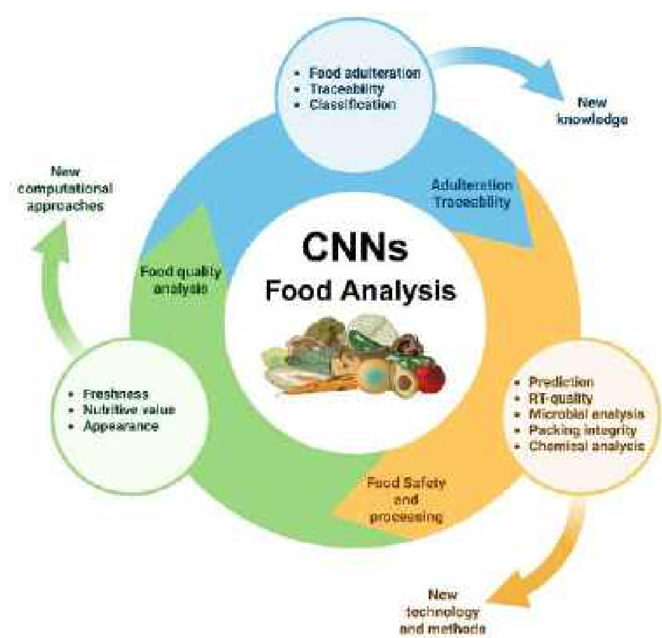

Fig. 3. Modern era framework of convolutional neural networks (CNN) for food safety and quality analysis. Created with Biorender.com.

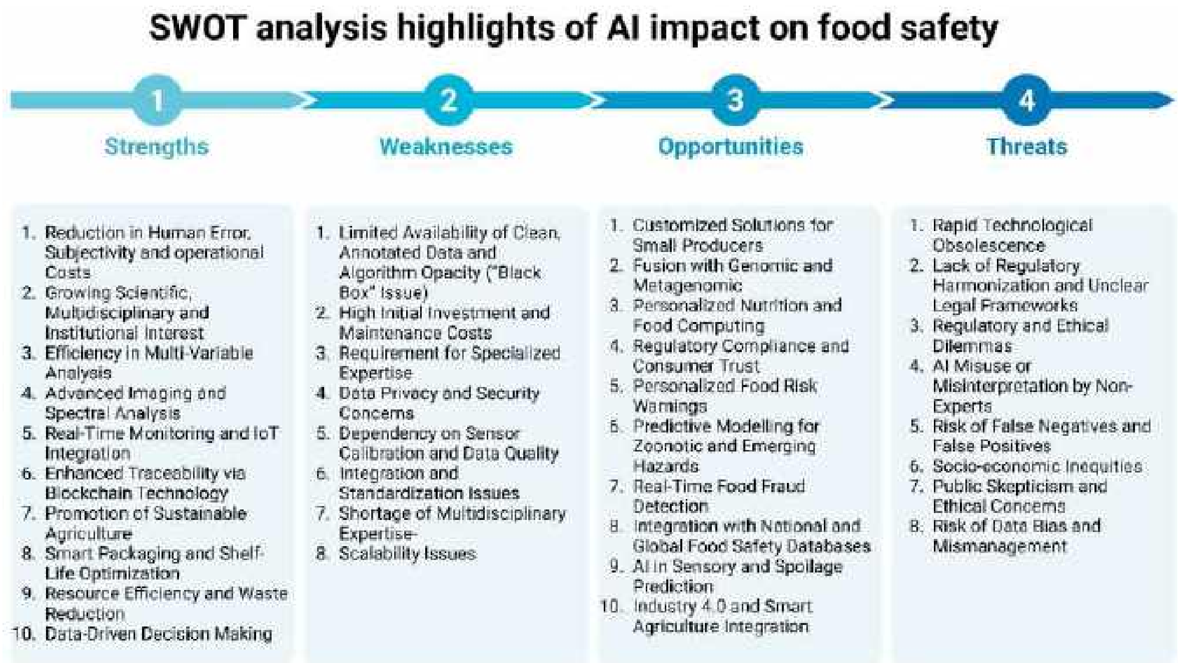

Fig. 4. SWOT analysis highlights and their impact on food safety main management characteristics. Created with Biorender.com.

enable proactive rather than reactive interventions, thereby overall food safety (Dakhia et al., 2025). We chose to describe in more detailed analysis of each strength, weaknesses, opportunities and threats categories below:

4.1. Strengths

1. **Growing Scientific, Multidisciplinary and Institutional Interest-** There has been an exponential rise in publications and collaborations on AI in food safety, especially from China, the US, and Europe, indicating solid momentum in research and policy engagement (Liberty et al., 2025).
2. **Efficiency in Multi-Variable Analysis** -AI algorithms, particularly deep learning and ensemble models, can process high-dimensional data with complex interdependencies, improving predictive power (Dhal & Kar, 2025).
3. **Advanced Imaging and Spectral Analysis** = AI leverages hyperspectral imaging, infrared spectroscopy, and Raman data to enhance food quality and safety monitoring in a non-destructive, high-throughput manner (Naseem & Rizwan, 2025).
4. **Real-Time Monitoring and IoT Integration**: The integration of IoT-enabled sensors into smart packaging offers real-time monitoring capabilities for early detection of microbial contamination, spoilage biomarkers, and environmental variations (temperature, humidity). This enables rapid decision-making, food inspection, and corrective actions during food storage and transportation, substantially reducing response times and enhancing consumer safety, allowing for swift, preventive action (Sobhan et al., 2025).
5. **Enhanced Traceability via Blockchain Technology**: Blockchain ensures secure, decentralised, and immutable data sharing, strengthening outbreak response and data storage, critical for combating food fraud and ensuring transparency throughout complex global supply chains (De Cock et al., 2025b). This technology, complemented by AI algorithms, provides robust, verifiable traceability, improving consumer trust and regulatory compliance (Issa et al., 2024; Liu et al., 2025). To better illustrate how it works, we provide an example outside the food safety domain, specifically the textile industry. It involves a network architecture in which partners agree to a smart contract and transaction validation rules at the operational level (e.g. organic cotton supply chain). Through this network, based on trust between the partners, a distributed ledger will store and authenticate the supply chain transactions, providing a unique opportunity to all partners to trace back their supply network and create a transparent and sustainable supply chain (Agrawal et al., 2021). Blockchain technology allows information, not only to be stored, but also to be transmitted securely and transparently.
6. **Promotion of Sustainable Agriculture**: AI technologies enhance agricultural productivity through precision agriculture practices, including optimised irrigation, fertilisation, crop surveillance, disease identification, and yield forecasting (Khan et al., 2025). This significantly boosts resource efficiency and food security, particularly in developing regions, contributing to both economic growth and environmental sustainability (Ahmad et al., 2024; "US Food and Drug Administration," 2021).
7. **Smart Packaging and Shelf-Life Optimisation -** AI integrates with smart packaging specifically for extremely perishable products, such as fruits, vegetables, meat, poultry, milk, and dairy products, compared to beverages and baked goods. Using such technologies in combination with AI will increase awareness among consumers due to the increased positive results for the consumer (Thirupathi Vasuki et al., 2023).
8. **Resource Efficiency and Waste Reduction** AI technologies like Winnow and smart scales identify food waste patterns and optimise sanitation and energy use, contributing to sustainability and food system efficiency (Zatsu et al., 2024).
9. **Data-Driven Decision Making** - Predictive analytics enable proactive safety interventions based on trends in contamination and spoilage, thereby reducing recalls and improving traceability.

4.2. Weaknesses

- **Limited Availability of Clean, Annotated Data and Algorithm Opacity ("Black Box" Issue)** -The efficiency of AI models depends heavily on the quality and quantity of data, and insufficient labelled datasets can impair performance, especially in microbiological hazard identification (Shraddha Karanth, Benefo, et al., 2023). Complex

AI models often lack explainability, making it difficult for food safety authorities to trust or validate AI-based conclusions.

- **High Initial Investment and Maintenance Costs**: Implementing sophisticated AI and IoT infrastructures requires substantial financial investments, potentially limiting accessibility, particularly for small to medium-sized enterprises (SMEs) and stakeholders in resource-constrained regions or in developing countries (Zatsu et al., 2024). In some instances, farmers still prefer solutions such as direct contact with the market agent, even though the digitalised option is still available. Some examples, such as *Hello Tractor in Nigeria*, which still uses live booking agents and phone calls to deliver services to its clients, or *Lersha* in Ethiopia, which requires local agents to help users access the digital services, indicate low levels of digital literacy among users in such areas (Abate et al., 2023).
- **Requirement for Specialized Expertise**: Effective utilization of AI and related technologies necessitates specialized technical knowledge, posing barriers for widespread adoption, especially in developing countries posing a challenge for resource-constrained stakeholders with limited access to skilled personnel (Pegoraro & Curzel, 2023).
- **Data Privacy and Security Concerns**: Extensive use of IoT devices and blockchain raises significant concerns regarding data privacy and cybersecurity risks, potentially hindering consumer acceptance and trust.
- **Dependency on Sensor Calibration and Data Quality.** Many AI models rely on sensor outputs that require consistent calibration and environmental control to ensure reliability and reproducibility (Khan et al., 2025).
- **Integration and Standardisation Issues**: Interoperability challenges between diverse AI, IoT, blockchain, and legacy systems complicate seamless integration, creating potential inefficiencies and increased operational complexities.
- **Shortage of Multidisciplinary Expertise**: Implementation requires coordination between food technologists, data scientists, engineers, and regulators—a rare skillset combination in most settings (Ikram et al., 2024).
- **Scalability Issues**: Transitioning from pilot to full-scale AI deployment in food facilities can face operational and performance bottlenecks due to environmental variability and cost constraints (Zatsu et al., 2024).

4.3. Opportunities

- **Customised Solutions for Small Producers**: Affordable mobile-based AI platforms or cloud services can democratize access to safety monitoring technologies for small-scale farmers and food processors (Khan et al., 2025).
- **Next-Generation Surveillance Systems**: Integration with national surveillance enhances early outbreak detection and pathogen source attribution (Yi et al., 2024).
- **Fusion with Genomic and Metagenomic Tools:** AI can analyse next-generation sequencing (NGS) data for pathogen characterisation, antimicrobial resistance tracking, and microbiome shifts relevant to food safety (Yi et al., 2024).
- **Expansion into Developing Markets**: AI-driven agriculture and food safety solutions offer vast opportunities for improving food security, nutrition, and economic conditions in developing regions (Liu et al., 2023; Zatsu et al., 2024). These technologies can bridge infrastructural gaps and promote sustainable agricultural practices, addressing significant global food security challenges (Onyeaka et al., 2024).
- **Personalised Nutrition and Food Computing**: Integrating AI with food computing applications enables personalised dietary recommendations, optimising individual nutritional outcomes (Zatsu et al., 2024). Technologies such as natural language processing (NLP) and AI-driven computer vision offer innovative approaches to consumer engagement and dietary planning (Dakhia et al., 2025).
- **Regulatory Compliance and Consumer Trust**: AI technologies facilitate automated and efficient compliance management across global food safety regulatory frameworks. This not only ensures adherence to stringent international standards but also significantly boosts consumer confidence through transparent traceability mechanisms (Issa et al., 2024).
- **Personalised Food Risk Warnings**-By integrating health and dietary data, AI can provide allergen alerts, contamination risk forecasts, and nutrition-sensitive safety advice tailored to individuals (Bhat et al., 2025).
- **Predictive Modelling for Zoonotic and Emerging Hazards.** With climate change and globalisation, AI offers tools to anticipate novel pathogen outbreaks and monitor cross-species transmission vectors (Ikram et al., 2024).
- **Real-Time Food Fraud Detection:** AI can analyse supply chain data to detect anomalies indicating potential fraud, contributing to more transparent and secure food systems (Shraddha Karanth, Benefo, et al., 2023).
- **Integration with National and Global Food Safety Databases**: Harmonising AI with Academic-industry initiatives like Codex, FAO/WHO INFOSAN, EFSA and FDA's GenomeTrakr opens new avenues for cross-border hazard prediction and information exchange (Ikram et al., 2024).
- **AI in Sensory and Spoilage Prediction**: Enhanced consumer satisfaction and sensory analysis through AI-powered tools that align food quality with expectations (Zatsu et al., 2024).
- **Industry 4.0 and Smart Agriculture Integration**: Adoption of digital twins, robotics, drones, and advanced analytics within Industry 4.0 frameworks presents substantial opportunities for optimising and revolutionising food production processes, resource utilization, supply chain management, and sustainability (Ding et al., 2023; Liu et al., 2025; Zatsu et al., 2024).

4.4. Threats

- **Rapid Technological Obsolescence**: Continuous advancements in AI and related technologies pose significant threats to rapid obsolescence, necessitating ongoing investments in technological updates and infrastructure, which may strain financial resources and compromise operational sustainability.
- **Lack of Regulatory Harmonisation and Unclear Legal Frameworks:** The rapid evolution of AI outpaces legislative development, along with the absence of standardised AI protocols across countries, complicates compliance, especially for cross-border food safety regulations (Shraddha Karanth, Benefo, et al., 2023).
- **Regulatory and Ethical Dilemmas**: The accelerated pace of AI and IoT integration may outstrip regulatory frameworks, creating legal uncertainties and ethical dilemmas, particularly concerning data privacy, consumer rights, and AI transparency (Zatsu et al., 2024).
- **AI Misuse or Misinterpretation by Non-Experts** = Without sufficient training, operators may misuse models or misread output, resulting in inappropriate decisions or public misinformation (Ikram et al., 2024).
- **Risk of False Negatives and False Positives:** Without proper validation, AI decisions can fail to detect contamination or falsely trigger recalls, leading to safety lapses or reputational damage (Pandey & Mishra, 2024).
- **Socio-economic Inequities**: Unequal access to advanced AI technologies could exacerbate existing socio-economic disparities, with advanced economies benefiting disproportionately compared to resource-limited countries, thereby widening the global digital divide (Capraro et al., 2024).
- **Public Scepticism and Ethical Concerns**-Resistance to AI-based food safety systems may arise due to perceived job loss, lack of

transparency, or fear of surveillance technologies (Shraddha Karanth, Benefo, et al., 2023).
- **Risk of Data Bias and Mismanagement**: The reliance on vast and diverse datasets raises concerns about data quality, bias, and potential manipulations, which could negatively impact AI-driven decisions and outcomes in food safety and security.

5. AI in pathogen detection and microbial risk assessment

Identification and critical analysis of microbial risk assessments from a historical perspective is not possible as they were first introduced only in the last 40 years as a valuable tool in the treatment of water in microbiological risk management in the 1990s (Rose et al., 1991) More specifically, related to food, the first known quantitative microbial risk assessment (QMRA) was the USDA Food Safety and Inspection Service's (FSIS) 1998 assessment of *Salmonella Enteritidis* in shell eggs and egg products (Schroeder et al., 2006). The primary objective of QMRA is to assess the risk to human health from exposure to pathogens. Using AI in QMRA is indeed seen as a natural transition given the significant amount of data involved, including from identified hazards, assessing exposure, and characterising the overall risk.

AI's versatility is evident through the breadth of its applications in food safety. It has been effectively applied to outbreak detection, spoilage and allergen monitoring, food fraud detection, supply chain monitoring, traceability systems, quality control, shelf-life prediction, and risk assessment (Dimitrakopoulou & Garre, 2025; Yu et al., 2025). These diverse applications typically integrate three key elements of AI systems, including sensing (data collection), reasoning (analytics and modelling), and actuating (decision support or automated action) to form more intelligent surveillance and control cycles. AI has already shown potential: machine learning (ML) helps recognise hidden signs of pollution that standard approaches might miss, and computer vision can quickly and consistently check food products better than humans. At the same time, experts note that AI's success depends on having strong and accurate data, as well as continued human involvement. For instance, a recent review emphasises that while AI can indeed transform food safety management, its insights must be built on *"timely access to robust, comprehensive, and unbiased data"* and accompanied by a human-in-the-loop approach for critical decisions (Dimitrakopoulou & Garre, 2025). Considering all these factors, the following sections examine how AI is being applied globally in various areas of food safety and security, ranging from detecting microbiological hazards to ensuring supply chain integrity, and highlight recent developments, current challenges, and future trends. Every section relies on recent scientific and policy reports to give a thorough and reliable overview that can be read by researchers, industry members and policymakers.

Traditional pathogen detection methods (e.g. culture plating, immunoassays, PCR) are reliable but often time-consuming, labour-intensive, and require specialized lab infrastructure (Onyeaka et al., 2024). AI offers a way to accelerate and enhance these processes. For example, ML algorithms can analyse complex biological data—from sensor outputs to genomic sequences—much faster than manual methods, enabling near real-time pathogen identification. For example, ML models paired with novel biosensors have demonstrated the ability to significantly reduce detection times for foodborne pathogens while maintaining high accuracy (Onyeaka et al., 2024; Sobhan et al., 2025). By leveraging techniques such as AI-enhanced spectroscopy and deep learning image analysis, the identification of bacteria like *E. coli*, *Listeria*, *Pseudomonas,* or *Salmonella* can be achieved in hours instead of days (Garcia-Vozmediano et al., 2024; Onyeaka et al., 2024; Taiwo et al., 2024). One study combining Raman spectroscopy with the *k*-nearest neighbours (*k*NN) ML algorithm, achieved over 98 % accuracy in distinguishing pathogen serotypes, underscoring the power of AI for rapid microbial diagnostics (Ciloglu et al., 2020), reducing contamination and allowing earlier interventions to prevent illness.

AI is also transforming microbial risk assessment through the use of predictive analytics. For example, advanced models can sift through historical outbreak data, microbiological test results, and even environmental factors to predict the likelihood of contamination events before they occur (Yu et al., 2025). In practice, this means AI can help prioritise which hazards or products merit the most attention (Shraddha Karanth, Benefo, et al., 2023). Recent research has demonstrated the efficiency of ML in not only detecting pathogens but also in disease prediction and contamination source identification by analysing patterns from past incidents (Onyeaka et al., 2024). For instance, ML algorithms have been trained on patterns of contamination (from climate data, supply chain records, etc.) to predict conditions under which pathogens like *Salmonella* or *Listeria* are likely to proliferate (Garcia-Vozmediano et al., 2024; Shraddha Karanth, Benefo, et al., 2023), which together can act as an "early warning" for heightened risk, allowing food producers and regulators to implement controls proactively. The benefits of these AI-driven approaches include stronger epidemic prevention, improved consumer safety, and enhanced operational efficiency in managing foodborne threats (Ciloglu et al., 2020).

6. AI in food traceability and supply chain monitoring

Similarly to the introduction of QMRA, food traceability monitoring programs were also initiated less than 40 years ago; however, actual implementation was only introduced in the early 2000s, particularly after regulations such as EU Regulation (EC) 178/2002 and the FDA's Bioterrorism Act of 2002. These regulations fuelled the development and adoption of more comprehensive traceability systems. Current AI techniques can be applied to track and monitor food products from farm to table, providing end-to-end visibility into the supply chain. By automatically aggregating data from various points (production, processing, transport, storage, retail), AI systems help create a live "digital twin" of the food supply chain. Because the risks are more visible, organisations can address them more quickly. If an unsafe ingredient or contaminant is found at one location, AI-based traceability systems can quickly identify other products or sites that may be affected, allowing for the rapid recall of those items. Sensors and IoT (Internet of Things) devices play a key role in this ecosystem. Temperature and humidity sensors monitor cold chain conditions, and RFID (Radio-Frequency Identification) tags and barcodes track the movement of goods. All these data streams feed into AI analytics dashboards (Cheng, 2024). An AI-powered supply chain platform might automatically flag if a refrigerated truck's temperature rose above a safety threshold or if a batch of raw material fails to arrive at its destination on time, prompting immediate corrective actions.

One significant development is the use of blockchain and AI together to ensure data accuracy and maintain traceability. Blockchain securely stores all transactions, and when used in conjunction with AI, it provides both transparent records and valuable insights. Industry leaders have piloted such systems; for instance, Walmart's Food Traceability Initiative utilises a blockchain-based platform to document every step of selected products through its supply chain. After collecting the data, AI algorithms analyse it to identify if a supplier has a history of quality issues or if a route is associated with damaged goods. The use of these technologies enables regulators and companies to trace products securely and transparently on a much larger scale, which helps them verify the authenticity and safety of products moving worldwide. When different data streams are combined, AI helps monitor the supply chain for risks and tracks the movement of its products. Machine learning models can learn the normal operating parameters of a supply chain and alert managers to out-of-bound conditions that may indicate a food safety risk (for example, detecting signs of deliberate adulteration or fraud in the supply chain data). In practice, companies are deploying AI-driven track-and-trace solutions that consolidate data from proprietary systems and third-party logistics, providing a consolidated view that enables executives to make data-driven decisions (Cheng, 2024). In practice, AI-based monitoring has been shown to identify problems earlier. For example, in one case, adding AI analytics to RFID tracking enabled a distributor to identify a storage unit issue that could have resulted in food spoilage, thereby avoiding a potential safety incident (Dhal & Kar, 2025; Sonwani et al., 2022).

7. AI in predictive modelling for contamination events and outbreaks

Modelling has been used for more than a century to investigate the evolution and assess the impact of public health interventions in controlling emerging infectious diseases (Siettos & Russo, 2013), One approach is to develop AI-based Early Warning Systems (EWS) that continuously analyse diverse data sources to flag potential food safety threats. They gather both structured data, such as laboratory findings, climate records, and trade statistics, as well as unstructured data, including media articles and consumer feedback. With ML, EWS can find patterns in the data that occurred before contamination events or outbreaks happened. If there are more reports of a particular problem in health inspections or if imports of a specific product are rejected more often, that often indicates a broader issue. An AI early warning platform might leverage IoT sensor feeds (for real-time conditions in farms or factories), predictive analytics models (trained to forecast likely contamination incidents based on past patterns), and even blockchain traceability data (to trace the origin and flag any anomalies). Together, these components create a multilayered safety net, including IoT sensors that generate real-time data, ML models that predict issues based on that data, and traceability tools that localise the problem's source for rapid action.

A vivid illustration of predictive modelling comes from innovative projects analysing non-traditional data, such as online consumer reviews and social media, to detect outbreaks. In 2025, the UK Health Security Agency (UKHSA) reported on experiments using AI to scan online restaurant reviews for signs of foodborne illness(Laurence et al., 2025). By using natural language processing (NLP) models (including large language models), this system can "trawl" through thousands of reviews to spot mentions of symptoms like vomiting or diarrhoea alongside references to certain foods or establishments (Laurence et al., 2025). Early tests revealed that AI could identify groups of reviews that pinpointed the exact cause of illness, informing officials about outbreaks they might not have otherwise noticed. UKHSA scientists envision that *"gathering information in this way could one day become routine, providing more information on rates of GI illness not captured by current systems, as well as vital clues around possible sources and causes in outbreaks"* (Laurence et al., 2025). This novel surveillance approach could significantly enhance outbreak detection by capturing mild or moderate cases (where individuals do not seek medical attention) and by accelerating hypothesis generation about the source of the outbreak.

8. AI in the detection of food fraud and adulteration

As indicated in Fig. 1, food fraud and adulteration have been a significant concern throughout ancient times, often resulting in severe punishments for those involved once detected by the authorities. Food fraud and adulteration, involving the addition or removal of ingredients or the use of misleading labels for profit, pose significant risks to both the health of individuals and their trust in food. Traditional methods for detecting food fraud often involve using chemical tests or complex analyses, which can be both costly and time-consuming. AI-based approaches (i.e., deep learning, support vector machines (SVMs), or k-nearest neighbours (k-NN) trained on image datasets, spectroscopy coupled with AI, and others) are now providing powerful new tools for authenticity control, capable of detecting *subtle signs of adulteration* that might elude standard tests (Deng et al., 2024; Goyal et al., 2025; Magdas et al., 2025). With the help of ML and deep learning, scientists are developing fast, reliable, and inexpensive methods to keep foods such as olive oil, honey, meat, and spices safe.

Although significant achievements have been made, the field recognises that further efforts are needed to utilise AI for enhanced fraud detection. A recent review concluded that while several relevant experimental datasets demonstrated AI's promise, additional research is required for "affirmative" conclusions on specific methods (Vinothkanna et al., 2024). Building open reference databases of authentic vs. fraudulent samples could greatly aid ML model training (a call echoed by many researchers). Furthermore, the explainability of AI decisions remains crucial: food companies and regulators are more likely to trust AI findings if the model can indicate which specific features (e.g., a particular spectral peak or image texture) led it to label a sample as adulterated. Efforts in *explainable AI (XAI)* for food fraud are underway, using techniques like (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) to highlight the indicators of fraud in a sample (Buyuktepe et al., 2025). In summary, AI has rapidly become a *"valuable tool for quality and authenticity assessment"* (Magdas et al., 2025). It strengthens the effort to prevent food fraud by enabling continuous and high-speed testing of food, thereby safeguarding both customers and honest producers. As they improve and are used more frequently, they will be essential for maintaining global food security in terms of ensuring genuine and trustworthy food.

9. AI-powered decision support for regulatory enforcement and inspections

A key example in this field is the U.S. FDA's Artificial Intelligence Import Screening pilot, which was designed specifically for seafood. More than 90 % of U.S. seafood is imported, and past incidents have revealed significant safety concerns in some imports. In 2022, the FDA launched Phase 3 of a pilot program using ML to strengthen import screening at the ports. The AI model was trained on years of import data (covering millions of shipments) to identify patterns—combinations of product type, origin, supplier history, laboratory results, etc.—that correlate with shipments posing a higher risk of violations (such as contamination with pathogens, illegal additives, or decomposition) ("US Food and Drug Administration," 2021; "US Food and Drug Administration," 2022). The ML system can flag incoming shipments that are more likely to be unsafe, effectively triaging imports so that inspectors and labs concentrate on the riskiest ones (Alharbi, 2024; Omar, 2022). That approach strengthens the FDA's current PREDICT system for risk-based import checks by incorporating AI that can find patterns. Early findings have been promising: the AI can recognise subtle "connections and patterns that … the FDA's traditional screening system cannot see," thereby predicting which lots might be non-compliant ("US Food and Drug Administration," 2021). For example, it might learn that a particular combination of supplier and product has a hidden issue (such as shrimp from a region where antibiotic misuse is common) and ensure those shipments receive extra scrutiny. The ultimate goal is to *"better protect consumers from unsafe foods by advancing the FDA's ability to identify potential hazards"* before they enter the country ("US Food and Drug Administration," 2022). Insights from this pilot are expected to inform the broader application of AI across other commodities and help shape future risk-based surveillance strategies.

Likewise, AI is being used in domestic inspection programs to decide which food facilities should be checked first. The UK Food Standards Agency (FSA) recently tested an AI proof-of-concept tool to support food hygiene inspections by local authorities. The system, called the *Food Hygiene Rating Scheme – AI (FHRS AI)*, was designed to predict which restaurants and food businesses are at a higher risk of non-compliance with hygiene regulations ("Food Standard Agency," 2023). In the past, inspectors would schedule their visits according to regular schedules or based on compliance history; however, this approach often overlooked new risks and wasted time on places that were always compliant. The FSA's Strategic Surveillance team, instead, developed an ML model (in partnership with data scientists) that analyses a range of data – e.g., business history, ownership, previous inspection outcomes, and even local socio-economic factors – to prioritise establishments for inspection

(Magdas et al., 2025). This risk-based ranking helps identify "which businesses to inspect first" by predicting those most likely to have poor hygiene at present (Janga et al., 2023). By adopting this approach, the FSA aimed to help local councils utilise their limited inspection resources more efficiently, focusing on problematic establishments while potentially extending inspection intervals for low-risk ones (Janga et al., 2023). Notably, the FSA integrated an ethical governance layer, developing a Responsible AI framework with principles of fairness, transparency, and accountability, among others, to guide the AI's development and ensure it could be explained and justified to stakeholders (Janga et al., 2023). Although the tool was designed to test ideas and not implemented immediately, it demonstrated how regulators could responsibly apply AI to their work.

Beyond prioritisation, AI is improving the efficacy of inspections and monitoring themselves. Computer vision and ML are being deployed for the automated inspection of food and facilities. For example, AI-driven image analysis can assist meat inspectors by automatically detecting defects or contamination on carcasses during processing in plants (Bayer et al., 2022). High-resolution cameras, combined with trained algorithms, can detect issues such as faecal contamination or quality defects in meat at chain speed, serving as a decision support tool for human inspectors. Such systems, in pilot testing, show promise in reducing human error and ensuring more standardised inspection outcomes. Similarly, predictive analytics platforms ingest historical inspection data, violation trends, and even external factors to forecast where problems are likely to occur next (Magdas et al., 2025). As a result, it can help create a strategy. For example, a city's inspection team might use AI to predict more violations at seafood restaurants in the summer and deploy more inspectors on duty.

10. Implications and suggestions for stakeholders

Following up on the historical assigned impacts in Fig. 4, we now describe in Fig. 5 how AI can be utilised by stakeholders in managing food safety and its implications for human health. Using AI in food safety and security can have a significant impact on various stakeholders, enabling them to achieve optimal outcomes and effectively manage risks. We outline below the main points and suggestions for each group:

- Policymakers and Regulators: Governments and international bodies should update their regulatory frameworks to accommodate and guide the use of AI in food safety (Ijaiya & Odumuwagun, 2024). Ensuring that data protection laws (such as GDPR, in the European Economic Area) and food safety regulations work in concert is crucial – stakeholders must feel confident that sharing data for AI purposes won't compromise their privacy or trade secrets. Policymakers should also consider classifying food safety AI systems under emerging laws (for example, the EU's AI Act) as potentially high-risk AI, which would require strict oversight, transparency, and validation (Kinney et al., 2024; Paul, 2024). Creating standards and guidelines for AI in food safety is strongly advised. It could include protocols for validating AI tools (similar to validating laboratory methods), requirements for explainability (so that torsions understand the algorithm's decision), and benchmarks for performance. Regulatory agencies must also invest in building their internal capacity – hiring or training data scientists who can evaluate industry-deployed AI systems and perhaps certify them.
- Food Industry and Food Scientists: Food businesses, from farming and manufacturing to retail, along with food safety scientists, stand to gain immensely from AI—if they prepare adequately (Zatsu et al., 2024). Initially, it is essential to prioritise data management and literacy. As one expert put it, "we cannot stress enough about having good data" (Food and Agriculture Organisation of the United Nations, 2024). Companies should ensure their food safety data (testing results, sensor logs, etc.) are well-organised, digital, and of high quality, because these are the fuel for AI algorithms. Training programs to enhance AI and data literacy among food safety professionals will empower them to make informed decisions on when and how to utilise AI (S. Karanth, Benefo, et al., 2023). Second, industry should adopt a proactive stance by participating in trials and pilots of AI technologies (such as blockchain traceability, predictive analytics platforms, and AI inspection systems) and sharing outcomes. We recommend that research institutions and universities encourage joint programs (e.g., food safety and AI) and include coursework on ML applications in food systems (Shraddha Karanth, Benefo, et al., 2023). The scientific community can help by sharing results of AI method tests, offering open data and improving AI so that industry users feel confident in its results. Importantly, both industry and scientists must remain conscious of ethical considerations: bias in AI models (if the training data isn't representative) could lead to, say, unfair targeting of certain suppliers or regions as "high risk." It is essential to employ ongoing monitoring and techniques to mitigate bias when utilising AI in monitoring. To sum up, those involved in food production must utilise AI wisely – acquire the necessary skills, leverage data, and collaborate with regulators to ensure these tools are making our food safer.
- Academic and Research Community: Academia plays a dual role as both innovator and educator in the AI revolution. Researchers should

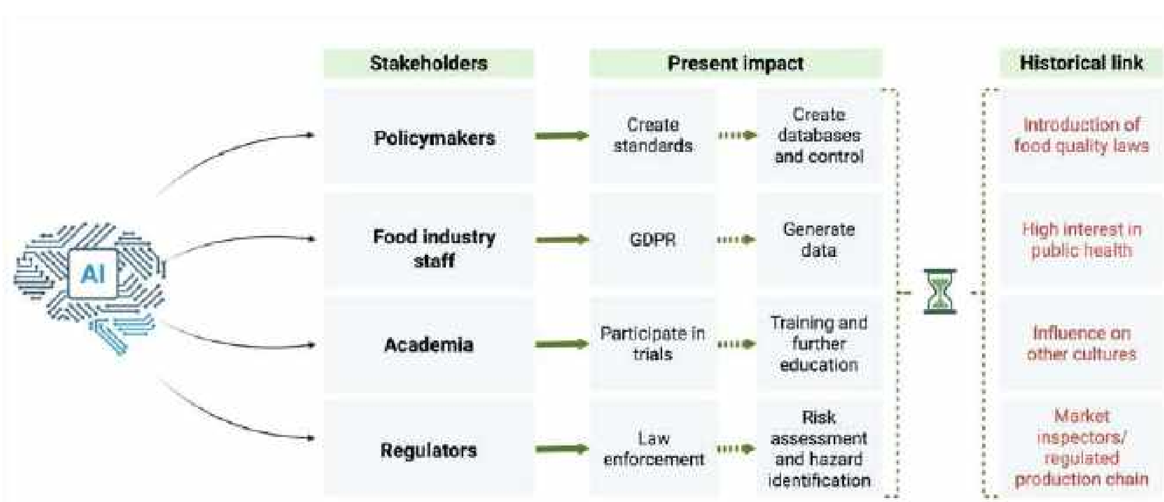

Fig. 5. AI interaction with stakeholders and their determined present impacts and the linked historical connections. Created with Biorender.com.

continue to push the frontiers of what AI can do in food safety – whether it's developing more accurate predictive models, novel sensors that pair with AI, or algorithms that can integrate multidisciplinary data (from genomics to economics) for holistic risk assessment (Yu et al., 2025). As technology advances rapidly, academics should also focus on rigorously testing AI approaches. Peer-reviewed studies should critically assess not just successes but also limitations, helping to separate hype from reality. One particular need is to develop publicly available benchmark datasets and simulation environments for food safety AI (Min et al., 2023). These would allow different algorithms to be compared objectively and foster improvements (much as ImageNet accelerated computer vision, a curated "FoodNet" could accelerate AI for food safety). The academic community should work closely with agencies like EFSA (European Food Safety Authority), FDA, and others to align research with regulatory needs – for example, focusing on the explainability and reliability of AI models, as these are top concerns for regulators (Dimitrakopoulou & Garre, 2025; Food and Agriculture Organisation of the United Nations, 2024). Interdisciplinary research – bringing together food science, computer science, and social science – will be crucial to address not only technical issues but also risk communication and public acceptance of AI-driven food safety measures (Almoselhy & Usmani, 2024).

Education is equally important, and universities should update their curricula to prepare the next generation of food safety experts who are fluent in AI (Tagkopoulos et al., 2024). This might mean new courses at the intersection of food safety and data analytics, case studies on AI applications, and even practical training on relevant software or coding for students of food science and public health. Academic journals and conferences can help transfer knowledge by setting up special issues and forums on "AI in Food Safety," making it easier to share best practices. Academia can also act as a neutral source to give input on policies. For example, university researchers might be commissioned to audit the performance of an AI system used by a government, lending credibility and transparency. Finally, the academic community, alongside institutions like FAO/WHO, should help ensure that the benefits of AI in food safety are global (Organization, 2022). This could involve capacity-building initiatives – training programs or toolkits – for developing countries so they can also implement AI solutions appropriate to their context (perhaps focusing on mobile-based or low-cost AI tools for local food safety challenges) (Issa et al., 2024).

11. Conclusions and future impact

Artificial intelligence is poised to revolutionise food safety and security globally. As AI is integrated with other leading technologies, we are approaching a time when food safety issues can be better handled, and many problems can be identified and prevented before they occur. We analyse some possible future impacts and new ideas, drawing on information from recent research and strategic planning exercises conducted by international groups. A key anticipated impact is the shift towards a "zero contamination" paradigm in food safety, whereby advanced predictive and control systems drastically reduce the incidence of hazards in the food supply (Janga et al., 2023). AI will be central to this by enabling *real-time, continuous monitoring* across the food chain. We can envision intelligent processing lines where AI vision systems and sensors instantly detect contaminants (microbial, chemical, or physical) and trigger automatic corrective actions (e.g., removing a contaminated product from the line or adjusting a process parameter). Some pilot food factories are already implementing such closed-loop AI systems. As these technologies become more affordable and advanced, their widespread use may lead to significant safety improvements, just as industrial automation has in enhancing manufacturing quality. Predictive maintenance of food safety is another concept: just as AI is used to predict machine failures in industry, it can also predict food safety failures (for instance, forecasting when a slaughterhouse's processes might lead to contamination events if cleaning is not performed sooner).

The global integration of data is likely to create a "nervous system" for food safety spanning the planet. We anticipate an expansion of data-sharing platforms and consortia where stakeholders contribute surveillance data (testing results, illness reports, environmental data) into shared AI-powered networks. This would enable every nation to receive early warnings. Suppose an AI in a particular country detects a new form of food adulteration. In that case, it can alert authorities and companies worldwide to be aware of the same issue in imported products. The FoodSafety4EU project in Europe highlights this trajectory, emphasising *"a culture of data sharing among stakeholders"* as essential to AI's transformative potential (Bayer et al., 2022; Lattanzio et al., 2025). By breaking down data silos, AI can analyse a composite picture of food safety that no single agency or company could assemble alone. In practical terms, this might mean a future where a dashboard at the WHO or FAO, powered by AI, continuously assesses global risks: integrating climate data to warn of aflatoxin surges in certain crops, trade data to flag unusual import patterns that could indicate fraud, and health data to catch outbreak signals early across borders.

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