Food and Agriculture Organization of the United Nations

ARTIFICIAL INTELLIGENCE FOR FOOD SAFETY

A literature synthesis, real-world applications and regulatory frameworks

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Contents

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Abbreviations

AFINN	adaptive fuzzy inference neural network
AI	artificial intelligence
AISI	AI Security Institute
AIVF	AI Verify Foundation
ANN	artificial neural network
BERT	bidirectional encoder representations from transformers
BiLSTM	bidirectional LSTM
BN	Bayesian network
BP-NN	back propagation neural network
BSE	bovine spongiform encephalopathy
CART	classification and regression tree
CEB	UN Systems Chief Executive Board of Coordination
CNN	convolutional neural network
CPDP	computers, privacy and data protection
DAE	denoising autoencoder
DARPA	Defense Advanced Research Projects Agency
DCNN	deep convolutional neural network
DFNN	deep feedforward neural networks
DL	deep learning
DNN	deep neural network
DT	decision tree
DTNN	deep tensor neural network
EFSA	European Food Safety Authority
ELM	extreme learning machine
ENR	elastic net regression
ERISS	emerging risk identification and screening system
ExtraTrees	extremely randomized trees
FAIR	findable, accessible, interoperable and reusable
FAO	Food and Agriculture Organization of the United Nations
FCNN	fully connected neural network

FDA	Food and Drug Administration
FL	fuzzy logic
FNN	feedforward neural network
FSA	Food Standards Agency
FSAI	Food Safety Authority of Ireland
GA	genetic algorithm
GAN	generative adversarial network
GBM	gradient boosting machine
GBR	geographical BSE risk assessment
GENPAT	Italian National Reference Centre for WGS of microbial pathogens
GNB	Gaussian naïve Bayes
GPAI	Global Partnership on Artificial Intelligence
GPR	Gaussian process regression
GPT	generative pre-trained transformer
IMDA	Infocomm Media Development Authority
IZS	Istituto Zooprofilattico Sperimentale
kNN	k-nearest neighbors
LASSO	least absolute shrinkage and selection operator
LCA	life cycle assessment
LDA	linear discriminant analysis
LDA	latent Dirichlet allocation
LIME	local interpretable model-agnostic explanations
LLM	large language model
LMIC	low- and middle-income country
LR	logistic regression
LSTM	long short-term memory
MGADE	multi-grained adverse drug events detection network
MINICT	Ministry of Information and Communication Technology and Innovation
ML	(traditional) machine learning
MLP	multilayer perceptron
MLR	multiple linear regression
MMI	maximum mutual information
MoCo	momentum contrast technique
NB	naïve Bayes
NIST	National Institute of Standards and Technology
NITI	National Institution for Transforming India

NLP	natural language processing
NN	neural network
NSW AIAF	New South Wales Artificial Intelligence Assessment Framework
NTU	Nanyang Technological University
OECD	Organisation for Economic Co-operation and Development
OSTP	Office of Science and Technology Policy
PDPC	Personal Data Protection Commission
PLS-DA	partial least squares discriminant analysis
PLSR	partial least squares regression
PRISMA	preferred reporting items for systematic reviews and meta-analyses
QDA	quadratic discriminant analysis
RAG	retrieval-augmented generation
RASFF	rapid alert system for food and feed
ResNet	residual network
RF	random forest
RNN	recurrent neural network
RoBERTa	robust optimized BERT pretraining approach
SFA	Singapore Food Agency
SGB	stochastic gradient boosting
SHAP	Shapley additive explanations
SSL	self-supervised learning
SVM	support vector machine
SVR	support vector regression
UK	United Kingdom of Great Britain and Northern Ireland
UN	United Nations
UNESCO	United Nations Educational, Scientific and Cultural Organization
USDA	United States Department of Agriculture
US AISI	United States Artificial Intelligence Safety Institute
USA	United States of America
WFSR	Wageningen Food Safety Research
WIT	what-if tool
WUR	Wageningen University & Research
XAI	explainable AI
XGBoost	extreme gradient boosting
YOLO	you only look once
YOLOv4	you only look once version 4

Executive summary

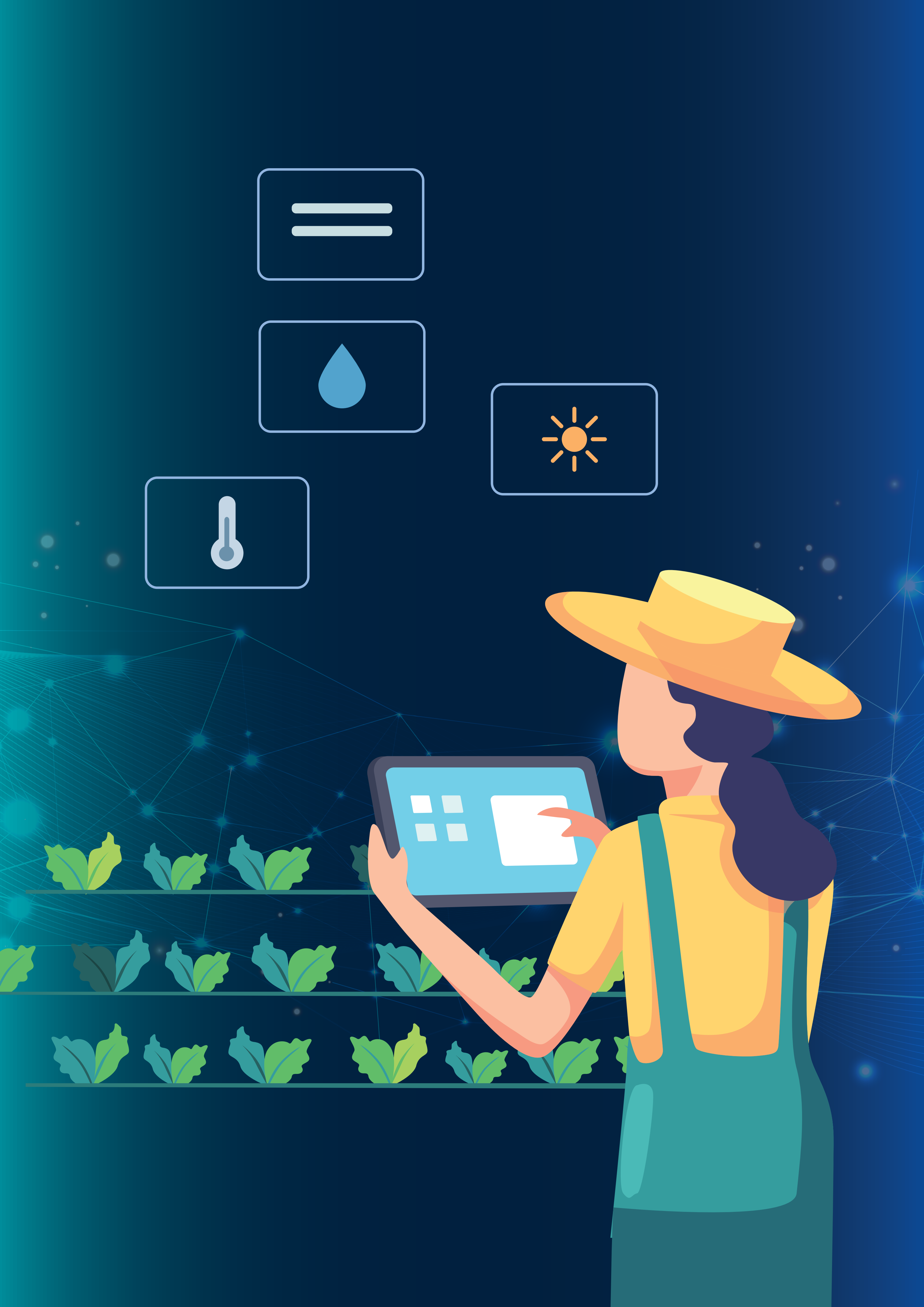
Artificial Intelligence (AI) is increasingly applied in food safety management, offering new capabilities in data analysis, predictive modelling, and risk-based decision-making. A review of the literature identifies three primary areas of application: scientific advice, inspection and border control, and operational activities of food safety competent authorities. Five country examples with the real-world use cases illustrate diverse uses of AI tools, including pathogen detection, import sampling prioritization, and language models for regulatory data processing.

Regulatory frameworks, as well as voluntary governance, addressing AI in the public sector are emerging worldwide. National and international initiatives often highlight the importance of data governance, transparency, ethical considerations, and human oversight. Challenges such as biased data, explainability, and data governance gaps appear across different contexts, along with potential risks from deploying AI systems prematurely. Access to high-quality, interoperable data and collaboration among stakeholders can support effective integration of AI technologies.

AI readiness often depends on understanding specific problems to be addressed, current capacities, and the quality of available data. Human oversight and continuous evaluation contribute to maintaining trust in AI systems. Collaborative efforts involving academia, the private sector, and international organizations help build shared knowledge and resources for AI development in food safety.

Overall, AI presents opportunities to enhance resilience, efficiency, and responsiveness in food safety systems. Careful consideration of governance, data management, and multi-stakeholder cooperation can shape AI's contribution to achieving sustainable and equitable outcomes in agrifood systems.

Keywords: Artificial Intelligence (AI), food safety, data governance, predictive modelling, machine learning, risk-based decision-making, ethical AI, explainable AI, cross-sector collaboration, capacity development, AI use case, food safety competent authority.

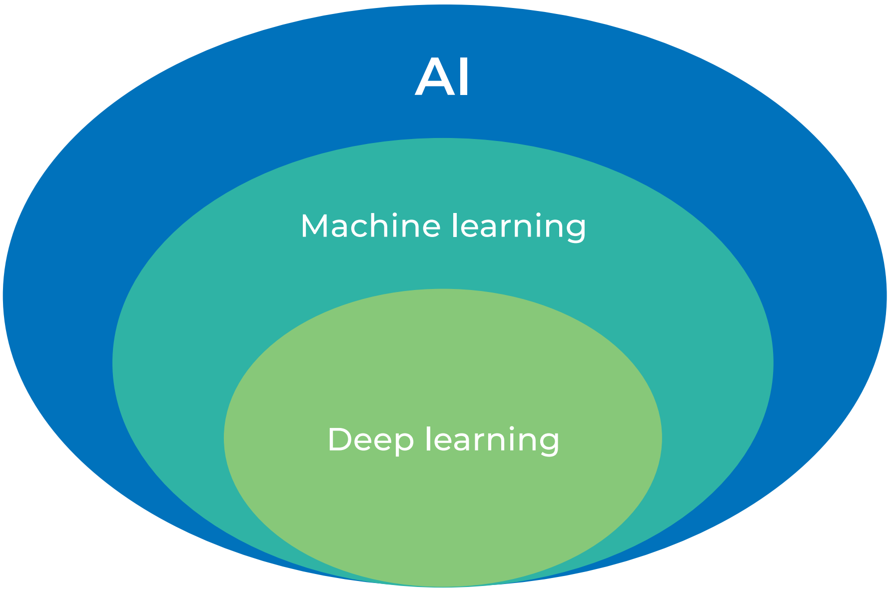


1. Introduction

1.1. Background

Artificial intelligence (AI) has been revolutionizing a wide variety of domains, including finance, marketing, manufacturing, transportation, education and healthcare, including food safety (Ding *et al.*, 2023). The integration of AI into food safety regulatory frameworks may offer great potential for enhancing regulatory effectiveness (Qian *et al.*, 2023). While the United Nations Educational, Scientific and Cultural Organization (UNESCO) defines AI systems as “systems which have the capacity to process data and information in a way that resembles intelligent behaviour and typically includes aspects of reasoning, learning, perception, prediction, planning or control” (UNESCO, 2021), AI can simply be explained as a field of research in computer science that focuses on developing and studying methods and software that enable machines to perceive their environment, learn from it, and take intelligent actions to maximize the chances of achieving defined goals (Russell and Norvig, 2021) (Figure 1). In the context of food safety, the term “AI” typically refers to machine learning (ML) and/or deep learning (DL).

Figure 1 The relationship between artificial intelligence, machine learning and deep learning



Source: Authors’ own elaboration.

Machine learning is a subset of AI and in general, it uses algorithms to learn from training data and the relation is generalizable to unseen data (Koza *et al.*, 1996). In one of the common applications of machine learning, researchers or engineers extract characteristics (i.e. features) from raw data and use statistical methods to learn patterns (Mohri *et al.*, 2018). For example, a machine learning algorithm may be trained on a dataset containing apple colour at various ripeness levels. It can predict the ripeness of a new, unseen apple based on colour. While unsupervised machine learning explores data to identify structures without predefined labels, supervised machine learning learns from labelled examples and improves with more data. Consequently, unsupervised machine learning involves clustering, where samples are grouped based on feature similarity, while supervised machine learning focuses on predicting labels from features through classification or regression (Jordan and Mitchell, 2015).

Deep learning is a subset of machine learning that uses neural networks with many layers to analyze and learn from large amounts of raw data. It enables the AI applications to recognize patterns, make predictions and improve their performance with additional data, similar to how humans learn from experience. In this way, the explicit extraction of characteristics / features is often no longer needed (LeCun, Bengio and Hinton, 2015). Deep learning is not strictly a subset of either unsupervised or supervised learning, as it can be used in both cases, though it is commonly associated with supervised learning (Yuan *et al.*, 2020). Currently, deep learning is used in most state-of-the-art techniques, ranging from unlocking your smartphone with face / fingerprint recognition to self-landing rockets (Parloff, 2016). For example, in the context of food safety, deep learning algorithms can analyze raw data such as customer reviews and social media posts to detect early signals of foodborne disease outbreaks.

1.2. Relevance to food safety in the agrifood systems

While the importance of food safety is recognized by many, the relevant data generation, collection and consolidation may not be easily achieved by many countries, particularly low- and middle-income countries (LMICs), hence, the real burden of foodborne disease remains dramatically underreported, which stymies public investments in food safety (Grace, 2023). On the other hand, in most high-income countries, vast amounts of food safety-related data generated within agrifood systems have been of benefit (Mu *et al.*, 2024; Qian *et al.*, 2023) for the development of AI applications, particularly within scientific research, in predicting and identifying food safety issues, prioritizing them and efficiently carrying out relevant regulatory activities in a more efficient manner. High-income countries are witnessing an accelerated adoption of digital technologies across all stages, from farm to table. This digitization, while offering numerous benefits in terms of efficiency, transparency, and sustainability, also creates new vulnerabilities. Cyberattacks can disrupt critical logistics networks, compromise data integrity related to food safety, and lead to the theft of valuable intellectual property (Leligou *et al.*, 2024). Data breaches and data manipulation caused by cyberattacks may lead to theft of sensitive information, including customer data, financial records, proprietary business information (e.g. recipes, processes), or intellectual property (e.g. crop genetics). A critical concern is the manipulation of food safety data, either to hide contamination or fabricate evidence of it, potentially causing public health crises or severe reputational damage. False data injection can tamper with decisions and results (USDA, 2024).

Conventional procedures for ensuring food safety, such as detecting food contamination or adulteration, are currently considered by many countries, especially in LMICs, as costly, elaborate, sample destructive, time-consuming; and as requiring specialized infrastructure and intensive manual labour (Magnus *et al.*, 2021). Also, the use of human senses, such as appearance and smell, for example, to determine the freshness of vegetables or meat products is inadequate and may result in variable outcomes. This illustrates the problem of noise in subjective judgements (Kahneman *et al.*, 2021). Furthermore, resources are often inefficiently allocated to inspections that are not risk-based or fail to prioritize efficiency in their execution.

High expectations from AI applications are reported in the area of food safety (Deng, Cao and Horn, 2021; Taneja *et al.,* 2023). The application of AI in food safety may offer an avenue to develop cost-effective and automated systems that are fast and user-friendly procedures for food classifications, quality control, food safety assurance, and food grading (D'Amore *et al.*, 2022; Miyazawa *et al.,* 2022). Furthermore, in some food testing, the use of AI may reduce the need for rigorous laboratory experiments that require various expensive chemical reagents, thus, a strategy that is environmentally friendly with timely results can be potentially developed (Sharma and Sawant, 2017). This could lead to proactive approaches in managing food safety risks, therefore significantly reducing overall costs of foodborne disease outbreaks and economical losses resulting from food recalls, food waste, hospitalization, medications, and deaths in the long run (Pal and Kant, 2018). It is important to note, however, the energy demands of large-scale AI systems may carry environmental costs; a comprehensive life cycle assessment (LCA) would be necessary to fully evaluate the trade-offs between AI-driven and traditional experimental approaches.

1.3. Purpose of the document and target audience

The main objective of the document is to synthesize current AI applications for food safety reported in the literature as of April 2024, with the aim to assist food safety competent authorities who would like to consider integrating some in their regulatory activities. It is crucial for those competent authorities, especially those in LMICs, to stay informed of the available AI applications, as these technologies may at some point greatly enhance their work, while they may pose potential risks and challenges.

While all countries can equally benefit from the responsible use of AI applications in food safety, the level and availability of data relevant to food safety varies among countries. Food safety competent authorities in LMICs may find some AI applications to be too dependent on data that do not currently exist in sufficient amounts. Nevertheless, improving understanding of the potential of AI can empower regulators to leverage recent advancements, collaborate with experts, and implement effective, data-driven strategies. The knowledge gained would further strengthen the rationale to improve and streamline the countries' data collection strategies for food safety.

For this reason, a scoping review was conducted to explore the diverse applications of AI for various areas of food safety. Given the context of various socio-economic situations in LMICs, the analysis of preliminary activities prior to employing high-efficiency AI for food safety competent authorities has been conducted. The current regulatory landscape surrounding AI deployment in food safety was also included, as it is important to ensure fair and responsible implementation. Moreover, the boundary conditions which are necessary for AI to be trustworthy, unbiased, and explainable have been described.

1.4. Methods

The method used for this literature synthesis was a scoping review using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework. The search was performed in Scopus and restricted to peer-reviewed publications written in English, using the search terms described in Annex 1. The publication years for the review were initially set from 2004 to 2024 to cover the last two decades. However, since almost no directly relevant articles were found between 2004 and 2012, the final cut-off was determined to be from 2012 to 2024. Active learning facilitated the curation of literature using the AI tool ASReview (ASReview, 2023; Van de Schoot *et al.,* 2021). Conference proceedings and book chapters were not included in the review.

2. Literature synthesis results

2.1. Overview

The systematic search yielded a total of 133 (out of 783 screened papers; 17 percent) relevant peer-reviewed publications (Annex 2). Forty papers were published in North America, 42 papers in China, 28 in Europe, 19 in Asia other than China and 4 from Latin America. Deep learning was utilized in 43 papers, while classical machine learning was employed in 89 papers (with one being unknown).

Studying the identified research papers, three categories were established based on their ultimate purposes / use goals (AI objectives) related to food safety and the specific hazards or targets they aim to address. These goals include 1) AI for scientific advice, including laboratory-related activities; 2) AI for inspections, including border control; and 3) AI for other regulatory activities in the domain of food safety. Within these categories, studies that looked at various food safety hazards, ranging from microbiological and chemical hazards to issues of food fraud and authenticity, were analyzed. Table 1 summarizes these objectives and associated hazards, alongside the AI techniques employed, with concrete examples drawn from the reviewed literature.

Table 1 Analysis of the literature synthesis

AI objective	AI technique	Target/Hazard (#)	Examples
Scientific advice			
Laboratory testing and efficiency	DL (N=9): CNN, GAN, and autoencoders ML (N=15): SVM, RF, and ANN	Microbiological (24)	• Classification and identification of food-borne pathogens by Raman spectra • Identifying Shigatoxigenic Escherichia coli using hyperspectral microscope images • Biosensing for rapid pathogen detection in liquid food to agricultural water
	DL (N=5): NN and CNN ML (N=12): SVM, ELM, and XGBOOST	Chemical (17)	• Pesticide residue detection using hyperspectral imaging combined with machine learning • Identification of unknown chemical contaminants in food using liquid chromatography–high-resolution mass spectrometry and machine learning
	DL (N=7): CNN such as ResNet ML (N5): SVM	Fraud/authenticity (12)	• Dairy fraud identification using Raman spectroscopy and fusion machine learning
	DL (N=1): LSTM ML (N=1): DT	Other (2)	• Long short-term memory model with laboratory equipment to predict salmon storage time

AI objective	AI technique	Target/Hazard (#)	Examples
Scientific advice			
Fundamental research and risk factors	DL (N=2): DNN ML (N=10): RF and SVM	Microbiological (12)	• Identifying environmental factors associated with Salmonella in agricultural watersheds • Identifying farm practice variables associated with Listeria prevalence in pastured poultry farms
	DL (N=2): DNN and MoCo ML (N=7): RF, BN, and XGBOOST	Chemical (9)	• Modelling bioaccumulation of heavy metals in soil-crop ecosystems and identifying its controlling factors
	DL (N=2): DNN	Fraud/authenticity (2)	• Pattern recognition based on machine learning to identify adulteration of oil
	DL (N=8): DNN and BERT ML (N=7): RF, SVM, and XGBOOST	Other (15)	• Identify the confounding factors of foodborne disease outbreaks or recalls • Using text data to examine public opinion of food safety
Prediction	DL (N=2): CNN ML (N=8): ANN, RF, SVM, and XGBOOST	Microbiological (10)	• Predict delay in growth of Salmonella enteritidis after heat and chlorine treatment • Using patterns of whole genome sequencing data to predict disease outcome or virulence
	DL (N=2): BP-NN ML (N=4): RF, NB, and SVM	Chemical (6)	• Predict cadmium concentration in rice grain to support soil management
Efficiency	ML (N=1): SVM	Microbiological (1)	• Identification and classification of bacterial classification using image processing and distributed computing
	ML (N=1): XGBOOST	Fraud/authenticity (1)	• Non-targeted detection of milk adulteration using infrared spectra
	DL (N=1): LSTM	Other (1)	• Rapid risk assessment of microbiological and chemical contamination in rice

AI objective	AI technique	Target/Hazard (#)	Examples
Inspection and border testing			
Testing	DL (N=1): ResNet ML (N=1): SVM	Fraud/authenticity (2)	• Fourier transform near-infrared / DNA barcodes with machine learning without damaging the product to check for authenticity of mushroom or fish
Prediction	ML (N=1): RF	Other (1)	• Predicting which imported foods pose an increased food safety risk
Prioritization	ML (N=2): RF	Other (2)	• Trade data analysis to make a priority list for hazards or risk assessment of imported food
Efficiency	ML (N=2): RF and BN	Other (2)	• Species identification of food-contaminating beetles Enhanced border inspection of imported fish
Activities of competent authorities			
Prediction	ML (N=1): RF	Microbiology (1)	• Source attribution (Salmonella) using sequencing data
	ML (N=3): BN, RF, and XGBOOST	Chemical (3)	• Prediction of mycotoxin contamination
Prioritization	ML (N=1): DT	Chemical (1)	• Pattern detection of vet drug residues
	ML (N=1): LDA	Fraud/authenticity (1)	• Identification of beeswax adulteration
	ML (N=4): RF and log-linear maximum entropy	Other (4)	• Using text data from e-invoices to screen for food safety risks
Efficiency	DL (N=1): BERT	Other (1)	• Utilizing text data from social media to examine consumer perception of alternative proteins

ANN = artificial neural network; BERT = bidirectional encoder representations from transformers; BN = Bayesian network; BP-NN = back propagation neural network; CNN = convolutional neural network; DL = deep learning; DNN = deep neural network; DT = decision tree; ELM = extreme learning machine; GAN = generative adversarial network; LDA = linear discriminant analysis; LSTM = long short-term memory; ML = (traditional) machine learning; MoCo= momentum contrast technique; NB = naïve Bayes; NN = neural network; ResNet = residual network; RF = random forest; SVM = support vector machine; XGBOOST = extreme gradient boosting.

Source: Authors' own elaboration.

2.2. Applications of artificial intelligence in food safety management

2.2.1. Scientific advice for food safety

A total of 115 papers applied AI in the domain of scientific advice for food safety. Among them, 55 papers examined how AI can aid scientific advice by improving the accuracy, speed and efficiency of laboratory testing. Forty papers focused on the use of AI to aid risk assessment and management to be used in scientific advice. AI to enable prediction to aid in scientific advice was examined by 17 papers. The remaining three papers focused on using machine learning to improve the efficiency and speed in the domain of scientific advice.

Machine learning can aid various laboratory testing processes to be less expensive and more efficient. For instance, He *et al.,* (2022) employed a support vector machine and an artificial neural network to detect pesticide residues in red wine using fluorescence sensing data, eliminating the need for the usual complex pretreatment procedures. Furthermore, beef adulteration detection has been demonstrated by using deep learning-aided spectroscopy (Jo *et al.*, 2023).

More fundamental research investigating the causes of contamination of food or the food environment with microbes, mycotoxins or heavy metals or foodborne disease in general has also relied on AI. For example, Camardo Leggieri, Mazzoni, and Battilani (2021) examined the influence of meteorological factors on mycotoxin levels in fields using a deep neural network. Zhang *et al.,* (2021) used extreme gradient boosting to assess how to best recognize suspected outbreaks of foodborne disease, which could in the future possibly alleviate the burden on medical staff and food safety regulators. Understanding the causes of food safety hazards or foodborne diseases could inform foresight to ensure a safe food environment.

In addition to examining possible causes, AI has been used to make predictions of food safety hazards. For instance, Tanui *et al.,* (2022) utilized a random forest model to predict the virulence of specific Salmonella strains in ground chicken through whole genome sequencing. Additionally, other studies have used machine learning in order to predict the presence of contaminants such as mycotoxins or heavy metals in foods (Wang, Liu and van der Fels-Klerx., 2022; Mi *et al.*, 2023; Huang *et al.*, 2023; Ma *et al.*, 2023c; Marzec-Schmidt *et al.*, 2021; Liu *et al.*, 2021). Such predictions could facilitate more targeted, evidence-based monitoring. For example, if unusually warm temperatures are indicative of higher pesticide residue due to increased pest activity, food safety authorities could better target their monitoring efforts, thus gaining more value from the effort.

Use case 1. Electronic nose

Gonçalves *et al.* (2023) used an electronic nose based on ionogel composites in combination with principal component analyses and several classifier algorithms to differentiate *Salmonella* from different microorganisms. Depending on the media microorganisms were incubated on, the classifier algorithms had an accuracy of 85 to 100 percent for the discrimination of *Salmonella*. The authors stated that the proposed electronic nose methodology offers a simple and more cost-effective alternative to traditional microbiological analysis for detecting *Salmonella* in food. It has the potential to complement existing diagnostic methods by reducing analysis time, costs, and the number of manipulation steps required.

2.2.2. Inspection and border control

Seven papers used AI in the domain of inspection and border testing. Of these papers, two focused on testing and efficiency. One paper examined prediction in the domain of inspection and border testing, two papers on prioritization and two papers on efficiency.

The use of AI to aid food safety in the domains of inspection and border control has received less attention than in the field of scientific advice. Traditional machine learning methods such as random forests were mostly used to assess possible frauds, product authenticity and general food safety.

In the field of inspection, AI can be applied to verify the authenticity of food products such as mushrooms or fish (Liu *et al.*, 2023; Kusuma and Nurilmala, 2016) and to identify contaminating beetle species (Bisgin *et al.*, 2018). The application of AI in these areas has the potential not only to enhance the accuracy and speed of inspections but also to reduce the reliance on manual labour, which can be costly, time-consuming and prone to human error.

Several studies have looked at the application of AI in border control. Machine learning was used to predict the risk of imported foods (Wu *et al.*, 2023a) and imported fish (Tu *et al.*, 2024). Furthermore, machine learning was used to build models to prioritize which products should be sampled when crossing country borders (Talari *et al.*, 2024; Wu *et al.*, 2023a). Such models could greatly enhance food safety management by increasing the likelihood of detecting high-risk products, ensuring that a greater number of hazardous items are identified before they reach consumers. This targeted approach not only boosts the effectiveness of food safety protocols but also leads to cost savings. By better targeting samples that are likely to pose a risk, resources could be allocated more efficiently, cutting down on unnecessary testing, likely leading to and allowing for quicker response times. Additionally, the use of AI-driven models could streamline operations, making the border control process more efficient and responsive. However, it is important to recognize that the implementation of such technologies must comply with existing national or Supranational regulations and control protocols, which may limit or shape their practical application at borders.

Use case 2. Prediction for prioritization in imported food control

Wu *et al.* (2023) aimed to use a machine learning approach to determine whether quality control sampling should be performed on imported food at the border. A newly developed ensemble learning prediction model was compared to a previously used model with random sampling. For cases flagged for inspection by the ensemble learning prediction model, the non-compliance rates of the foods were up to three times higher compared to those identified through random sampling. AI-powered border control could enhance risk prediction capabilities and allow for quick adaptation to new trends in response to changes in the international environment.

2.2.3. Efficiency for activities of competent authorities

The use of AI to assist in the activities of competent authorities was the subject of 11 papers. Four of these papers focused on using machine learning for prediction. A further six papers examined how machine learning can be used in prioritization strategies. A final paper examined efficiency in the activities of competent authorities.

AI was also found to be applied in foodborne disease outbreak investigations and surveillance, as well as general operational competent authority activities in the area of food safety. Traditional machine learning techniques such as random forests and gradient boosting were typically used. For example, several studies have used machine learning models in different ways to detect foodborne disease outbreaks (Sadilek *et al.*, 2017; Sadilek *et al.*, 2018; Chang *et al.*, 2020). In cases of limited capacity, the ability to prioritize resource allocation becomes crucial. AI-driven models were reported to be able to offer significant value by helping determine how to best utilize available human and financial resources. For example, when food safety inspectors face constraints in manpower or time, machine learning models can assist competent authorities to identify which restaurants or food establishments should be prioritized for inspection by indicating some key geographical locations or hot spots of concern, where the likelihood of foodborne disease outbreaks is possibly higher. Furthermore, AI may be developed to provide real-time data analytics and predictive insights, allowing regulatory bodies to respond swiftly to emerging threats.

The use of text sources like social media posts, news websites, and food recall reports is rapidly advancing. For example, Chen and Zhang (2022) used language analysis to explore consumers' food safety perception of the alternatives to animal-sourced foods. This development presents new opportunities, as potential food safety hazards or concerns can be identified. By leveraging natural language processing (NLP) and machine learning, these text sources can be analyzed in real-time to detect emerging threats. This method may enable quicker responses to consumer concerns.

Use case 3. Smartphone-based syndromic surveillance for outbreak detection

Sadilek *et al.* (2018) used aggregated an anonymized search and location data from smartphones to detect potential sources of food safety problems in real-time. The method identified the ongoing internet searches on the symptoms of foodborne diseases from various websites, such as the Wikipedia articles about foodborne diseases or the governmental websites devoted to foodborne diseases, using a log-linear maximum entropy model. It then looked up the restaurants visited by users who made those queries, using their anonymized location histories. For each relevant restaurant, the model calculated the proportion of users who visited and subsequently showed the increased interest in information related to foodborne diseases, hinting at the possibility of having some of the symptoms of the disease. The findings showed that this approach can improve the identification of problematic venues by more than threefold compared to current methods and indicated that health departments can use this tool to more rapidly pinpoint and investigate locations where outbreaks may be occurring.

2.3. Algorithms

2.3.1. Algorithm used in reviewed studies

In 133 articles reviewed, a total of 43 distinct AI techniques have been identified. Table 2 shows the selected common AI techniques used in food safety research, with the relevant explanations and examples of which articles they have been used in. The techniques can be further categorized as either deep learning or machine learning methods, though deep learning is a subcategory of machine learning. It is important to note that, at present, there are no internationally harmonized definitions for the terms listed in Table 2. Therefore, the explanations provided in the table should not be interpreted as formal definitions. At the top are the simpler models, such as linear regression, and towards the bottom of the table, the models become increasingly complex, ending with transformers. The full list of AI techniques found in the literature review process is available in Annex 3.

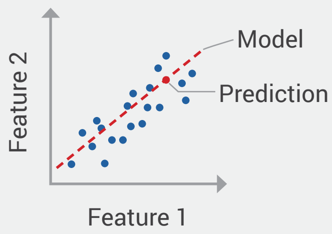
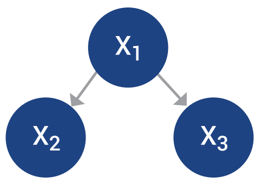
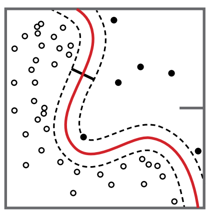
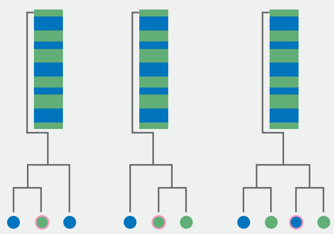
With current technological developments, it is possible that by the time that this document is published, increasingly sophisticated AI models are being studied to address food safety problems. However, in this literature review, the majority of studies still used traditional machine learning. Model suitability for food safety research depends on several factors, such as the available data type, the type of problem to address and the quantity of available data. Deep learning techniques such as neural networks usually require a lot more data than machine learning-based models (e.g. regression models or support vector machines) (Liang *et al.*, 2022). As such, careful consideration is essential when selecting an AI model to ensure it aligns with both the nature of the data and the objectives of the eventual use.

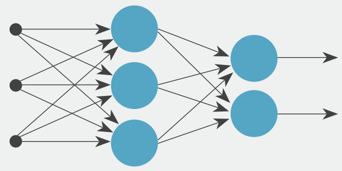
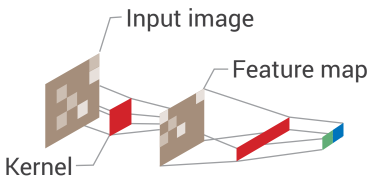
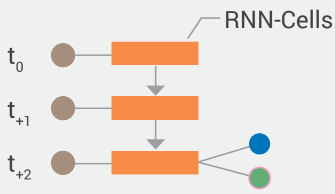
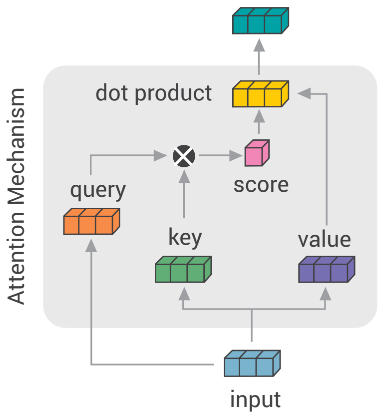
2.3.2. Predictive and generative artificial intelligence

Predictive and generative AI represent two fundamental applications of AI with relevant implications in the area of food safety. Predictive AI focuses on forecasting events or behaviours based on historical data (Collins and Moons, 2019). For example, predictive AI with a backpropagation neural network was used to predict cadmium concentration in rice near an active copper smelter (Mi *et al.*, 2023).

Generative AI is designed to create new data instances that resemble existing data (Feuerriegel *et al.*, 2024). For example, ChatGPT (Achiam *et al.,* 2023), a chatbot that is arguably the most widely known example of generative AI, generates coherent and contextually relevant text based on the input it receives, enabling it to assist with a wide range of tasks based on a large language model called generative pre-trained transformers (Brown *et al.*, 2020). Generative AI can also be used in various innovative ways within the food safety domain. For instance, Generative Adversarial Networks (GANs) can simulate realistic contamination scenarios to train food safety inspectors or develop robust testing protocols (Wang *et al.*, 2024b). Additionally, generative AI can create synthetic datasets to improve the training of machine learning models without compromising sensitive information if designed well (Goyal and Mahmoud, 2024). Together, predictive and generative AI technologies can enhance food safety by enabling more precise risk assessments and creating advanced tools for monitoring potential food safety hazards.

Table 2 Machine learning (ML) algorithms identified in the papers included in the literature review

ML algorithms	Description	Data Type	Examples from this review
Regression models 	Regression models estimate the relationship between dependent variables and independent variables via a mathematical function. Some regression models, such as LASSO, ridge, and elastic net, can perform both variable selection and regularization to enhance the prediction accuracy and interpretability.	Tabular	• LR (Stanoscheck *et al.*, 2024) • LASSO, elastic-net (Weller *et al.*, 2020)
Bayesian models 	Bayesian models are probabilistic models that represent a set of variables and their conditional dependencies via a directed acyclic graph. Their goal is to infer the probability of a variable based on its conditional dependencies.	Tabular	• BN (Bouzembrak *et al.*, 2024), • GNB (Talari *et al.*, 2024) • Bayesian Gaussian process regression (Zhu *et al.*, 2023)
Clustering 	Clustering groups measurements such that measurements in the same group (i.e., a cluster) are more similar to each other than to those in other clusters.	Tabular	• kNN (Talari *et al.*, 2024)
Support vector machine (SVM) 	SVMs use kernel functions to transform data into a higher-dimensional space such that the data is linearly separable in that dimension.	Tabular	• SVM (Al *et al.*, 2024; van den Bulk *et al.*, 2022)
Tree-based algorithms 	Tree-based algorithms typically construct a multitude of decision trees, which make very few assumptions about the data. Bagging (such as random forest, RF) and boosting (XGBoost, CatBoost) can be used to improve the model's performance by reducing variance and bias, respectively.	Tabular	• RF (Al *et al.*, 2024) • XGBoost (Zhao, Liu and Song, 2023)

ML algorithms	Description	Data Type	Examples from this review
(Deep) artificial neural network (ANN) 	Neural networks consist of nodes connected by edges. Neural networks apply mathematical functions to the combination of the input each node receives. Deep neural networks have multiple hidden layers, ranging from just a couple to thousands of hidden layers.	Tabular	• ANN (Al *et al.*, 2024; Smeesters *et al.*, 2021) • ELM (Smeesters *et al.*, 2021) • Denoising autoencoder (Li *et al.*, 2022)
Convolutional neural network (CNN) 	CNNs learn features by themselves via filter optimization. They use convolutional layers to detect features and patterns in the input at different resolutions in order to make predictions.	Image	• AlexNET (Jo *et al.*, 2023), • CNN (Chen *et al.*, 2024b) • ResNet (Chen *et al.*, 2022a) • YOLO (Ma *et al.*, 2023b)
Recurrent neural network (RNN) 	RNNs are used for sequential data processing using recurrent units. These units maintain a hidden state, essentially a form of memory, which is updated at each time step based on the current input and the previous hidden state.	Sequence	• LSTM (He, 2024)
Transformers 	Transformers take input (like text) and turn it into numerical units called tokens. Each token is converted into a vector using an embedding table. At each layer, the transformer looks at how each token relates to the others in the context, using an attention mechanism that highlights important tokens and downplays less relevant ones. It is the main technique behind generative pre-trained transformers (GPT) models such as ChatT).	Text Image	• BERT (Maharana *et al.*, 2019) • BERTweet • RoBERTa (Tao *et al.*, 2023)
Explainable AI (XAI)[1] 	XAI techniques try to explain how an AI-based system came up with a given result. For example, SHAP (SHapley Additive exPlanations) enables visualization of the contribution of each input feature to the output.	All data modalities	• LIME, SHAP, WIT (Buyuktepe *et al.*, 2023)

[1] SHAP and other explainable artificial intelligence (XAI) techniques are not machine learning algorithms per se, but post hoc interpretability methods developed to analyze and elucidate the internal logic and output of trained machine learning models.

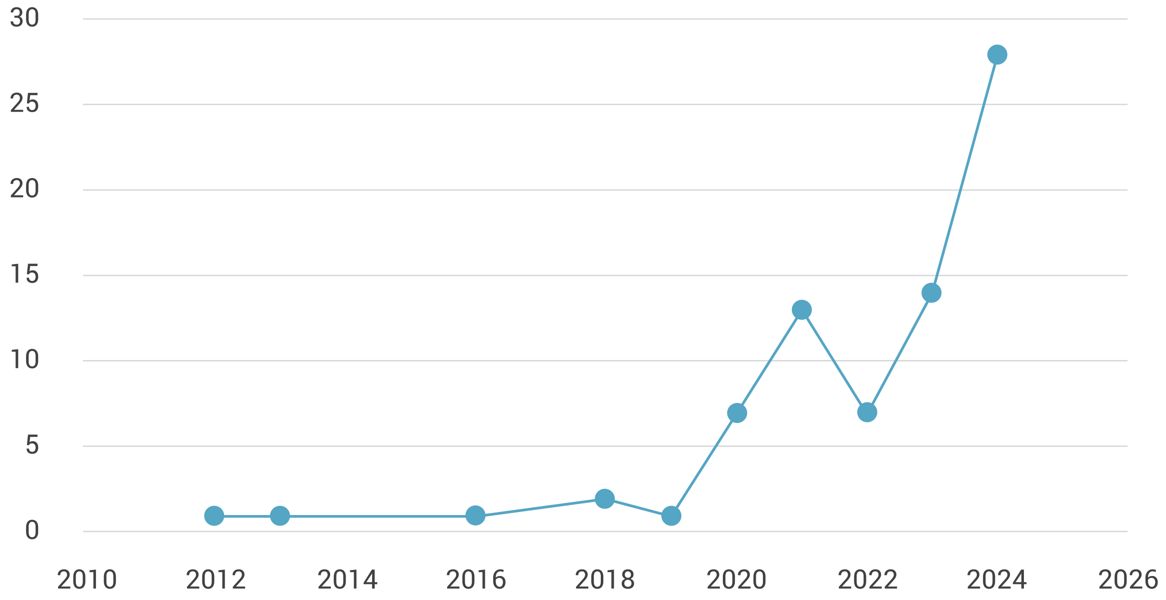
2.3.3. Data types

Table 2 has shown that different AI techniques are suited to different data types. Tabular data can be used with many AI methods ranging from traditional machine learning models to advanced deep learning models. Tabular data is data that is organized in a structured, row-and-column format (Hernandez *et al.,* 2022). For example, a data file that contains information about the concentration of chemical contaminants in grains would be tabular data. Specific AI methods such as convolutional neural networks or transformers can also use images or multimodal data as input. These techniques could, for example, be used to aid in the automatic analyses of microscopic images for colony counting for specific microorganisms. Lastly, transformers such as Bidirectional Encoder Representations from Transformers (BERT) (Devlin, 2018) or ChatGPT can also analyze text as input data to, for example, pick up early warning signals by scraping social media platforms such as X feeds.

2.3.4. Trends in artificial intelligence research in the area of food safety

The number of publications that use AI in food safety is steeply increasing, rising from just 1 publication in 2012 to 28 in 2024 (Figure 2). This growth is expected to continue in the coming years as AI techniques advance and become more widely available.

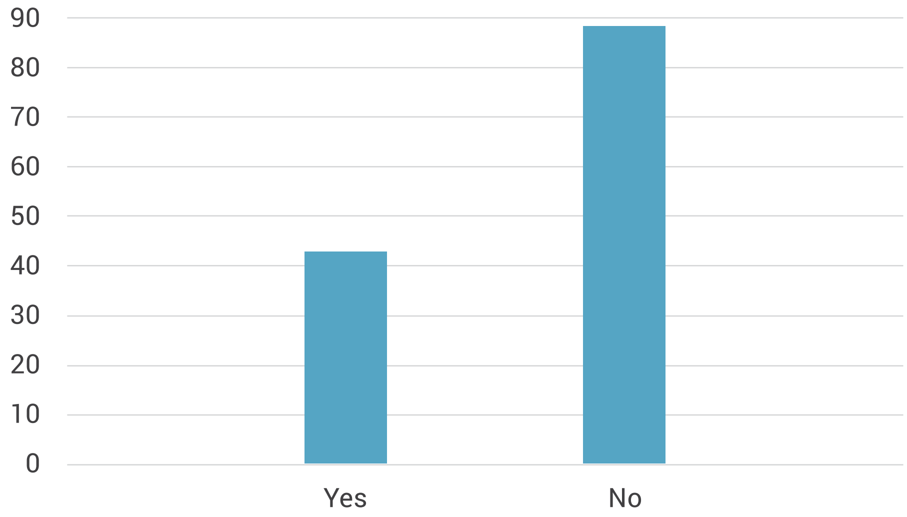
Figure 2 Number of publications using artificial intelligence for food safety research



Source: Authors' own elaboration.

In the literature review conducted, the majority of studies employed traditional machine learning methods rather than deep learning approaches (Figure 3). There is, however, a noticeable trend showing a rapid shift, as the number of papers leveraging deep learning for food safety has increased from 2 in 2019 to 18 in 2023. This trend is expected to continue as the potential for deep learning to enhance food safety protocols becomes more widely recognized. Advancements in computational power, expanded data availability, and the evolution of AI methodologies are likely to further accelerate this growth, enabling more robust and real-time solutions for ensuring food safety.

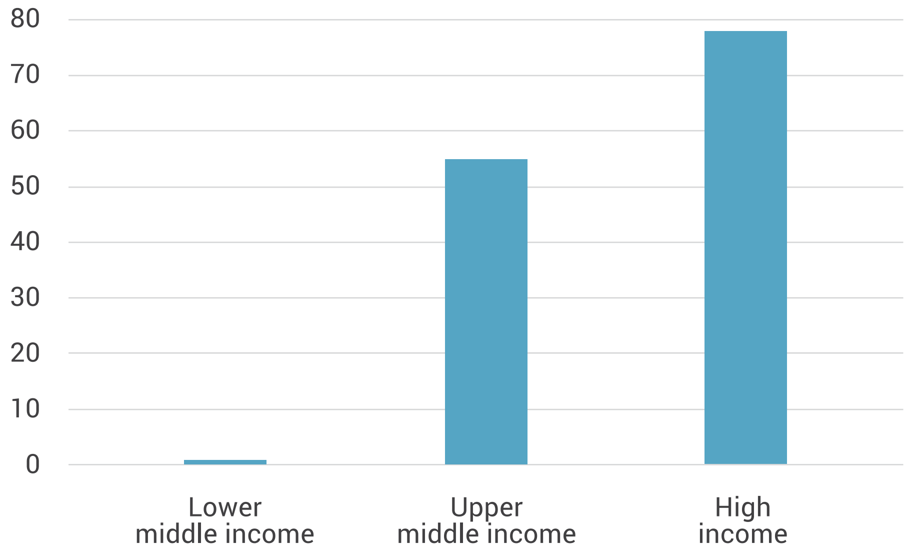
Figure 3 Number of articles using deep learning for food safety research among machine learning-based articles included in the present study



Source: Authors' own elaboration.

Figure 4 shows that a large number of the articles (59 percent) included in the literature review were from high-income countries (78 out of 133), followed by 41 percent from upper-middle-income countries (55 out of 133). Less than 1 percent originated from lower-middle-income countries (1 out of 133), and none were found from low-income countries.

Figure 4 Income category of the country of origin of the articles identified in the literature review



Source: Authors' own elaboration.

2.3.5. Summary of the literature review

To summarize the findings of the literature review, the application of AI in food safety was found to be predominantly focused on supporting the generation of scientific advice. This literature review showed that AI has been applied to enhance laboratory testing by making it more cost-effective and efficient. Research using AI has extended to understanding the causes of food contamination and foodborne diseases, thereby informing preventive measures. Predictive models have been used to help target evidence-based monitoring, enabling authorities to intensify efforts based on various conditions, such as environmental factors or historical data.

In inspection and border control, AI has been reported to have the potential to become powerful in verifying food authenticity and visually identifying contaminants, thereby improving the accuracy and efficiency of these processes. The potential of AI-driven models designed to detect food safety problem in imported foods and prioritize border checks to enhance detection rates and optimize resource allocation has been examined. This targeted approach could potentially streamline operations, reduce possibly unnecessary testing, and minimize human error.

Additionally, the application of AI to support regulatory activities utilizing real-time analytics to allow swift responses to emerging threats has been examined. The use of text sources like those found in social media, news websites, and food recall reports could further enhance food safety monitoring. By analyzing these sources, AI could identify these potential risks by partially shifting the costs of in vitro analysis laboratories to human forces involved in the development and maintenance of computer systems, contributing to the overall efficiency and effectiveness of food safety efforts.

3. Artificial intelligence case studies for food safety management

3.1. Overview

In order for food safety competent authorities to understand and learn from some currently developed and utilized AI applications for food safety management, five agencies, namely the Food Standards Agency (FSA) of the United Kingdom of Great Britain and Northern Ireland, the Istituto Zooprofilattico Sperimentale (IZS) of Italy, the Food and Drug Administration (FDA) of the United States of America, the Singapore Food Agency (SFA) of Singapore, and the Food Safety Authority of Ireland, have provided case studies on their AI applications for regulatory activities. While there are many elements to learn from these case studies, they are not necessarily tested, validated nor endorsed by FAO. They are generously shared by these agencies for the readers to see the real-life and concrete examples.

3.2. Use cases of traditional and generative artificial intelligence

The Food Standards Agency (FSA) is a government department working across England, Wales, and Northern Ireland. The FSA uses both traditional and generative AI to maintain food safety and authenticity.

AI use case. Signals

A lot of the data that the FSA receives is in the form of unstructured text. FSA leverages AI to extract, standardize, and classify information from this text, enabling the linking of datasets and aggregation of records to identify trends and risks. Throughout this process, the agency carefully considers the ethical and legal implications at every stage of the data lifecycle, ensuring compliance and responsible use. To maintain accuracy and reliability, AI models are continuously evaluated against ground truth data, allowing the detection of model drift and necessary adjustments over time. Importantly, FSA adopts a "human-in-the-loop" approach, ensuring that expert oversight remains integral to decision-making and risk assessment.

The Signals workflow (Amanatidou *et al*., 2024) uses food alerts such as those reported by the European Union's rapid alert system for food and feed (RASFF), the FDA of the United States of America, or other competent authorities, in both English and other languages. The data is automatically updated every 24 hours. If necessary, Azure is used to translate the reports to English. A BERT-based model classifies signals into categories like food, feed or food contact materials, while a sentence encoder generates embeddings to match products and hazards against preset dictionaries.

A key example of this system's effectiveness is the identification of *Listeria* contamination in Enoki mushrooms. The Signals team observed a growing number of global alerts for *Listeria* in these mushrooms, prompting closer scrutiny despite no reported listeriosis outbreaks in the United Kingdom of Great Britain and Northern Ireland. Given the serious health risks associated with consuming contaminated raw products, the Imported Foods Sampling Programme conducted targeted testing through port health and local authorities, ultimately detecting high levels of *Listeria*. As a result, additional preventative measures are being implemented to mitigate future risks.

AI use case. data sampling

Large language models (LLMs) have advanced rapidly in recent years, largely driven by commercial technology companies such as OpenAI and Google. These models have the potential to enhance the data available to the FSA, supporting more informed, data-driven decisions and policies. However, they also present risks, including challenges in verifying the accuracy of outputs and vulnerabilities to prompt injection attacks. To address these concerns, any project or service incorporating generative AI is assessed against a set of eight guiding principles. These principles have been adapted from the UK Government's Generative AI Framework to ensure responsible and secure implementation. Firstly, there is a need for low risk and low exposure, ensuring that AI applications are safe and do not pose significant threats. The lifecycle of generative AI must be carefully managed, with continuous evaluation and regular monitoring to adapt to evolving risks and needs. It is also essential to use the right tools for each specific task to ensure effectiveness. Security is a top priority. The application of generative AI must comply with legal and ethical standards, aligning with FSA policies. Transparency is crucial, and the processes must be open to scrutiny. Finally, a "human in the loop" approach ensures that expert oversight is maintained, with humans playing a critical role in decision-making and monitoring.

FSA receives 40 000 analytical test results in the form of reports every year. Extracting key information from free-text sampling data poses significant challenges, particularly in accurately interpreting contextual nuances. For example, distinguishing between "No milk protein was detected" and "Milk protein was detected," which have opposite meanings. Previously, this process was manual, limiting speed and accuracy. The goal was to enhance data shareability, improve linkage across datasets, and extract intelligence more efficiently.

To address this, an LLM-based solution was implemented using OpenAI's GPT via an existing Azure subscription to ensure adherence to FSA's security requirements. The approach incorporated contextual information to structure the extracted data, transforming it into a tabular format that could be easily accessed and visualized in dashboards.

AI use case. International Disease Monitoring+ Model

The International Disease Monitoring+ Model is a risk categorization tool to provide risk scores for animal origin products from specified countries due to microbial risk that FSA uses to inform border check rates through scientific methodology. Although the model itself does not use AI techniques, the methods used in the use cases above provide clean and up-to-date data that can be inserted into the model. This allows model outputs to be produced seamlessly every six months. Since this eliminates the time-consuming task of manual data cleaning, it enables researchers to spend more time on data analysis.

3.3. Using machine learning to predict pathogen adaptation to food sources

The Istituto Zooprofilattico Sperimentale (IZS) aimed to use a machine learning approach to predict whether pathogens have adapted to specific food sources based on genomic data (i.e., accessory genes, core genome alleles, core genome variants and pan genome kmers). This approach would be particularly valuable for outbreak investigations, where tracing a pathogen back to its food source can be extremely challenging. If the genotype of a pathogen found in an infected individual could reliably indicate its food source, it would significantly enhance the response to foodborne disease outbreaks. To explore this, the IZS trained supervised machine learning models (boosted logistic regression, extremely randomized trees, random forest (RF), stochastic gradient boosting (SGB), support vector machine (SVM) and extreme gradient boosting (XGBoost)) to classify Listeria monocytogenes as originating from dairy, fruit, leafy greens, meat, poultry, seafood and vegetables. Initial results using balanced datasets of *Listeria* isolated in the United States of America were promising (Castelli *et al*., 2023). However, when using unbalanced datasets of samples isolated in Italy from other sources, accuracy declined sharply. This drop in performance may have been due to imbalanced elements, such as variations in case distribution across food labels and geographic regions, as well as potential mislabeling of food sources—an issue that cannot be verified retroactively.

To address these challenges, the team implemented a simplified version of the workflow (i.e. using input core genome alleles with an extreme gradient boosting model) and streamlined the classification problem by reducing the number of food categories from six to two: meat and non-meat. This adjustment improved the model's accuracy to 85 percent. The resulting expert system was integrated into the IZS's bioinformatics platform, the Italian National Reference Centre for WGS of microbial pathogens (GENPAT), enabling the National Reference Laboratory to rapidly assess whether a given pathogen is associated with meat or another food type. Additionally, the importance of publicly available datasets has been emphasized in this case study for developing machine learning models, especially when local data is limited. In such cases, external datasets can be used for training, while local data can serve as an independent test set to validate the model's performance. Furthermore, IZS advocates for the development and improvement of versatile analytical workflows in supervised machine learning, enabling users to build models by selecting methods of their choice for key steps such as data balancing, feature selection, cross-validation-based modelling, and performance evaluation.

3.4. Import sampling prioritization with machine learning

The Food and Drug Administration (FDA) of the United States of America protects public health by ensuring the safety of the nation's food supply, cosmetics and radiation-emitting products. It also oversees the safety, effectiveness and security of human and veterinary drugs, biological products, and medical devices.

AI use case. Import sampling prioritization with machine learning

Every year, millions of food shipments come into the United States of America. On a typical day, there are a few inspectors in a port of entry that have to choose the right five to seven containers to examine physically and / or sample. The FDA aims to use machine learning to complement risk-based targeting of food products and supply chains likely to violate regulations for microbiological or chemical hazards in order to get the maximum efficiency out of their resources. FDA has opted to focus on classical machine learning instead of deep learning to be able to better explain their application of the regulations in a transparent manner.

The objective of the machine learning models developed by the FDA is to predict the probability that a sample will violate regulations. For samples, that means the presence of a hazard being found in the product, and for inspections, that means a serious violation that requires official regulatory action. This prediction comes in two forms: 1) the probability, ranging from 0 to 1, of being non-compliant; and 2) whether that probability is above a threshold that optimizes sensitivity (i.e. finding all violations) and specificity (i.e. not targeting those that are in compliance). This threshold can either be chosen by the model based on the training dataset or set manually by FDA staff. It varies depending on the hazard and resource capacity when deployed.

The FDA assesses model performance by determining model's ability to accurately predict violations. In addition to this, overall accuracy is assessed, which looks at how often the model's predictions are correct. Statistical significance is also analyzed using a confusion matrix and other statistical tests to ensure that the model's performance is not due to chance. Feedback from FDA staff plays a crucial role in determining the practical value of the model, as it helps assess whether the predictions are aiding in the complex targeting work of the FDA and supporting the execution of the annual work plan. Lastly, the public health impact is measured by the volume of violative food removed from commerce and the potential illness or harm that has been prevented.

Using these principles, the FDA has developed and deployed several hazard-specific models. An example is the microbiology import model. Here, more than ten years of import data was combined with past oversight and compliance information and demographic data. A boosted-tree algorithm (LightGBM) was used due to its superior ability to encode variables and explainability. Further, SHAP values helped explain the magnitude (strength) and direction (positive or negative) of a feature's predictive value. This model revealed that out of 600 000 active supply chains, only 12 percent were predicted to be violative, allowing the FDA to focus their resources. Demographic variables such as how long a firm has been in business were important predictors of violations.

All models that the FDA develops go through three stages of assessment. First the models are trained and tested on historic data, which has been randomly assigned to a train or test set using an 80/20 percent split. If the model performance is good enough, a retrospective analysis will be done, where the model is applied to all active foreign supply chains. This model is then set aside while natural sampling activities conducted by the FDA in the field continue as usual. Once sufficient data has been collected, the model's performance is evaluated using a confusion matrix to assess its accuracy, identifying false positives and false negatives. A deeper analysis is conducted to determine statistical significance and whether the model performs better than the baseline. If the model proves to be effective, the process advances to the next stage, prospective application. Here the model is deployed; and the model predictions are shared with the field staff. These predictions can help inform decisions at the point of entry, but there is always a human-in-the-loop; and the models are not dictating sample decisions. The models' predictions are meant to advise and guide.

In practice, the models show about 70 – 92 percent accuracy when used retrospectively, and their percentages stay similar or even improve when used prospectively. In the fourth quarter of 2024, 184 samples violating regulations have been sampled primarily based on model recommendation. This represents 47 million kg of food, with a declared value of USD 9.1 million. Assuming a 500 g serving size and a 10 percent illness rate, 9.4 million people did not get harmed thanks to the FDA's machine learning implementation.

The lessons that the FDA has learned from its machine learning deployment are that data quality is crucial for accurate predictions. Complete and consistent information, such as up-to-date registrations, product codes, and manufacturer details, improves model performance, while missing or inconsistent data serve as red flags. By narrowing the focus, machine learning models identify only about 17 percent of active supply chains (8 percent of total lines) as potentially violating regulations, allowing the FDA to concentrate on higher-risk shipments while facilitating trade for the rest.

Machine learning also bridges gaps in surveillance and compliance, revealing that 35 percent of flagged supply chains had never been sampled before. This dual benefit strengthens both oversight and enforcement. Additionally, applying machine learning at the supply chain level enables a shift from reactive to proactive intervention. Problematic shipments can then be removed before outbreaks or recalls occur, while insights at the industry or country level can guide training and outreach efforts to prevent violations altogether.

3.5. Proof-of-concept experimentation using language models for food safety

The whole agrifood system is connected globally; hence, food safety incidents reported around the world can be useful as early warning indicators of incoming food safety threats. However, the manual monitoring and analysis of the vast amounts of global food safety news across multiple online sources is labour-intensive and hinders timely detection of potential risks to Singapore's food supply chain. The Singapore Food Agency (SFA) is a statutory board under the Ministry of Sustainability and the Environment. SFA is the national food agency overseeing food safety and food security in Singapore.

AI use case. Online food safety news monitoring

Together with the Nanyang Technological University (NTU), SFA co-developed a system that utilises language models to retrieve, categorise and analyse relevant news articles on food safety from online sources. The system automatically processes international news and food safety reports, extracting key information such as affected products, contaminant types, and source countries. It generates structured metadata, enabling systematic tracking of emerging food safety trends and potential threats.

The AI system has the potential to significantly enhance SFA's food safety surveillance capabilities by enabling rapid detection of food safety incidents worldwide. Through automated trend analysis, it is able to support early identification of emerging risks and more targeted testing priorities, strengthening SFA's ability to proactively protect Singapore's food supply chain.

AI use case. Pathogen information tracking

The constant evolution of foodborne pathogens demands effective surveillance through the comparison of local and global pathogen characteristics. This comprehensive monitoring is crucial for protecting public health and enabling swift response to emerging threats. However, the manual process of gathering, curating and analysing pathogen data from scientific literature and multiple databases is labour-intensive and limits timely detection of food safety risks.

The SFA and NTU collaborated once again to develop an automated system that scans the scientific literature, using Large Language Models (LLMs) to filter for relevant publications on foodborne pathogens. The system extracts and systematically curates pathogen data (e.g. *Salmonella, Campylobacter* and *Escherichia coli*) into a comprehensive database. This database enables efficient comparison between local and global pathogen characteristics, significantly reduces manual processing effort, and supports swift identification of emerging threats and more targeted food safety risk assessments.

The system significantly reduces manual processing efforts while enabling rapid identification of contamination sources through enhanced data analysis. By facilitating comprehensive comparison of pathogen characteristics, it allows for swift identification of emerging threats and persistent issues, strengthening SFA's ability to protect Singapore's food safety.

3.6. Building human-centric artificial intelligence systems for emerging food safety risk identification

The early-stage integration of Artificial Intelligence (AI) into food safety systems is becoming more common. At the Food Safety Authority of Ireland (FSAI), AI is being strategically applied to assist some areas to anticipate and manage emerging risks more effectively. One of the FSAI's flagship initiatives in this space is the Emerging Risk Identification and Screening System (ERISS), which harnesses AI technologies to enhance the Authority's ability to identify and detect potential threats to food safety and security at an early stage.

AI use case. Emerging risk identification and screening system

Emerging risks, as defined by the European Food Safety Authority (EFSA), encompass newly identified hazards or significant changes in exposure or susceptibility to known hazards. These can arise from diverse sources such as climate change, supply chain shifts, novel food technologies, or geopolitical disruptions. The FSAI's ERISS monitors such developments across a time horizon ranging from six months to twenty years. Through advanced data analytics and AI-supported screening, the system triangulates intelligence from a range of scientific publications, digital media, regulatory developments, and global trade patterns to identify weak signals that may indicate future food safety risks. This approach is in line with Ireland's "National Artificial Intelligence Strategy: AI Here for Good".

To operationalize this approach, the FSAI employs a suite of AI-driven tools. These include literature mining algorithms for scientific databases, automated digital media monitoring systems, and custom alert systems for tracking driver trends. The goal is to create a rich and almost real-time view of the emerging risks landscape. These tools not only allow faster and broader scanning and screening of relevant information but also help synthesize and summarize complex datasets into actionable insights. Importantly, AI supports, but does not replace, human expertise within the authority. The ERISS system is structured to be human-centric, with domain specialists validating any AI outputs and engaging in multidisciplinary review processes to interpret findings.

Beyond horizon scanning, the FSAI also explored the use of Computer Vision and NLP in regulatory contexts. For example, the FSAI has conducted pilot projects using Convolutional Neural Networks (CNNs) to automate the recognition and classification of nutritional information on food labels. Parallel efforts have also tested text classification algorithms to assist with monitoring digital media for food safety threats, such as food fraud or consumer reports of adverse health effects.

In another proof-of-concept initiative, the FSAI has developed a bespoke large language model (LLM) using a retrieval-augmented generation (RAG) framework hosted on Microsoft Azure. This model is designed to ingest and reason over documents to assist with rapid information identification, retrieval, collation and summarizing. While promising, these efforts underscore the importance of careful model training, supervised learning, and continuous ongoing multi-expert validation of outputs to ensure the trustworthiness and interpretability of any AI-assisted results.

Despite the growing capabilities of AI systems, their use in food safety still requires rigorous expert oversight. Outputs must be carefully interpreted within the regulatory and scientific context. As such, the FSAI adopts a cautious, phased approach: these AI tools have been first developed and tested in a sandbox environment, allowing for experimentation and adjustment without affecting live operations or introducing risks. Only after thorough testing, expert review, and the establishment of appropriate safeguards are the systems considered for production-level deployment.

Overall, the FSAI's approach to AI reflects the balance needed in regulatory innovation, leveraging the efficiency and reach of machine learning and automation, while maintaining the critical role of expert judgement, ethical design, and transparency. As AI tools mature, they offer the potential to improve food safety surveillance, regulatory compliance, and consumer protection. However, the responsible deployment of such tools, underpinned by robust governance and interdisciplinary collaboration, remains paramount.

4. A global regulatory snapshot of artificial intelligence frameworks

4.1. Responsible use of artificial intelligence within the public sector

To harness the potentials and opportunities offered by AI within and beyond the field of food safety, it is important to be conscious about concomitant challenges and risks. A logical analysis of potential risks, before jumping into AI use, can help anticipate problems and advance mitigation actions (Tzachor *et al.*, 2022). Moreover, implementing the appropriate principles in digital ethics is essential for promoting the use of AI technology to the benefit of humanity and the environment. Given the innovative and complex nature of AI and the potential risks, a collective reflection is challenging but imperative (RenAIssance Foundation, 2020). In particular, when it comes to the AI use within the government agencies, this is not only a benefit but also an essential step to follow through (Alhosani and Alhashmi, 2024).

The use of AI in global agrifood systems may entail various types of risks, including data-related limitations in data acquisition, access, quality and trust. Even more because good data-driven evidence generation relies on vast amounts of high-quality data. The data on which AI systems are trained can significantly and unexpectedly change over time, affecting system functionality and trustworthiness (NIST, 2023). To train AI models, currently available data are often partial, biased, difficult to access, or of poor quality. Additionally, AI use in data generation raises ethical concerns such as data privacy and ownership, further constraining data accessibility and reusability.

The AI ethics discussion primarily involves the protection of the rights and the freedom of individuals against any sort of algorithm discrimination. This is possible when AI systems are designed and implemented to serve and protect human beings, which is reflected in the need for governments and all AI stakeholders to commit to developing and respecting frameworks and principles that structure and regulate AI. In this way, as transparency, traceability and responsibility grow, the risk of it impacting human rights will likely lessen (RenAIssance Foundation, 2020).

Awareness of the risks that can be associated with improper AI use is essential to put in place mitigation measures. Among the most efficient risk mitigation options are for the respective governments to develop AI ethics guidelines and data governance frameworks. These are essential to avoid the technological process that comes at the expense of ethical integrity, particularly when government use is involved. In this regard, several national, regional and global governance frameworks for responsible AI have emerged in recent years. The OECD observatory on AI governance offers a repository of national AI policies and strategies, gathering over 1 000 AI policy initiatives from 69 countries (OECD.AI, 2021). These initiatives reflect a global effort to ensure AI development is ethical, transparent, and beneficial to society.

4.2. Example of preliminary activities conducted by authorities (as of April 2024)

In **Australia**, the Office of the Information Commissioner published a guide to data analytics and privacy principles in 2018 and is developing a national ethics framework for AI standards and conduct (Australian Government, 2018; Australian Government, 2024). New South Wales has independently created guidance for regulators and government agencies on AI, emphasizing transparency, community benefit, fairness, privacy, and accountability (NSW AIAF, 2024).

Canada has adopted AI guiding principles requiring public institutions to incorporate ethical considerations like privacy and transparency. A Treasury Board directive outlines federal responsibilities for assessing and mitigating risks of automated decision systems, focusing on transparency and data-driven decision-making (Government of Canada, 2021). The Montreal Declaration, initiated by the University of Montreal, guides AI development with principles such as well-being, autonomy, privacy, solidarity, democratic participation, equity, diversity, caution, responsibility, and sustainable development (Université de Montreal, 2017).

China's 2017 New Generation AI development plan aims to establish AI laws, regulations, and ethical norms (Webster *et al.*, 2017). In 2019, the Chinese AI Industry Alliance released self-regulation guidelines promoting human-orientated, secure, and transparent AI (Laskai and Webster, 2019). The New Generation AI Governance Expert Committee outlined eight non-binding principles for AI development, and in 2023, measures were drafted to ensure ethical application of generative AI, addressing issues like discrimination, intellectual property, and personal information use (Seaton *et al.*, 2023).

The **European Union's** guidelines on AI ethics advocate for lawful, ethical, and robust AI, emphasizing a human-centric approach aligned with European values (High-Level Expert Group on AI, 2019). Partly entered into force in 2024, the AI Act is the first-ever comprehensive legal framework on AI worldwide, setting out clear risk-based rules for trustworthy AI in Europe (European Parliament and the Council of the European Union, 2024).

India introduced its inclusive AI strategy, #AIFORALL, in 2018, followed by the 2021 Principles for Responsible AI, which focus on safety, inclusivity, equality, privacy, transparency, accountability, and positive human values (NITI Aayog, 2018, 2021). The Digital Personal Data Protection Act of 2023 aims to create a comprehensive legal framework for the digital economy, addressing cybercrime, data protection, online safety, and intermediary regulation (Ministry of Law and Justice, 2023).

Japan's 2017 AI R&D guidelines emphasize ethics, human dignity, and autonomy, while the 2019 Social Principles of Human-Centered AI further outline ethical considerations in AI development (The Conference toward AI Network Society, 2017; Council for Social Principles of Human-centric AI, 2019).

Latin American countries are actively developing AI regulations to promote ethical AI development, protect human rights, and foster innovation. National initiatives in Argentina, Brazil, Colombia, Mexico, Chile, and Peru focus on AI regulation bills and data protection laws, targeting academia, industry, and civil society (CPDP Conferences, 2022).

In **New Zealand**, the AI Forum NZ's Trustworthy AI in Aotearoa AI Principles provide high-level guidance for AI stakeholders to ensure access to trustworthy AI (AI Forum New Zealand, 2020). These principles offer a foundation for organizations to develop their own AI ethical principles, focusing on fairness and justice, reliability, security and privacy, transparency, human oversight and accountability, and well-being.

The Republic of Korea's AI Ethical Standards, announced in 2020, are a key part of the National Strategy for AI. These standards emphasize respect for human dignity, the common good of society, and the proper use of technology. They include ten core requirements to promote 'humanity' in AI: safeguarding human rights, protecting privacy, respecting diversity, preventing harm, promoting the public good, fostering solidarity, managing data responsibly, ensuring accountability, maintaining safety, and ensuring transparency (MSIT and KISDI, 2020).

Rwanda's National AI policy, developed in 2022, aims to position the country in AI, enhance skills and AI literacy, create an open ecosystem, transform the public sector, and promote responsible adoption in the private sector (MINICT, 2022). The policy includes 14 recommendations, such as reskilling, education, international collaboration, accessibility, public AI service delivery, and responsible AI principles.

In **Singapore**, the AI Verify Foundation (AIVF) and Infocomm Media Development Authority (IMDA) developed a draft Model AI Governance Framework for Generative AI with nine dimensions to be looked at in totality for a trusted AI ecosystem (AIVF and IMDA, 2024). This framework builds on the existing Model Governance Framework that covers traditional AI, last updated in 2020 (IMDA and PDPC, 2020).

In **the United Arab Emirates**, the four Dubai principles of ethics, security, humanity, and inclusiveness for AI were established as part of a collaborative living document to create a common foundation for industry, academia, and individuals in navigating AI development. Each principle includes sub-principles to clearly define goals for AI design and behaviour (Smart Dubai, 2018).

In **the United Kingdom of Great Britain and Northern Ireland**, the AI Security Institute (AISI), part of the Department of Science, Innovation and Technology, operates as a governmental startup combining government authority with private sector expertise. Its initiatives focus on testing advanced AI systems, informing policymakers about risks, fostering collaboration across sectors to mitigate risks, and advancing publicly beneficial research. Ongoing evaluations address AI misuse, societal impacts, autonomy, and safeguards (AISI, 2024).

In **the United States of America**, the United States Artificial Intelligence Safety Institute (US AISI) was established to advance and disseminate AI safety practices, and support institutions and communities in AI safety coordination, in collaboration with diverse AI industry and civil society members, as well as international partners (US AISI, 2025). In California, the proposed bill SB-1047 aims to enact the Safe and Secure Innovation for Frontier Artificial Intelligence Models Act (Wiener *et al.*, 2024). This bill would require developers to comply with various safety and security requirements before training AI models, with the goal of reinforcing existing laws to determine digital content provenance and reduce the impact of deepfakes. Meanwhile, the 2022 blueprint for an AI Bill of Rights aims to foster innovation and trust in AI by promoting responsible stewardship of trustworthy AI while ensuring respect for human rights and democratic values. It complements existing OECD standards and sets a flexible standard for the evolving AI field (OSTP, 2022).

4.3. Global efforts and good practices

On top of national and regional frameworks, international efforts have also been made. The Rome Call for AI Ethics was signed in 2020 to promote a sense of shared responsibility among international organizations, governments, institutions and the private sector in an effort to create a future in which digital innovation and technological progress grant mankind its centrality (RenAIssance Foundation, 2020). The Global Partnership on Artificial Intelligence (GPAI) is an international initiative that involves multiple stakeholders and aims to steer the responsible development and utilization of AI, with 29 international members (GPAI, 2024).

In 2024, the GPAI announced an integrated partnership with the OECD to advance an ambitious agenda for implementing human-centric, safe, secure and trustworthy AI (OECD, 2024). The United Nations System has also acted in this space. The UN Systems Chief Executive Board of Coordination (CEB) has developed ten Principles for the Ethical Use of AI in the United Nations System to provide a basis for UN system organizations to make decisions on how to develop, design, deploy and use AI systems (CEB, 2022). Additionally, the General Conference of the United Nations Educational, Scientific and Cultural Organization (UNESCO) has independently issued a Recommendation on the Ethics of Artificial Intelligence in 2021, followed by a Readiness Assessment Methodology in 2023 for AI to be utilized, developed, and applied ethically for the benefit of humanity and our planet (UNESCO, 2021, 2023).

Overall, findable, accessible, interoperable and reusable (FAIR) data frameworks and improved standards for transparency, ownership rights and oversight, across all phases of data generation, acquisition, storage and analysis are a necessity for responsible AI (Tzachor *et al.*, 2022). Additionally, privacy and cybersecurity risks also deserve consideration to address AI trustworthiness characteristics. Therefore, when and if governments consider use of AI for their work, developing standards and guidelines, or leveraging available ones, it is a critical prerequisite to reduce security and privacy risks and promote ethical AI implementation (NIST, 2023). Since recurrent principles such as transparency, security, FAIR data, accountability and inclusivity are overarching across AI, food safety competent authorities may largely benefit from closely liaising with their government agencies in other sectors for the guidelines to be the result of a multisectoral collaboration, and even beyond national borders, in cooperation with relevant international organizations.

4.4. International and multisectoral collaboration and partnership

International and multisectoral collaborations are found to be key in developing and successfully deploying AI tools for food safety (Qian *et al.*, 2023). This includes collaborations between universities, companies, food safety competent authorities, and international organizations. Collaboration fundamentally means sharing initial investments and technical capacities, as well as fostering an AI-friendly culture. For long-term sustainability, it will become important to include AI development and AI usage in educational curricula (Chen *et al.*, 2020b). Furthermore, the UN strongly emphasizes the need for international cooperation and inclusive, multi-stakeholder partnerships, including with governments, the private sector, civil society, and academia, to ensure that AI systems are safe, secure, trustworthy, and equitably beneficial, particularly for developing countries and in support of the Sustainable Development Goals (UN General Assembly, 2024).

Collaboration is also essential in ensuring all relevant opinions are considered but also that all relevant datasets are included, thus alleviating the risk of bias in the data (Qian *et al.*, 2023). This can be done using open-source sharing, but, realistically, this is not always possible. Especially in the case of sensitive data, such as food safety data, sharing of data might not always be feasible (Magdovitz *et al.*, 2021). Fortunately, methodologies exist for AI systems to optimize without data being disclosed. One of the most promising techniques for this is federated learning (Konečný, McMahan, and Ramage, 2015). Unlike traditional approaches that require data to be centralized for model training, federated learning enables the algorithm to travel to local data sources, or “data stations”, and learn from the data without transferring it. This approach is metaphorically similar to a train stopping at various stations to collect insights without removing the cargo. Federated learning is gaining traction in food safety research, where privacy, data ownership, and regulatory sensitivity are paramount (Fendor *et al.*, 2024).

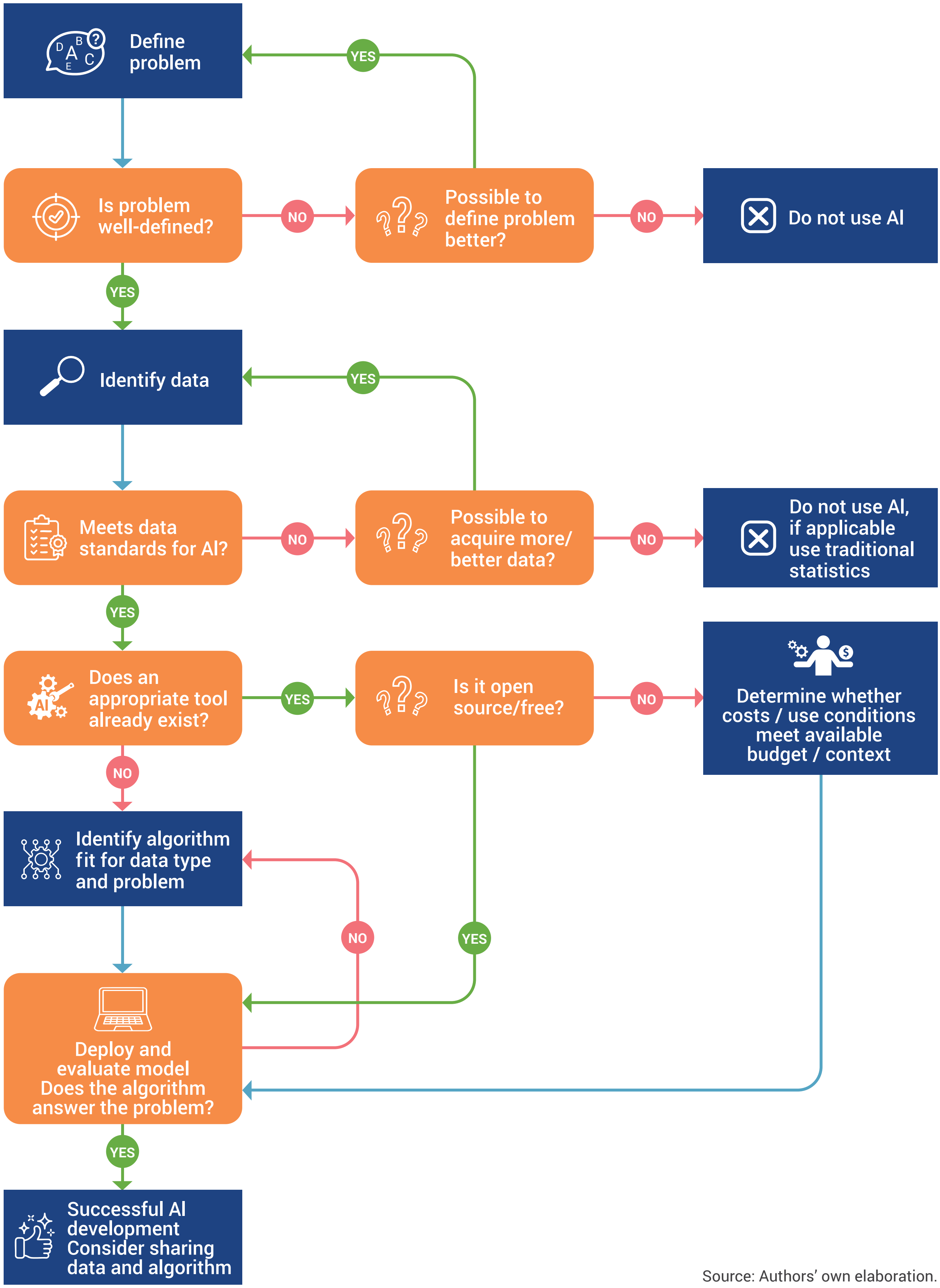
5. Considerations for the use of artificial intelligence in food safety management

5.1. Identify the problem first

When considering the use of AI for food safety in the context of governmental work, it is important to set out a clear objective to state what problem is to be resolved by developing an AI tool (Domingos, 2012). Qian *et al.*, (2023) stated that in the context of food safety, it is crucial to recognize that AI is not a universal solution, but that the focus should be on applications where AI effectively addresses specific needs and questions. To illustrate the importance of identifying the problem first, Figure 5 shows what the generic flow of the planning process could look like.

Even though it can be useful to develop algorithms without a specific objective for coding training purposes, it may sometimes be possible that certain algorithms/devices or machine learning techniques are developed before identifying a problem to solve. However, considering the substantial requirements of AI applications to be developed and used within the public systems using the public resources, the sustainability of such AI tools is questionable without a clear and valuable outcome, which is to solve an existing problem (Zatsu *et al.*, 2024). Indeed, some studies have recognized that using AI without a clear goal can lead to a waste of time and resources (Rouger, 2019; Cappaert and Muilwijk, 2023). Even though AI has been creating momentum with a lot of creative and ad hoc ideas, the use of AI in food safety management is only valuable if it offers clear net benefits, such as solutions to specific problems.

Figure 5 Generic flow of the artificial intelligence tool development for food safety
Note that traditional statistical methods often require less data



Source: Authors' own elaboration.

5.2. Value of the artificial intelligence tools

For the AI tool to be perceived as valuable to the end user, its user-friendliness is most likely essential (Evans *et al.,* 2022). For example, generative pre-trained transformers (GPT) have been around since 2018 (Radford *et al.,* 2018), but have been embraced by a critical mass since the launch of ChatGPT in 2022, which has an intuitive and user-friendly interface. In addition to usability, a successful AI tool typically is also compatible with existing tools and data (Campos Zabala, 2023). Examples include Copilot from Microsoft, Gemini for Google, and Siri for Apple. The measurable value of AI tools can typically be in automating a process and thus saving time or in achieving something with the tool that could not be achieved before. For example, conventional cancer screening can be improved by developing automated AI tools (Verburg *et al.*, 2022) utilizing CNNs for the accurate and rapid identification of breast cancer on magnetic resonance images. An example is the 2024 Nobel Prize-winning AI method AlphaFold (Jumper *et al.*, 2021). AlphaFold is an AI tool that precisely predicts the 3D structure of proteins and even designs entirely new proteins, thereby enabling experiments and scientific breakthroughs that were previously unimaginable (Callaway, 2024). Cancer screening and AlphaFold are typical examples of what the value of AI can be in task automatization and achieving novel results, albeit in specialized context.

5.3. Value of the artificial intelligence outputs

It is important to consider the value of the outputs that AI tools generate / produce. The reliability of AI output is important, and by developing AI tools in compliance with data protection standards and minimizing potential bias, one can govern reliable AI systems (Diaz-Rodrigues *et al.*, 2023).

In machine learning, accuracy is typically assessed in an independent testing dataset to prevent overfitting (Goodfellow, Bengio and Courville, 2016). Overfitting can be explained as a machine learning model performing well on the data it is trained on (seen data), but it performs poorly on new or unseen data. A proper separation of randomized data used for training the model and a holdout dataset for testing the model (e.g. 70 percent training set and 30 percent testing set) is good practice to manage overfitting and to ensure reliable, reproducible and robust models are developed. It is important to keep the holdout testing dataset separate until the very end to prevent unintentional optimization on the testing dataset (Goodfellow, Bengio and Courville, 2016).

Although a random split such as 70/30 percent is often used, in the case of data encompassing multiple years, a temporal split, using earlier years for training and more recent years for testing, closely resembles prospective validation. Of course, prospective validation of an AI model provides even higher evidence (van Calster *et al.*, 2023). Continuous monitoring of prospective performance furthermore embeds trust in these systems. This can be done (semi-)automatically or with a human-in-the-loop (Wu *et al.*, 2022).

Furthermore, it is important to note that the data used to train AI models generally have in-built bias based on where the data were collected and thus the outputs of the AI models would likely have some local adequacy. This means that the outputs of the model are fit for the specific context of the data that they were trained on (Ayling and Chapman, 2022). For example, an AI model can be designed to yield reliable and accurate outputs for a high-income country, but that does not necessarily mean that these outputs would also be adequate for a low- and middle-income context, and vice versa.

5.4. Explainable artificial intelligence

Some simple AI models, like linear regression or least absolute shrinkage and selection operator (LASSO), can easily explain the relationship between input and output, and these are called model-based explanations (van der Velden *et al.*, 2022). However, deep learning is often seen as a "black box", since neural networks are made up of many layers with complex connections, making it very hard to fully understand how the outputs are produced, even if each layer is specifically examined. Therefore, there are growing concerns that these black box models may have hidden biases, which can go unnoticed (van der Velden *et al.*, 2022). If such models directly influence food safety decisions or policies, the eventual impact can become substantial. To address this, experts support methods to make these systems more understandable (Adadi and Berrada, 2018; Murdoch *et al.*, 2019). Instead, explainable AI (XAI) methods can be used to explain them. One such method is SHapley Additive exPlanations (SHAP), which explains how much each feature contributes to the model's output using Shapley values (Shapley, 1953; Lundberg and Lee, 2017).

XAI is a relatively young field, kickstarted by Defense Advanced Research Projects Agency (DARPA) XAI program of the United States of America in May 2017 (Gunning and Aha, 2019). It has achieved tremendous uptake among multiple fields (Adadi and Berrada, 2019; Murdoch *et al.*, 2019; van der Velden *et al.*, 2022), yet it is still not mature enough to, for example, serve as an interrogable tool in a lawsuit (Rudin, 2019). These aspects also require a proper legal framework. Many jurisdictions have developed such frameworks, with one example being the European Union's AI ACT (European Commission Directorate-General for Communication, 2024).

5.5. Possible pitfalls, challenges and risk management

5.5.1. Artificial intelligence governance challenges

Due to growing concerns about the "black box" of AI, governance of AI has become key, and various legislative initiatives have started in different parts of the world. Such legislation establishes frameworks and policies to guide the ethical and responsible development and use of AI (Gyevnar, Ferguson, and Schafer, 2023). It addresses data quality, privacy, security, transparency, and accountability (both at the data and algorithm level), preventing misuse, and ensuring public trust. A typical example is removing, or correcting for, bias from AI systems (Rudin, Wang and Coker, 2020).

One way to promote and facilitate responsible AI is to use XAI, as explained in the previous section (Adadi and Berrada, 2018). This is crucial in dealing with high-stakes issues, since relevant regulations may be able to provide individuals the rights to receive meaningful information about how a decision was rendered. XAI is abundantly used in the field of medicine (van der Velden, 2022) and will likely become more and more important to yield explanations in food safety. An example of the use of XAI in food safety is Hao *et al.,* (2024), who used graph representation learning to model and interpret complex relationships between environmental factors, enabling more accurate and transparent predictions of heavy metal concentrations in soil-rice systems.

Additionally, given the growing environmental impact of AI technologies, it is crucial to align their development with sustainability principles; approaches such as green AI aim to reduce computational costs and energy consumption, making AI both more accessible and environmentally responsible (Bolón-Canedo *et al.*, 2024).

5.5.2. Biased data and hallucinations of artificial intelligence

Since AI learns from data, biased data can lead to biased AI outcomes, perpetuating or amplifying existing prejudices. For example, there is concern about unfairness in recidivism prediction in the United States of America (Rudin, Wang and Coker, 2020). Trust in AI systems can be elevated by the aforementioned examples of AI governance, responsible AI, and explainable AI. At the same time, it can also be harmed by, for example, hallucinations of AI or by malefactors. Hallucinations in AI refer to instances where artificial intelligence models, especially language models, generate incorrect, fabricated, or misleading information that may seem plausible but is actually not based on any real data or facts (Waldo and Boussard, 2024). For instance, hallucinations of AI might be details or events that never happened, confident-sounding answers that are entirely false or nonsensical, or responses that appear coherent but lack factual accuracy. It is pivotal for AI developers to address these potential threats and for AI users to develop a certain level of "AI-literacy" (Ng *et al.*, 2021). In a widely discussed incident, the New York Times reported on a lawyer who used ChatGPT to generate case citations, only to later discover that they were entirely fabricated, or 'hallucinated' (Waldo and Boussard, 2024). The potential risk of these hallucinations is highlighted by this incident, since they are often subtle and can go undetected. Human-in-the-loop, checking sources and acquiring the aforementioned AI literacy are therefore critical steps to mitigate the risks.

5.5.3. Risk management of wrongdoing

Techniques that can be used by malefactors include adversarial attacks (Kurakin, Goodfellow, and Bengio, 2018). This means that the input data is altered slightly to trick the AI into misclassifying it. These modifications are often so minimal that they are imperceptible to human observers. However, the AI will still make a mistake based on this very subtle modification. Another related threat is data poisoning, where manipulated or misleading data is introduced during the training phase to corrupt the model's behaviour. While there are several technical solutions to making AI robust against such wrongdoing (Tramèr *et al.*, 2017), a crucial step towards preventing such wrongdoing is to know your data and to always consider domain-specific sanity checks.

5.5.4. Premature use of artificial intelligence

The risk of prematurely using AI in food safety, whether by applying techniques that are not yet suitable for the specific data or problem or by implementing AI without the necessary expertise to interpret its output, lies in potentially undermining the trust and credibility of the organization employing it (Santoni de Sio and Mecacci, 2021; Smith, 2018). Maintaining consumer trust in food safety authorities is crucial, as it strongly influences both food safety practices and purchasing decisions (Chen, 2008). As with all advanced tools, the ability to determine appropriateness can be a continuous matter of debate. Guardrails for proper AI use are continuously constructed; nevertheless, it is wise to consult with AI experts before applying such techniques (Lekadir *et al.*, 2025). Mitigation strategies could include extensive validation of AI in different contexts, thorough risk assessment (legal, ethical and social), user testing, and appropriate and extensive documentation.

5.6. Data governance and data gaps

Data governance involves defining who has authority and control over data and how that authority is exercised through decision-making on data-related issues (Janssen *et al*., 2020). One of the best-known examples of good data governance is FAIR (Wilkinson *et al*., 2016), which aims to ensure that data are findable, accessible, interoperable, and reusable (FAIR). Findable data includes metadata, which is descriptive information about the given data. The availability and the accessibility of data and metadata for both humans and machines are key. This can include authentication or authorization, especially if the data is sensitive, which can be the case for food safety data. FAIR does not mean that the data has to be openly available (Wilkinson *et al*., 2016). Storing data in standardized formats helps accomplish interoperability. Interoperable means that both humans and machines are able to use the data.

Reusability of data by others can be achieved by providing good documentation and selecting a proper sharing license for your data (Wilkinson *et al*., 2016). At many research centres, such as universities, data management plans are mandatory (WUR, 2025). This facilitates collection and storage of data in a FAIR manner. Once data are FAIR, they can be stored online in publicly available repositories such as Zenodo (European Organization for Nuclear Research and OpenAIRE, 2013) and Harvard Dataverse (King, 2007) or in data spaces such as the European Union's Common European Data Spaces (European Commission Directorate-General for Communication, 2025). Many funders and publishers encourage researchers to publicly share their research data whenever possible after publishing their research papers (Wendelborn, Anger, and Schickhardt, 2024). Data sharing is a part of the Open Science philosophy, which aims for transparent and accessible knowledge that is shared and developed through collaborative networks (Vicente-Saez and Martinez-Fuentes, 2018). Ensuring that data is FAIR (and shared whenever possible) will significantly advance AI-driven research in food safety. By making data widely available, researchers, including those who lack the resources to collect their own datasets, can still conduct meaningful studies, thereby contributing to the collective progress of the field.

5.7. Public algorithm sharing mechanisms

In recent years, the practice of sharing algorithms has become increasingly prevalent. This shift is in part driven by the desire for greater collaboration and transparency within the research and development communities. Open-source platforms such as GitHub (GitHub, 2025) or GitLab (GitLab, 2025) have become central hubs where developers and researchers across the globe can share, modify, and build upon each other's code. By making algorithms publicly available, these platforms enable others to replicate studies, verify results, and contribute to improvements. Other platforms like Docker Hub (Docker, 2025) and Anaconda Hub (Anaconda, 2025) are dedicated to hosting transportable images of algorithms that can be transferred between operational systems to contribute to the exchange and reproducibility of algorithms.

Additionally, AI community platforms like Hugging Face (Hugging Face, 2025) have emerged as popular spaces where researchers, developers, and companies can share pre-trained models, datasets, and tools. Hugging Face offers an extensive library of state-of-the-art AI models, including NLP models that can be fine-tuned and adapted for various applications, from sentiment analysis to text generation. These platforms foster a collaborative environment, enabling individuals and organizations to accelerate the development of AI models and reduce the duplication of efforts. It is important to check that models are developed or governed by trusted sources.

Tech companies have also contributed significantly to the open-source movement, particularly in the realm of deep learning. Meta AI, for example, developed the PyTorch framework, which has become one of the most widely used tools in deep learning (Patel, 2017). PyTorch has rapidly gained popularity due to its flexibility, ease of use, and strong support for research-oriented tasks. Regarding Python libraries, it is important to note that PyTorch is designed for deep learning (Paszke *et al.*, 2019), whereas scikit-learn is primarily used for machine learning (Pedregosa *et al.*, 2011). By making PyTorch open-source, Meta AI has allowed researchers and developers to access and modify the framework, fostering innovation across a variety of industries, from healthcare to finance (Patel, 2017).

Alongside PyTorch, TensorFlow, developed by Google, is another widely used open-source framework that has played a major role in democratizing access to deep learning tools. In parallel with these code-based platforms, zero-code and no-code AI tools are also gaining traction, further democratizing access to AI technologies. Tools such as Google's AutoML, Microsoft's Lobe, IBM Watson Studio, and Teachable Machine allow users to build, train, and deploy AI models through visual interfaces without writing a single line of code. These platforms enable subject-matter experts, educators, and small business owners to apply AI to real-world problems without the need for advanced technical expertise. By lowering the barrier to entry, no-code tools contribute to broader participation in AI development and innovation. Such public sharing mechanisms are pivotal to the continued growth of the AI field, ensuring that advancements are not only built upon but also scrutinized, improving the overall quality and ethical standards of the technologies being developed.

5.8. Artificial intelligence literacy and capacity development

AI literacy can be defined as the basic competencies to know and understand, use and apply, as well as evaluate and create AI (Ng *et al.*, 2021). The development of AI literacy through training and education is a critical step to prepare for a future in which AI will likely play an increasingly large role in food safety management. The development of AI capacity is essential before integrating AI in food safety management. Without this foundation, individuals and organizations would risk implementing AI systems that are ineffective, unreliable, or unable to generate meaningful insights from complex food safety data, thereby compromising the potential benefits of AI (Díaz-Rodríguez *et al.*, 2023). It is furthermore important for training and education to include responsible data management and use (Frugoli, Etgen, and Kuhar, 2010).

5.9. Support for data-driven decision-making

5.9.1. Required data for artificial intelligence development

When considering the development of AI applications to solve a defined problem, one of the first steps is to identify the relevant data that are already existing and readily accessible (Zatsu *et al.*, 2024). Having a sufficient amount and appropriately high-quality data is an essential basis for AI applications, because such data is necessary to effectively train and validate AI models (Liang *et al.*, 2022). In the area of food safety, the whole food supply chains from production through retail to consumers within the agrifood systems have, in theory, a great potential in generating large volumes of data that can feed into AI applications (Rugji *et al.*, 2024). The outputs from such AI tools could be applied to various food safety-related assessment, prediction, categorization and prioritization methodologies so that they can be useful in proactive risk management actions and data-driven decision-making for the competent authorities (Strawn *et al.*, 2013).

Data can be structured or unstructured and can be in the form of raw data such as numeric data, texts, images, audio and / or video, or can be obtained from secondary sources such as existing databases. However, if the relevant dataset does not exist in sufficient quantity or high quality, or if it is not readily accessible, then developing AI applications might not be appropriate, especially because the amount and quality of required input data cannot be predicted beforehand to estimate the model performance (Zatsu *et al.*, 2024). Once an adequate dataset has been identified or built, the next step is to assess the data quality and governing structure, including the ownership of the data as well as the legal and ethical considerations of the collected data (Rugji *et al.*, 2024). The legitimacy of the data also needs to be evaluated together with the sensitivity assessment for responsible AI development (NIST, 2023).

Potentially sensitive information contained in the data may be securely removed or anonymized before use and can be verified for correctness and completeness. To streamline the data governance assessment processes, having a comprehensive AI policy as a prerequisite activity may be useful, and part of such a policy can be dedicated to ensuring the responsible use of data for AI applications actions (Tzachor *et al.*, 2022).

With the presence of such a structure, it is important that ethical compliance is assessed through human supervision to guarantee proper use of data as well as adherence to relevant laws. Furthermore, transparency assurance is important, availing information to data providers on how their data are used and the resulting AI system's outcome. Experts in data protection and other relevant legal matters can be designated to work with the AI development team to follow through on ethical responsibility.

Box 1. Checklist for data requirements for responsible artificial intelligence

- ☐ Does the required dataset exist?
- ☐ Who owns the dataset?
- ☐ Is the use of the dataset allowed by the owner in a sustainable manner?
- ☐ Is the dataset accessible?
- ☐ Is the dataset legally and ethically usable?
- ☐ Is the source of the data credible, and is the dataset reliable?
- ☐ Are there any sensitivity issues in the dataset / parameters? If yes, is it manageable?
- ☐ Is the dataset sufficient in its amount?
- ☐ Is the quality of the data sufficiently high?
- ☐ Is the data structure appropriate for AI applications?
- ☐ Can the use of data be transparent and sustainable?
- ☐ Is there a need to pre-process / improve / optimize the dataset prior to AI development?

5.9.2. Quality of data

It can be considered that data quality is more important than its quantity in AI applications. Figure 6 illustrates general components of quality data standards. Accuracy of AI learning models is highly dependent on the quality of data. However, obtaining uniform and high quality food safety data is often a challenge due to the complexity and diversity of agrifood systems. Because of this, imbalanced, heterogenous, skewed or missing data may occur, and this can affect the performance of the AI algorithms (Qian *et al*., 2022). Additionally, diversity of food matrices leads to a variety of data types because various protocols and testing methods exist. For example, on-site contaminant detection emphasizes efficiency and portability, while laboratory-based contaminant detection focuses on accuracy and precision. Sample sizes also affect the overall data quality. Also, as negative (safe) results are not usually reported publicly, there is a possibility that data may be already skewed with positive (unsafe) results that are reported and documented.

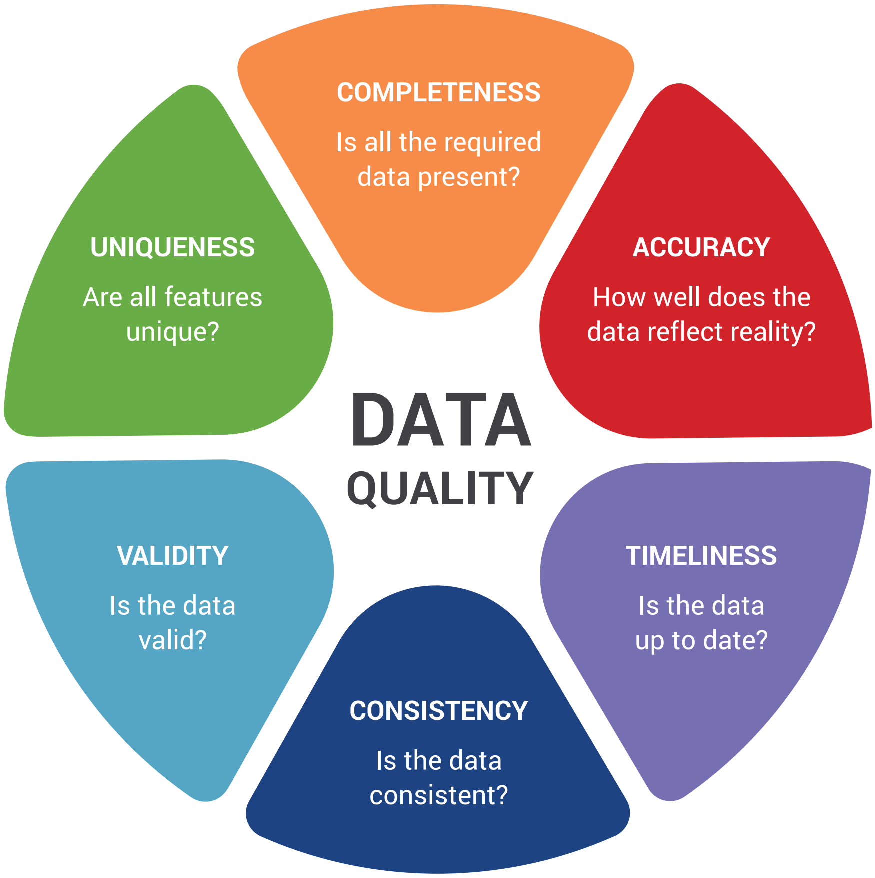
Another key factor in maintaining the quality of data is bias reduction. For example, when using data from social media to predict public opinion of a given novel food, it is not possible to capture all the behavioural and demographic factors by the gathered data (Deng, Cao and Horn, 2021). This introduces bias into the AI model, so data selection must be performed in a balanced manner or artificially rebalanced through computational methods. Concerted efforts can be made to ensure standardized approaches to the collection, analysis and sharing of data.

Preprocessing the data can contribute to data consistency, thus potentially improving and optimizing the data to train the AI models. For preprocessing, the data can be optimized to extract the essential parameters only. It is a common practice in AI applications to build models with many parameters at first, as this helps verify the ability of the model to capture underlying patterns and associations. However, in classical machine learning approaches such as logistic regression, it becomes important to limit the number of parameters to only those that are essential. This practice prevents overfitting and ensures that model performance does not deteriorate due to excessive complexity (Friedman, 1997).

Box 2. Questions to validate if the data meets the data standards

- Is the dataset of sufficient quality and quantity?
    - Can the dataset be split into sufficiently large training and test sets?
- Is the dataset fit for the problem? (examine descriptives)
- Is metadata available?
- Does the dataset meet ethical and legal standards?
    - Does the dataset meet FAIR standards?
- Does the dataset contain known biases?
- Does the dataset pass a sensitivity check / does the output comply with sensitivity regulations?

Figure 6 General components of data quality standards



Source: Authors' own elaboration.

Box 3. Options for improving / preprocessing data for artificial intelligence

- Standardizing the data collection approaches
- Increasing the sample sizes
- Addition / removal of parameters
- Bias reduction
- Sensitivity management

5.9.3. Data gaps and preparedness for artificial intelligence development

It is more than possible for many countries to have only a limited amount of food safety data sets that are currently available and digitalized, and it can create a significant obstacle in the development of AI applications (Qian *et al.*, 2022). While it is not realistic to aim at effective AI development in this data-gap situation, working on some key prerequisite activities meanwhile can be useful, as they are in any case necessary for the steps forward.

Bridging the data gap would most likely involve allocating financial and human resources to establish effective data generation, collection and consolidation systems, therefore, it can be useful to start exploring collaborations and partnerships among the relevant government agencies, research institutions, universities and laboratories, as well as with some reputable organizations to find resource-effective strategies, as mentioned in the AI policies in the regulatory snapshot chapter. Developing a strategy to nurture a data-sharing culture between public and private sectors is also one of the forward-looking activities for future AI development. Development of the national AI policy to be applied in the food safety sector is also considered to be a good practice for responsible AI, and referring to the examples introduced in the regulatory snapshot chapter can be a good starting point.

Box 4. Example prerequisite activities for artificial intelligence development in case of data gap

- Explore collaborations and partnerships to establish effective data collection systems
- Strategize to develop a data-sharing culture between public and private sectors
- Develop an AI policy document, including an ethical and responsible AI strategy
- Capacity development training for food safety competent authorities on privacy data protection, awareness and data literacy
- Technical training on AI applications currently used for food safety in the public sector
- Development of combined expertise in food safety, data analytics and AI

6. Tips for food safety competent authorities

Food safety competent authorities who wish to benefit from AI applications to improve the effectiveness and efficiency of their work may like to consider following tips provided by some early adopters.

6.1. Consider some key activities to be completed first

Before implementing AI, it would be valuable and almost essential for food safety competent authorities to assess the **AI governance** framework within the **country context**. Various AI institutes, as well as national and regional bodies, emphasize the importance of ethical and responsible AI use. Many of these guidelines highlight key principles, including transparency, inclusivity, accountability, impartiality (lack of bias), reliability, and respect for user and data privacy (RenAIssance Foundation, 2020; GPAI, n.d.; OECD, 2024; CEB, 2022; UNESCO, 2021, 2023). **Transparency** is a very common central theme among multiple guidelines, as AI systems and their output production processes are often invisible; thus, clear explanations are necessary in a way that is accessible to relevant stakeholders. Ensuring that AI systems and the data they rely on comply with legal and regulatory requirements, including intellectual property laws, is also a critical consideration.

Example actions

- Review the AI governance framework within the country to fully understand ethical and responsible AI use. If there is no policy, consider developing one.
- Hold a stakeholder meeting to discuss the governance issues with various sector experts to understand what needs to be done from the government side prior to developing AI applications.
- Consult international knowledge resources to understand the trend in AI applications to understand how transparency can be maintained.

6.2. Assess the current capacity for artificial intelligence development

Adequate **AI capacity** for the development and application of AI tools has been described as a critical step in order to ensure responsible AI usage (Ng *et al.*, 2021). Therefore, evaluating whether such capacity is in place before deploying AI is important. If there is a limitation, enhancing education and literacy in **data science, computer science**, and **design thinking** will enable food safety professionals to communicate more effectively across disciplines and articulate specific needs (Qian *et al.*, 2023).

Furthermore, several organizations have emphasized the importance of ensuring that the AI tools can be sustained after their initial development (US AISI, 2025; Université de Montreal, 2017). For example, the American Artificial Intelligence Safety Institute (AISI) states sustainable development as one of their five value-based principles (US AISI, 2025). Likewise, sustainable AI development is one of the seven principles of the Montreal Declaration for Responsible AI (Université de Montreal, 2017). Including AI development and usage in **educational curricula** could be considered as an important tool to promote the **long-term sustainability of AI** (Chen *et al.*, 2020b).

Example actions

- Consider holding an expert consultation meeting to discuss the national capacity in AI and relevant fields.
- Collaborate with academic partners (e.g. university professors) to conduct research on the current national status of AI development in general as well as in the area of food safety.
- Consult academic partners and higher education authorities to review the educational curriculum on AI and relevant fields.

6.3. Ensure the readiness of data

Before developing and using an AI tool, food safety competent authorities will likely need to evaluate the training data to determine its **representativeness** and / or **the presence of potential biases**. For example, the Japanese government has documented that such efforts should be made to prevent the creation of unbalanced datasets of humankind that could result from an AI model trained on biased data (Council for Social Principles of Human-centric AI, 2019).

The **FAIR** principles can provide a good approach to help ensure data and metadata are easy to locate, with clear access conditions, even for sensitive data (Wilkinson *et al.*, 2016). **Interoperability** is achieved through standardized formats, enabling both humans and machines to use the data. **Reusability** depends on proper documentation and appropriate licensing).

Example actions

- Consider adopting relevant principles like FAIR; and sharing data to advance AI-driven food safety research.
- Strategize effective data standardization and responsible data sharing for future AI development in the field of food safety.

6.4. Step back and take a strong agrifood systems approach

Agrifood systems include the entire range of actors and their interlinked value-adding activities and involve the entire food supply chain, as well as the broader economic, societal and natural environments in which they are embedded (FAO, 2018). The importance of a systems approach is demonstrated by the European Geographical Bovine Spongiform Encephalopathy Risk Assessment (GBR), which integrated multiple factors, such as trade patterns, surveillance capacity, and national feed and farming practices, to evaluate and manage Bovine Spongiform Encephalopathy (BSE) risk. By accounting for both external challenges and the internal stability of national systems, the GBR enabled preventive, risk-based decision-making at national and international levels (Salman *et al.*, 2012).

The agrifood systems are complex, and every part of the system may have a completely different way to manage, communicate and store data. Therefore, using AI to create a **holistic model** of the global agrifood system to assess food safety aspects has been reported to have great potential benefits (Nayak and Waterson, 2019). Because of the complexity of the global food system, it has been suggested **a system-of-systems approach** may be used, where systems are modelled both at the micro and macro level first to eventually form a holistic model (Nayak and Waterson, 2019). In this way, one system's success can positively influence surrounding systems, and many different actors within the system may benefit from various AI applications at the same time.

Example actions

- Hold an internal meeting with various colleagues in the agency / authority to discuss possible interests, needs and opportunities for jointly developing AI applications.
- List up issues / problems that may be addressed by AI and share with colleagues and partner agencies who may share the same issues / problems.

6.5. If the data is not ready, consider generating quality data for a long run

When evaluating the training data, it is possible to conclude that the data sets are possibly biased, insufficient in amount, or not easy / ready to be accessed, thus not suitable for use for AI (Schwartz *et al.*, 2022). If this happens, this means the AI development using the data sets will not succeed, as the outputs will become unreliable. In this case, food safety competent authorities may like to consider it as an opportunity to review and improve the mechanisms of relevant data generation, collection and consolidation (Alhosani and Alhashmi, 2024). Although the data generated and collected through the revised mechanism would not be immediately useful for AI development, maintaining such mechanisms to collect high-quality data will likely result in the improvement of food safety activities (EFSA, 2018). And in the long run, this may contribute to a better opportunity for future AI applications.

Example actions

- Redirect the final goal from development of AI to improvement of food safety situations to focus on quality data collection.
- Highlight the issues with the data sets that are not AI-ready so that they can be used as valuable lesson-learned material.

6.6. Actively collaborate with various stakeholders for artificial intelligence development

Several guidelines have emphasized the importance of having strong and effective partnerships among stakeholders, including private sectors, government agencies and academia at all national, regional and international levels, to work together in AI development (The Conference toward AI Network Society, 2017; Council for Social Principles of Human-centric AI, 2019; Webster *et al.*, 2017). Such cooperation would foster innovation while helping to mitigate potential risks associated with AI deployment (AISI, 2024).

Example actions

- Look for and join a pilot programme to develop AI in the related public health fields.
- Consider developing regional networks on AI for food safety to discuss the current status and pipeline applications that may benefit various countries in the region.
- Consult international organizations such as FAO to obtain good practices and lessons learned, as well as to learn about the methods to assess the feasibility of using AI for food safety management.

7. Conclusions and the way forward

This document has explored the integration of artificial intelligence (AI) into food safety management, highlighting both the significant opportunities and the pressing challenges. AI tools have so far shown potential to support a range of food safety activities, including scientific advice, inspection, border control and other relevant activities typically carried out by food safety competent authorities. However, the effective and responsible use of AI demands robust AI governance frameworks, high-quality data, cross-sectoral collaboration, and an inclusive approach that leaves no one behind.

The literature synthesis, case studies, and regulatory insights presented in this document collectively emphasize that, for food safety competent authorities, AI is not a goal in itself but a means to enhance the efficiency and timely responses for food safety activities to achieve public health protection, sustainability and resilience of agrifood systems. Those competent authorities can identify and define clear problems that AI may be able to assist with, assess their current capacities, and invest in fundamental elements such as data readiness and human capital development. Moreover, ethical and responsible use of AI are the priority issues for the public sectors to mitigate risks like bias, data misuse, and hallucinations, ensuring that AI-based decisions remain trustworthy and explainable.

Moving forward, key actions that can support the responsible and effective deployment of AI in food safety include:

- Strengthening AI governance and ethical frameworks: Governments and relevant stakeholders can collaborate and continue to develop, adopt, and update AI governance frameworks that emphasize transparency, accountability, fairness, and human rights.
- Building AI literacy and capacity: Food safety competent authorities can invest in capacity development, including training on AI fundamentals, data science, and risk communication, to ensure that staff can understand, evaluate, and oversee AI systems effectively.
- Improving data systems: High-quality, interoperable, and ethically governed data are essential. Authorities can work to bridge data gaps through partnerships, data-sharing initiatives, and the adoption of FAIR principles.
- Encouraging collaboration: Collaboration among public sector agencies, academia, the private sector, and international organizations is crucial for sharing knowledge, experiences, and best practices in AI development and deployment.
- Adopting a systems approach: Given the complexity of agrifood systems, AI would be best applied if it is done within an integrated framework, through systems thinking, that considers interactions across the entire food value chain, thereby enhancing risk-based decision-making and promoting sustainability.

In conclusion, while AI holds greater transformative potential for the future of food safety, its implementation must be grounded in rigorous governance, shared knowledge, and ethical responsibility. FAO, in collaboration with various partner agencies, remains committed to supporting countries in navigating this evolving landscape, ensuring that AI serves as a tool for building safer, more efficient, more sustainable, more resilient and more inclusive agrifood systems.

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Annex 1. Search Strategy

Introduction

This annex describes a strategy literature synthesis on the use of AI in food safety.

Scope

The PRISMA framework was chosen for scoping reviews for developing this review.

Bias management

To minimize the risk of bias, a balanced team composition was ensured. The team consisted of a gender and nationality balanced group of expert researchers from WFSR and FAO. The gender balance was 4/5 (80 percent) female, 1/5 (20 percent) male. The team members originated from three continents (Africa, Asia, Europe).

Databases

Scopus (Elsevier) was used for the search. Only peer reviewed journal publications were included. The publication years for the review were initially set from 2004 to 2024 to cover the last two decades. However, since almost no directly relevant articles were found between 2004 and 2012, the final cut-off was determined to be from 2012 to 2024.

Search string

Concept and the linked search terms used for the bibliographic search

Concept	Search terms
AI in Food Safety	(("artificial intelligence") OR ("machine learning")) AND ("food safety")

Limitations

As the period of publications had an upper time limit of April 1st, 2024, by the time of publication of the document in 2025, there can be more relevant articles which were not . Searches were performed for Title and Abstracts, and Keywords/Topic/Identifiers. The language of the body of the publication was limited to English. Editorials, opinions, reviews, abstracts, conference proceedings and all other works not representing original work were not be included in the core selection, yet some of these were retained for use (e.g. reviews).

Data storage

Records: Mendeley libraries, raw and edited excel spreadsheets.

AI assisted literature search

For the main search, ASReview was be used (ASReview, 2023; Van de Schoot *et al.*, 2021). ASReview guarantees a optimal procedure of literature review and is commonly accepted (used in 317 papers in three years).

Annex 2. Overview of the reviewed papers

Paper	Country of origin		Topic	Machine learning technique(s)	Deep Learning
Ahmed *et al.*, 2013	USA	Scientific advice	Efficiency	SVM	no
Al *et al.*, 2024	Turkey	Scientific advice	Prediction	ANN RF SVR MLR	no
Ataş, Yardimci and Temizel, 2012	Turkey	Scientific advice	Laboratory testing	SVM	no
Berhilevych *et al.*, 2019	Ukraine	Scientific advice	Prediction	ANN	no
Bisgin *et al.*, 2018	USA	Inspection & border testing	Efficiency	ANN SVM	no
Bolinger *et al.*, 2021	USA	Scientific advice	Prediction	RF	no
Bouzembrak and Marvin, 2019	Netherlands	Scientific advice	Research	BN	no
Branstad-Spates *et al.*, 2023	USA	Regulatory aspects	Prediction	GBM	no
Buyuktepe *et al.*, 2023	Turkey	Scientific advice	Research	LIME SHAP	yes
Camardo Leggieri, Mazzoni and Battilani, 2021	Italy	Scientific advice	Research	DNN	yes
Chang, *et al.*, 2020	Taiwan	Regulatory aspects	Prioritization	RF	no
Chen *et al.*, 2020a	China	Scientific advice	Research	unclear	unclear
Chen *et al.*, 2022	China	Scientific advice	Laboratory testing	ResNet	yes
Chen and Zhang., 2022	China	Regulatory aspects	Efficiency	SVM BERT	yes
Chen *et al.*, 2024a	China	Scientific advice	Research	multiple	yes
Chen *et al.*, 2024b	China	Scientific advice	Laboratory testing	ANN RF SVM BOOST	no
Cheng *et al.*, 2022	China	Scientific advice	Laboratory testing	ELM	no
Chung, Weller and Kovac, 2020	USA	Scientific advice	Laboratory testing	RF	no
Chung *et al.*, 2022	Hong Kong	Scientific advice	Efficiency	XGBOOST ExtraTrees	no
Cox, 2021	USA	Scientific advice	Research	RF BN GBM	no
Darwish *et al.*, 2022	France	Scientific advice	Laboratory testing	SVM	no

Paper	Country of origin		Topic	Machine learning technique(s)	Deep Learning
de Oliveira *et al.*, 2022	Brazil	Scientific advice	Laboratory testing	Decision Tree	no
Du *et al.*, 2022	China	Scientific advice	Laboratory testing	GAN with SVM	yes
Feng *et al.*, 2023	China	Scientific advice	Laboratory testing	Computer vision	no
Feng *et al.*, 2024	China	Scientific advice	Laboratory testing	multiple	no
Gao, *et al.*, 2022	China	Scientific advice	Laboratory testing	FNN RF SVM	yes
Goldberg *et al.*, 2022	USA	Scientific advice	Research	AFINN CC	no
Golden, Rothrock and Mishra, 2019	USA	Scientific advice	Research	RF	no
Gonçalves *et al.*, 2023	Brazil	Scientific advice	Laboratory testing	Multiple (LDA, MLP. Trees)	no
He *et al.*, 2022	China	Scientific advice	Laboratory testing	SVM ANN	no
Hu *et al.*, 2020	China	Scientific advice	Research	RF	no
Hu, *et al.*, 2023	China	Scientific advice	Laboratory testing	CNN	yes
Huang *et al.*, 2023	China	Scientific advice	Prediction	SVM RF BP-NN	yes
Im *et al.*, 2021	USA	Scientific advice	Research	RF	no
Jia *et al.*, 2021	USA	Scientific advice	Laboratory testing	DFNN	yes
Jia *et al.*, 2024	USA	Scientific advice	Laboratory testing	DFNN	yes
Jin *et al.*, 2023	China	Scientific advice	Laboratory testing	DF CNN	yes
Jo, *et al.*, 2023	South Korea	Scientific advice	Laboratory testing	AlexNet CNN	yes
Kalkan *et al.*, 2014	Turkey	Scientific advice	Laboratory testing	SVC ANN	no
Kang, Park and Chen, 2020	USA	Scientific advice	Laboratory testing	Autoencoder	yes
Kang *et al.*, 2020	USA	Scientific advice	Laboratory testing	unet	yes
Karanth *et al.*, 2022	USA	Scientific advice	Prediction	RF SVM etc	no
Karanth and Pradhan, 2023	USA	Scientific advice	Research	Elastic net	no
Kim *et al.*, 2015	South Korea	Scientific advice	Laboratory testing	SVM kNN	no
Kim *et al.*, 2023	USA	Scientific advice	Laboratory testing	multiple inv SVM	no
Kusuma and Nurilmala 2016	Indonesia	Inspection & border testing	Testing	SVM	no
Li *et al.*, 2022	China	Scientific advice	Laboratory testing	SVM CNN Denoising Autoencoder	yes

Paper	Country of origin		Topic	Machine learning technique(s)	Deep Learning
Lim *et al.*, 2020	Singapore	Scientific advice	Research	DNN	yes
Lin *et al.*, 2022	China	Scientific advice	Prediction	CNN	yes
Liu *et al.*, 2021	Netherlands	Regulatory aspects	Prediction	BN	no
Liu *et al.*, 2023	China	Inspection & border testing	Testing	ResNet	yes
Lu *et al.*, 2024	China	Scientific advice	Laboratory testing	BP-NN	yes
Lyu *et al.*, 2022	USA	Scientific advice	Laboratory testing	SVM RF LASSO	no
Ma *et al.*, 2021	China	Scientific advice	Laboratory testing	ELM	no
Ma *et al.*, 2023a	China	Scientific advice	Laboratory testing	SVM RF NN	no
Ma *et al.*, 2023b	USA	Scientific advice	Laboratory testing	YOLOv4	yes
Ma *et al.*, 2023c	China	Scientific advice	Prediction	RF ANN	no
Maeda *et al.*, 2019	Japan	Scientific advice	Laboratory testing	SVM RF	no
Maharana *et al.*, 2019	USA	Scientific advice	Research	SVM BERT	yes
Makridis, Mavrepis and Kyriazis, 2023	Greece	Scientific advice	Research	DNN ResNet	yes
Mangmee *et al.*, 2020	Thailand	Scientific advice	Laboratory testing	SNN kNN	no
Marcoux *et al.*, 2014	France	Scientific advice	Laboratory testing	BN	no
Marvin and Bouzembrak, 2020	Netherlands	Scientific advice	Research	BN	no
Marzec-Schmidt *et al.*, 2021	Sweden	Scientific advice	Prediction	SVM RF	no
Mateo *et al.*, 2023	Spain	Scientific advice	Prediction	XGBOOST RF NN	no
Mavani *et al.*, 2024	Malaysia	Scientific advice	Research	FL	no
Mi *et al.*, 2023	China	Scientific advice	Prediction	BP-NN	yes
Munck *et al.*, 2020	Denmark	Regulatory aspects	Prediction	RF logit boost	no
Murphy *et al.*, 2021	USA	Scientific advice	Research	RF MMI	no
Nagy *et al.*, 2023	Hungary	Scientific advice	Prediction	CNN	yes
Nallan Chakravartula *et al.*, 2022	Italy	Scientific advice	Laboratory testing	CNN	yes
Nanou, Pliatsika and Couris, 2023	Greece	Scientific advice	Laboratory testing	SVM	no
Nogales, Díaz-Morón and García-Tejedor, 2022	Spain	Scientific advice	Research	MLP CNN RF	yes

Paper	Country of origin		Topic	Machine learning technique(s)	Deep Learning
Oldroyd, Morris and Birkin, 2021	UK	Regulatory aspects	Prioritization	RF SVM	no
Park *et al.*, 2023	USA	Scientific advice	Laboratory testing	fusion-net	yes
Petrea *et al.*, 2020	Romania	Scientific advice	Research	RF	no
Pillai *et al.*, 2022	USA	Scientific advice	Research	GAN SHAP MLP XGBOOST RF	yes
Portz *et al.*, 2022	Brasil	Regulatory aspects	Prioritization	DT NN	no
Pradana-López *et al.*, 2022	Spain	Scientific advice	Laboratory testing	ResNet viz.	yes
Rahi *et al.*, 2021	Iran	Scientific advice	Laboratory testing	GA	no
Rodríguez *et al.*, 2023	Spain	Scientific advice	Research	RF	no
Rortais *et al.*, 2021	Italy	Regulatory aspects	Prioritization	LDA	no
Sadilek *et al.*, 2017	USA	Regulatory aspects	Prioritization	log-linear maximum entropy	no
Sadilek *et al.*, 2018	USA	Regulatory aspects	Prioritization	log-linear maximum entropy	no
Saha *et al.*, 2023	Canada	Scientific advice	Laboratory testing	CNN	yes
Setiawan, Adi and Widodo, 2024	Indonesia	Scientific advice	Research	DCNN ResNet	yes
Shin *et al.*, 2023	USA	Scientific advice	Laboratory testing	SVM ANN	no
Smeesters *et al.*, 2021	Belgium	Scientific advice	Laboratory testing	ELM LDA	no
Song *et al.*, 2022	China	Scientific advice	Research	BERT LSTM SVM	yes
Stanosheck, *et al.*, 2024	USA	Scientific advice	Research	SVM RF	no
Stocker, Pachepsky and Hill, 2022	USA	Scientific advice	Prediction	XGBOOST kNN SVM RF	no
Sun, Liu and Xue, 2024	China	Scientific advice	Laboratory testing	CNN ResNet	yes
Talari, *et al.*, 2024	Greece	Inspection & border testing	Prioritization	ML	no
Tan *et al.*, 2019	USA	Scientific advice	Laboratory testing	SVM	no
Tang, Guo and Shen, 2023	China	Scientific advice	Laboratory testing	SVM XGBOOST	no
Tang *et al.*, 2023	China	Scientific advice	Research	XGBOOST SVM kNN RF AdaBoost M:P	no
Tanui *et al.*, 2022	USA	Scientific advice	Prediction	RF	no

Paper	Country of origin		Topic	Machine learning technique(s)	Deep Learning
Tao *et al.*, 2023	USA	Scientific advice	Research	BERTweet, RoBERTa, BiLSTM, MGADE	yes
Thao *et al.*, 2023	Vietnam	Scientific advice	Research	MoCo	yes
Tonda, Reynolds and Thomopoulos, 2023	France	Scientific advice	Research	RF	no
Toro *et al.*, 2022	Chile	Scientific advice	Research	RF	no
Tsakanikas *et al.*, 2016	Greece	Scientific advice	Laboratory testing	SVR	no
Tu *et al.*, 2024	China	Inspection & border testing	Efficiency	Ensemble	no
van den Bulk *et al.*, 2022	Netherlands	Scientific advice	Prediction	NB SVM	no
Vangay *et al.*, 2014	USA	Scientific advice	Research	RF SVM etc	no
Wang, Greenwood and Klein, 2021	USA	Scientific advice	Prediction	ANN	no
Wang *et al.*, 2022	Netherlands	Scientific advice	Research	SVM XGBOOST	no
Wang, Liu and van der Fels-Klerx, 2022	Netherlands	Scientific advice	Prediction	RF	no
Wang *et al.*, 2023	China	Scientific advice	Laboratory testing	SVM BP-NN RF	yes
Wang *et al.*, 2024a	China	Scientific advice	Laboratory testing	multiple inv SVM	no
Weller *et al.*, 2020	USA	Scientific advice	Prediction	SVM kNN XGBOOST LASSO etc.	no
Weller, Love and Wiedmann, 2021a	USA	Scientific advice	Research	NN RF LASSO SVM etc	no
Weller, Love and Wiedmann, 2021b	USA	Scientific advice	Research	RF SVM etc	no
Wu and Weng, 2021	Taiwan	Inspection & border testing	Prioritization	RF BN GBM	no
Wu *et al.*, 2023b	China	Scientific advice	Laboratory testing	kNN, RF, SVM, PLS, CNN	yes
Wu, *et al.*, 2023a	Taiwan	Inspection & border testing	Prediction	RF BN GBM	no
Xiang *et al.*, 2023	China	Scientific advice	Research	RF SVM	no
Xie, *et al.*, 2022	China	Regulatory aspects	Prediction	RF XGBOOST	no
Xu *et al.*, 2022	China	Scientific advice	Efficiency	LSTM XGBOOST GBM	yes

Paper	Country of origin		Topic	Machine learning technique(s)	Deep Learning
Yamamoto *et al.*, 2021	Japan	Scientific advice	Laboratory testing	SVM	no
Yan *et al.*, 2020	China	Scientific advice	Laboratory testing	ENR SVR XGBOOST	no
Yan *et al.*, 2021	China	Scientific advice	Laboratory testing	decision tree	no
Yang *et al.*, 2022	USA	Scientific advice	Laboratory testing	NN	no
Yi *et al.*, 2023	USA	Scientific advice	Laboratory testing	CNN	yes
Zhang *et al.*, 2021	China	Scientific advice	Research	XGBOOST	no
Zhang *et al.*, 2022	USA	Scientific advice	Research	Active learning SSL	no
Zhang *et al.*, 2023a	USA	Scientific advice	Laboratory testing	Multiple	no
Zhang *et al.*, 2023b	China	Scientific advice	Research	LSTM MLP SVM	yes
Zhao, Liu and Song, 2023	China	Scientific advice	Laboratory testing	XGBOOST	no
Zheng, Gracia and Hu, 2023	USA	Scientific advice	Research	RF	no
Zhong *et al.*, 2021	China	Scientific advice	Laboratory testing	LSTM	yes
Zhu *et al.*, 2023	China	Scientific advice	Research	CART SVR	no
Zuo *et al.*, 2022	China	Scientific advice	Research	Denoising Autoencoder	yes

ANN= artificial neural network; AFINN= adaptive fuzzy inference neural network; BERT = bidirectional encoder representations from transformers; BiLSTM= bidirectional LSTM; BN = Bayesian network; BP-NN= back propagation neural network; CART= classification and regression tree; DCNN = deep convolutional neural network; DFNN= deep feedforward neural networks; DT NN= deep tensor neural network; ELM= extreme learning machine; ENR= elastic net regression; FL= fuzzy logic; FNN= feedforward neural network; GA= genetic algorithm; GAN= generative adversarial network; GBM= gradient boosting machine; kNN= k-nearest neighbors; LASSO= least absolute shrinkage and selection operator; LDA= linear discriminant analysis; LIME= local interpretable model-agnostic explanations; LSTM= long short-term memory; MGADE= multi-grained adverse drug events detection network; ML = (traditional) machine learning; MLP= multilayer perceptron; MLR= multiple linear regression; MMI= maximum mutual information; MoCo= momentum contrast technique; PLS= partial least squares; RF= random forest; RoBERTa = robust optimized BERT pretraining approach; SHAP= SHapley Additive exPlanations; SSL= self-supervised learning; SVM= support vector machine; SVR= support vector regression; XGBOOST= = extreme gradient boosting; YOLOv4= you only look once version 4.

Source: See References.

Annex 3. Artificial intelligence techniques mentioned in the reviewed articles and Wikipedia

#	AI technique	Explanation found in the relevant article	Category
1	artificial neural network (ANN)	ANN consists of nonlinear statistical data modeling tools that are based on biological neuron models to mimic the intelligent system in the human brain (Al *et al.*, 2024).	deep learning (DL)
		Wiki: An ANN consists of interconnected artificial neurons that process signals through weighted connections. Organized into layers, these networks transform inputs through activation functions.	
2	AlexNet	AlexNet is a type of CNN with an architecture capable of extracting features from spectral information (Jo *et al.*, 2023).	DL
		Wiki: AlexNet is a convolutional neural network architecture.	
3	Bayesian network (BN)	BN has its origin from Bayesian statistics and decision theory coupled with graph theory. They are a class of probabilistic models with the structure consisting of nodes (i.e., random variables) that are connected by directed arcs showing a dependence structure between the nodes (Bouzembrak *et al.*, 2024).	machine learning (ML)
		Wiki: A Bayesian network is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph.	
4	bidirectional encoder representation from transformations (BERT)	BERT is an unsupervised DL language model often trained on large text corpus (Maharana *et al.*, 2019).	DL
		Wiki: BERT is a language model which learns to represent text as a sequence of vectors using self-supervised learning. It uses the encoder-only transformer architecture.	
5	BERTweet	BERTweet is a variant of BERT trained to classify relevant data from Twitter (Tao *et al.*, 2023).	DL
		Wiki: No Wikipedia page. Type of BERT.	
6	convolutional neural networks (CNN)	CNN is a type of DL model that uses one or more layers of fully connected neurons (He, 2024).	DL
		Wiki: A CNN is a regularized type of feedforward neural network that learns features via filter (or kernel) optimization.	
7	decision tree (DT)	DT model builds a decision tree through a recursive splitting of a dataset from the most significant predictor variable until a stopping criterion is met (Talari *et al.*, 2024).	ML
		Wiki: A DT is a decision support recursive partitioning structure that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.	

#	AI technique	Explanation found in the relevant article	Category
8	deep convolutional neural network (D-CNN)	This model consists of five convolutional layers followed by a three-layer perceptron. The convolutional layer is used for the extraction of adjacent features, with the maximum pooling layer used after each convolutional layer to enhance the generalization ability of the model (Chen *et al*., 2024b).	DL
		Wiki: No Wikipedia page. Type of CNN.	
9	denoising autoencoder (DAE)	DAE is an ANN that works in an unsupervised manner. It could efficiently reduce the redundancy of the input data as well as encode it. DAE is often used for dimensionality reduction and to compress data so as to remove noise and to learn advanced features from the original input data (Li *et al*., 2022).	DL
		Wiki: An autoencoder is a type of ANN used to learn efficient codings of unlabeled data (unsupervised learning). A DAE is trained by intentionally corrupting the inputs of a standard autoencoder during training.	
10	Elastic net	Elastic net model combines the strengths of lasso and ridge regression models by using a ridge-type penalty to regularize and a lasso-type penalty to select features (Weller *et al*., 2020).	ML
		Wiki: Elastic net is a regularized regression method that linearly combines the L1 and L2 penalties of the lasso and ridge methods.	
11	extreme gradient boosting (XGBoost)	XGBoost algorithm is a powerful and efficient ML method suitable for data with complex structures. It is based on gradient boosted trees and has several advantages including regularization for preventing overfitting, a built-in routine to handle missing values, a parallel processing for faster computation, and an in-built cross-validation (Zhao, Liu & Song, 2023).	ML
		Wiki: Gradient boosting is a machine learning technique based on boosting in a functional space, where the target is pseudo-residuals instead of residuals as in traditional boosting. It gives a prediction model in the form of an ensemble of weak prediction models which are typically simple decision trees.	
12	extreme learning machine (ELM)	ELM is a type of ML method that can be operated with randomly assigned weights to cater for the hidden layer. It can use neurons together with the rectified linear unit (ReLU) for function activation and as a regularization factor of 10− 2 (Smeesters *et al*., 2021).	ML
		Wiki: ELMs are feedforward NNs for classification, regression, clustering, sparse approximation, compression and feature learning with a single layer or multiple layers of hidden nodes, where the parameters of hidden nodes (not just the weights connecting inputs to hidden nodes) need to be tuned.	
13	extremely randomized trees (ExtraTrees)	ExtraTrees in ML methods consist of multiple decision trees. It has a high discrimination ability when compared to random forest and can be less prone to noise in a dataset (Chung *et al*., 2022).	ML
		Wiki: RF is an ensemble learning method for classification, regression and other tasks that works by creating a multitude of decision trees during training. In the case of ExtraTrees, each tree is trained using the whole learning sample and the top-down splitting is randomized.	

#	AI technique	Explanation found in the relevant article	Category
14	fully connected neural network (FCNN)	FCNN in DL methods is capable of learning complex relationships. It has hundreds of neurons and multiple hidden layers and has found wide applications in predicting molecular properties as well as toxicity (Gao *et al.*, 2022). Wiki: No Wikipedia page. Type of NN with every neuron in one layer connecting to every neuron in the next layer.	DL
15	Fusion-Net	Fusion-Net as a type of DL method has multiple forms of predictors for use with, for example, spectra and band images (Park *et al.*, 2023). Wiki: No Wikipedia page. Type of deep fully residual CNN.	DL
16	fuzzy logic (FL)	FL is a form of AI capable of analysing vague and inaccurate data and help with important decision making (Mavani *et al.*, 2024). Wiki: FL is a form of many-valued logic in which the truth value of variables may be any real number between 0 and 1.	FL
17	Gaussian naive Bayes (GNB)	GNB uses Bayes' theorem in predicting the probability of a data point belonging to a given class (Talari *et al.*, 2024). Wiki: A naïve Bayes model assumes the information about the class provided by each variable is unrelated to the information from the others, with no information shared between the predictors. GNB assumes continuous features follow a Gaussian distribution.	ML
18	Gaussian progress regression (GPR)	GPR in ML methods was proposed by O'Hagan and is based on Bayesian analysis as well as statistical learning theory. It is suitable for handling nonlinear regression issues with high-dimensional and small-sample size (Zhu *et al.*, 2023). Wiki: Gaussian process is a stochastic process, such that every finite collection of those random variables has a multivariate normal distribution. Inference of continuous values with a Gaussian process prior is known as GPR.	ML
19	k-nearest neighbors (kNN)	kNN is a form of a non-parametric method that works by finding the K nearest data points in reference to the test point and by using their average or majority vote, make the predictions (Talari *et al.*, 2024). Wiki: The kNN algorithm is a non-parametric supervised learning method. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors.	ML
20	least absolute shrinkage and selection operator (LASSO)	LASSO is a regression methos that uses a penalty like ridge regression, although in this case, coefficient estimates of 0 are allowed (Weller *et al.*, 2020). Wiki: LASSO is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the resulting statistical model. The lasso method assumes that the coefficients of the linear model are sparse, meaning that few of them are non-zero.	ML

#	AI technique	Explanation found in the relevant article	Category
21	latent dirichlet allocation (LDA)	LDA is a model that can be applied in processing rapidly changing information in the media (Rortais *et al.*, 2021).	ML
		Wiki: LDA is a Bayesian network for modeling automatically extracted topics in textual corpora.	
22	local interpretable model-agnostic explanations (LIME)	LIME trains an understandable model by using new data points weighted according to how they are close to the original points (Buyuktepe *et al.*, 2023).	ML
		Wiki: LIME is an explainable AI technique that approximates locally a model's outputs with a simpler, interpretable model.	
23	linear discriminant analysis (LDA)	LDA is often trained using regularized, pooled covariance matrices (Smeesters *et al.*, 2021).	ML
		Wiki: LDA is a generalization of Fisher's linear discriminant to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.	
24	Log-linear maximum entropy model	A log-linear maximum entropy model can estimate an anonymized search query based on the probability that the query belongs to a particular class (Sadilek *et al.*, 2017).	ML
		Wiki: The principle of maximum entropy states that the probability distribution which best represents the current state of knowledge about a system is the one with largest entropy, in the context of precisely stated prior data. In the case of maximum entropy models the observed data itself is assumed to be the testable information.	
25	logistic regression (LR)	LR is a classical classifier in ML often used to analyse labeled sample data (He, 2024). It returns the probability of a case belonging to a particular class, for example, either Class 0 or Class 1 (Stanosheck *et al.*, 2024).	
		Wiki: A logistic model is a statistical model that models the log-odds of an event as a linear combination of one or more independent variables. Logistic regression estimates the parameters of a logistic model (the coefficients in the linear or non linear combinations).	
26	long short-term memory neural network (LSTM)	LSTM in DL methods has a special variant (recurrent neural network) and is less prone to gradient disappearance and explosion (He, 2024).	DL
		Wiki: LSTM is a type of recurrent neural network aimed at mitigating the vanishing gradient problem.	
27	momentum contrast technique (MoCo)	MoCo is a contrastive self-supervised learning technique with the capability for generating high-quality latent representations for input images from unlabeled data. This technique help overcome the challenges of training learning models with general and discriminative features (Thao *et al.*, 2023).	DL
		Wiki: In self-supervised learning a model is trained on a task using the data itself to generate supervisory signals, rather than relying on externally-provided labels. Contrastive self-supervised learning uses both positive and negative examples in the training data and use the loss function to minimize the distance between positive sample pairs, while maximizing the distance between negative sample pairs.	

#	AI technique	Explanation found in the relevant article	Category
28	multilayer perceptron (MLP)	Multilayer Perceptron (MLP) consists of feedforward supervised neural network system. It consists of an input layer, an output layer, and an arbitrary number of hidden layers. The basic MLP has a single hidden layer. Neurons use nonlinear activation functions, either sigmoid, hyperbolic tangent, or Rectified Linear Unit (ReLU) (Nogales, Díaz-Morón & García-Tejedor, 2022). Wiki: MLP is a feedforward neural network consisting of fully connected neurons with nonlinear activation functions, organized in layers, notable for being able to distinguish data that is not linearly separable.	DL
29	multiple linear regression (MLR)	MLR in ML techniques uses a straight line in estimating the relationship between the dependent variable and the several explanatory variables (Al *et al.*, 2024). Wiki: MLR is a model that estimates the linear relationship between a scalar response (dependent variable) and more than one explanatory variables.	ML
30	neural network (NN)	NN is executed using sigmoid as activation function and hidden layers with numerous small processing units known as neurons. The neurons provide inputs for generating inter-connected outputs and identification of specificities more easily (Smeesters *et al.*, 2021). Wiki: A neural network consists of interconnected artificial neurons that process signals through weighted connections. Organized into layers, these networks transform inputs through activation functions.	DL
31	partial least squares discriminant analysis (PLS-DA)	PLS-DA is a predictive model based on the classical PLSR method with advantages such as noise reduction and variable selection (Kim *et al.*, 2022) Wiki: Type of PLSR used when the dependent variable is categorical.	ML
32	partial least squares regression (PLSR)	PLSR method can relate two data matrices through establishment of a linear multivariate mode (Zhu *et al.*, 2023). Wiki: PLSR is a statistical method that finds a linear regression model by projecting the predicted variables and the observable variables to a new space of maximum covariance.	ML
33	quadratic discriminant analysis (QDA)	QDA is a form of ML that can use the pseudoinverse of the covariance matrix to make prediction. (Smeesters *et al.*, 2021). Wiki: Closely related to LDA, but in in QDA there is no assumption that the covariance of each of the classes is identical.	ML
34	random forest (RF)	RF in ML is a supervised learning regression technique that uses tree ensemble models. It builds numerous different decision trees in parallel and gives a prediction of built trees based on an output of the mean value of the classes (Al *et al.*, 2024). Wiki: RF is an ensemble learning method for classification, regression and other tasks that works by creating a multitude of decision trees during training.	ML

#	AI technique	Explanation found in the relevant article	Category
35	residual convolutional neural network (ResNet)	ResNet is a superior form of DL model capable of overcoming the problems of vanishing or exploding gradients that results from the addition of internal residual blocks (Chen *et al.*, 2022a).	DL
		Wiki: ResNet is a deep learning architecture in which the layers learn residual functions with reference to the layer inputs.	
36	RoBERTa	RoBERTa model has been used to analyse data form Twitter with high accuracy. However, limitations have been observed in the generalization capability in cases of unseen tweets (Tao *et al.*, 2023).	DL
		Wiki: No Wikipedia page. Type of BERT.	
37	Shapley additive explanations (SHAP)	SHAP model is used to identify the most influential features that impact the model's decisions. (Buyuktepe *et al.*, 2023).	ML
		Wiki: Explainable AI technique: SHAP enables visualization of the contribution of each input feature to the output. It works by calculating Shapley values, which measure the average marginal contribution of a feature across all possible combinations of features.	
38	support vector regression (SVR)	SVR is a type of ML with regression performed by kernel functions. The functions map the input data into a high-dimensional space using either linear or nonlinear transformations. (Al *et al.*, 2024).	ML
		Wiki: An extension of SVM. The model produced by SVR depends only on a subset of the training data, because the cost function for building the model ignores any training data close to the model prediction.	
39	support vector machines (SVM)	SVM in ML is a powerful technique used for classification and regression tasks (Talari *et al.*, 2024).	ML
		Wiki: SVMs are supervised max-margin models with associated learning algorithms that analyze data for classification and regression analysis.	
40	U-Net	U-Net, also known as U-shaped CNN, has been employed in analysis involving segmentations (Kang *et al.*, 2020).	DL
		Wiki: Type of CNN developed for image segmentation.	
41	what-if tool (WIT)	WIT is a visual interface used to understand the dataset and the outputs of ML models operating in a blackbox. It can be used for effective testing of trained ML models without writing any code. (Buyuktepe *et al.*, 2023).	ML
		Wiki: No Wikipedia page. Explainable AI technique.	
42	you only look once version 4 (YOLOv4)	YOLOv4 as a DL method has an architecture to enable it to achieve real-time object detection way above the human perception of 30 frames/second. It has found wide applications in locating and classifications of, for example, microcolonies. (Ma *et al.*, 2023b).	DL
		Wiki: Object detection system based on CNN.	

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