Artificial Intelligence in Food Safety

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Key Points

- Data can be used from numerous sources for artificial intelligence i.e., spectroscopy, computer vision and online databases.
- Description of Big Data is provided.
- The different types of artificial intelligence is explained.
- Machine learning and deep learning are described and applications in food safety discussed.

Abstract

Artificial intelligence (AI) used with different data sources is becoming a technology that can provide rapid solutions for determining food safety. Current data sources used for artificial intelligence are described, e.g., computer/machine vision, spectroscopy, i.e., NIR and temperature. Different AI approaches may be more applicable to some food safety applications than others. In particular, different machine and deep learning algorithms with supporting food examples are discussed and how they potentially affect future food safety considerations.

Introduction

Food safety has been described by the USDA as "the conditions and practises that preserve the quality of food to prevent contamination and food-borne illnesses" (USDA, 2023). This definition covers a wide variety of health hazards which are naturally present (e.g., toxins and allergens), introduced via the environment (e.g., heavy metals), microbial activity (e.g., infectious agents, bacterial toxins and mycotoxins), animal production practices (e.g., antibiotic and hormone residues, melamine) or arising from food processing (e.g., acrylamide and chloropropanols) (Waite and Yousef, 2010).

This article identifies data sources, data sorting, and the applications of artificial intelligence (AI) in contaminant detection and food safety prevention. In particular, types of AI used to solve food safety problems will be discussed. This article also describes the use of technologies (i.e., sensors and ′omics profiling), as innovative food safety tools.

Data Sources

Sensor technology is the first step in detecting contamination in the food supply chain early. Some quantitative detection methods are determined using time-consuming, destructive, laborious methods that can also depend on wet chemistry (e.g., liquid chromatography, mass spectrometry, microbial culture, and colony-counting). Although these methods can achieve a high detection accuracy, the long sample preparation steps and testing protocols make them impossible to use as rapid non-destructive online methods.

Conventional Process and Environment Parameters

Food spoilage (in particular for fresh fruit and vegetables) has been associated with insufficient temperature control in cold chain monitoring. To ensure fruit and vegetable quality, it is imperative to maintain the correct temperature and humidity balance. Insufficient cold chain monitoring (e.g., reduced temperature), can lead to chilling or freezing damage, whereas higher temperatures can increase enzymatic or microbial activity rates. In addition, due to the characteristics of food and the insulation effect from food packaging, temperature can be distributed in a non-homogeneous manner, and therefore it is not sufficient to use one temperature source for developing a prediction model (Paull, 1999).

From a food safety point of view, 50% of *Salmonella* outbreaks can be traced to a home setting. They commonly arise from inappropriate storage, inadequate cooking or cross-contamination. Temperature is recognized as the controlling factor for food safety due to its influence on microbial growth rates. Hence, a food's shelf-life also depends on the storage time and temperature relationship (Roccato et al., 2017).

Temperature data sources (now commonly being integrated into Internet of Things (IoT) platforms) and time series forecasting are ideal sources in the first step of artificial intelligence, particularly for artificial neural networks (Paull, 1999; Badia-Melis et al., 2018).

Spectroscopy

The definition of spectroscopy is the interaction between an electromagnetic wave with matter (Sun, 2009). Typically, vibrational spectroscopy methods such as Near Infrared (NIR), Mid Infrared (MIR), Raman and visible (VIS), have been used as rapid and high throughput measuring spectroscopic techniques.

Raman can provide information on the molecular vibrations on the sample of interest ranging from small molecules to biological compounds and cells (Huang et al., 2021). In particular, surface-enhanced Raman spectroscopy (SERS) is the combinational effect of a physical enhancement mechanism (EM) and a chemical enhancement mechanism (CT). EM waves interact with a metal surface, and if this surface is rough, the EM wave will excite a local surface plasma resulting in the amplification of the electric field near the surface. CT evaluates the charge transfer interactions between metal nanoparticles and the sample (i.e., charge transfers between chemical bonding, surface complexes, light-induced and the substrate). It has been widely used for the sensitive detection of pathogens (Zhou et al., 2021). Using this method, researchers have measured *Staphylococcus aureus* in milk, *Escherichia coli* in salmon, and *Listeria monocytogenes* in meat products, in minutes and hours compared to much longer periods using conventional methods (Zhu et al., 2023).

NIR is located between the visible and MIR regions and covers the 800−2500 nm wavelength range. It has been widely used for authentication and traceability of materials and products, adulteration detection (e.g., antibiotics, melamine), and detection of chemical hazards (e.g., fertilizers, cleaning residues, allergens and naturally occurring toxins) (Fu and Ying, 2016). NIR combined with a bacterial cultivation step, has been successfully used to determine the total bacterial count in raw milk (Numthuam et al., 2017).

These sensing technologies are constantly advancing, resulting in large volumes, types and velocity of data for interpretation by scientists. Therefore, it can be difficult to differentiate between the essential information and the non-essential information. More advanced and robust data analytical methods are required when compared to conventional classical statistics, which cannot handle the volume of data (spectra) from these technologies. Hence, Artificial Intelligence (AI) capable of multivariate data analysis (i.e., pattern recognition, clustering and predictive models), must be developed for the target application (Cozzolino, 2020).

Computer (Machine) Vision

Computer (machine) vision (CV) comprises an industrial camera (i.e., RGB camera, Hyperspectral Imaging, Near Infrared spectroscopy and Raman), a lighting source/lightbox (for controlled and consistent lighting) and image processing software used for non-destructive applications. End-uses include product quality measurements such as the use of L*a*b* derived measurements (e.g., marbling quality grades in meat, and meat defects in dark, firm and dry beef) (Shi et al., 2021). CV has been used as a sensing technology for grading and sorting products based on size and shape (e.g., fruit and vegetables), identifying physical contaminates accidently present in the end-product, and inspection of food production lines (Chen and Yu, 2021).

CV is the source for many image/artificial intelligence-related applications (e.g., optical design models, image processing, pattern recognition, signal processing, geometry and photometry). Due to the large number of images generated with multiple regions of interest, large volumes of information are available and suitable for AI analysis (e.g., machine learning and deep learning models) (Kakani et al., 2020).

Databases

Data sources commonly used in food safety analytics include online databases such as the Rapid Alert System for Food and Feed (RASFF) and the Import Refusal Report (IRR). Technologies based on ′omics profiling and data threads from sensors such as RBG or hyperspectral cameras provide big data for processing. In addition, conventional mobile devices, such as those used as handheld tools for compositional predictive mobile applications, and capturing images used for food monitoring purposes, the internet, and satellite imagery generate significant datasets. Finally, social media platforms, such as Facebook and Twitter, are becoming popular data sources for collecting online opinions or sentiment analysis. In particular, these platforms are useful for gaining a better understanding of public perception and promoting public awareness of food safety information (Harris et al., 2017). Data collected from these sources can be structured or unstructured and stored in many different formats, ranging from simple flat files to relational or NoSQL databases (Jin et al., 2020).

′Omics Technologies

Quality and safety are basic consumer expectations from any modern sustainable food system. Developments in digital technologies, and more recently AI, have enabled a total supply chain approach encompassing production, processing and retailing, to food safety. Molecular techniques coupled with bioinformatics can be used to ensure that potentially harmful bacteria do not enter the food supply chain, facilitating providence while ensuring quality and safety. In addition, the rapid advances in molecular biology and digital technologies have led to the emergence of integrated food safety systems driven by big data, AI, and blockchain-based platforms. Data generated by DNA-based methodologies are vast and highly variable, requiring machine and deep learning techniques for analysis and dissemination. AI can provide the solution here and is becoming even more important as the sensitivity of modern instrumentation increases, facilitating the generation and characterization of large datasets of biological material (i.e., the application of ′omic technologies). These developments include de novo genome assembly, genome resequencing, (meta) transcriptome analysis, single-nucleotide polymorphism (SNP) detection, microbial tracking, amplicon and shotgun metagenomic techniques. The emergence of these methodologies has changed how food scientists quantify microorganisms, residues and other compounds that impact food safety, quality and nutritive value. Using AI to interpret "big data" can generate substantial information on microorganisms, including bio/enzymatic activity in our food. The digital-based platform science of bioinformatics, applies mathematics to ′omic biological datasets (e.g., identifying target microorganism populations to define the microbiome of a food system). The power of digital technologies using state of the art sequencing technology coupled with bioinformatics has been used to track the microbiome throughout skim milk powder manufacture (Mchugh et al., 2020). High-throughput DNA sequencing (16S rRNA gene amplicon and shotgun metagenomic sequencing) were used to investigate microbial changes throughout production and processing environments by measuring the microbiomes of fresh mid- and late-lactation milk in farm bulk tanks, collection tankers, milk silos, skimmed milk silos, a cream silo, and skim milk powder samples. While amplicon sequencing (16S and ITS for bacteria and fungi, respectively) can be used to track changes in microbial composition at the genus level, whole metagenome shotgun sequencing can provide composition-related information at the species (or strain) level across various microorganisms. The development of DNA sequencing platforms has rapidly evolved over recent years, driven by advances in molecular biochemistry, computer chip architecture, data capture and AI-enabled analytics. These advances, combined with automated DNA extraction approaches and rapidly evolving computing applications, have increased the number and type of samples that can be measured, and decreased the cost. Yap et al. (2020) described the application of shotgun metagenomic sequencing for taxonomic and functional profiling of microbial communities in milk. It is not possible to carry out these types of studies using classical agar-based microbiology methods.

AI platforms can enable real-time monitoring of food and environment microbiota changes during sequential unit operations used in food processing. The information can be used to correlate the relative abundances of microbial species and the levels of metabolites generated during processing or storage. Scientists are working on next-generation techniques to differentiate between viable and non-viable cells; a limitation of the DNA-based measurement (i.e., that DNA is still present when the cell is non-viable (cannot be grown on media)), resulting in false positives. This limitation is highly relevant since most food processes have a heating step to reduce microbial load, produce a safe product, and ensure stability throughout shelf life. AI has the potential to aid in the development of new molecular approaches to address these microbial enumeration challenges, revolutionizing testing for food safety and quality applications. The digital output from molecular tests can be integrated into user interfaces such as mixed and augmented reality headsets, and combined with data from in-process sensors to realize a futuristic virtual quality map for quality assurance.

Today's computing power has enabled large quantities of sequencing reads to be analyzed more rapidly, with the ability to identify functionality within microbiome becoming a real opportunity. More targeted molecular approaches (i.e., quantitative PCR (qPCR)) can complement microbiota-based sequencing while studying microbial populations, providing sensitive quantification of specific target species or genes. While molecular approaches are currently benchmarked with culture and phenotypic data, particularly in the case of pathogenic microorganisms, as described above, there is an exciting future ahead in which AI can be an integral part of ensuring our food is safe, nutritious and sustainable.

Big Data

Big Data has been described as the rapid collection of complex data in huge quantities. Storage of this data can occupy space up to terabytes, petabytes and even zettabytes (Zhou et al., 2022).

The characteristics associated with big data have often been described in terms of the "4 Vs" (Schroeck et al., 2012):

- *Volume:* The scale of the data collected.
- *Velocity:* The rate at which the data is arriving (e.g., in real time or at increments).
- *Variety:* Data potentially having different formats (e.g., images, videos, text) and different spatial or temporal resolutions, coming from different sources and application domains.
- *Veracity:* The quality, reliability, accuracy, and overall confidence in the data.

Data Collection

The following approaches can be used to obtain food safety indicators:

- "*After the fact*" *data*: this approach analyses data arising post an event (i.e., information from end or finished products or after the problem has occurred) and are commonly referred to as *lagging indicators.*
- "*Warning indicators*" data: this is data on the effectiveness of a food safety training exercise, which then allows the prediction of a problem and can be referred to as *leading indicator*. This approach requires sophisticated data collection and management systems (Kudashkina et al., 2022).

Both approaches produce substantial information, necessitating the use of big data technologies for data gathering, storage, querying, and processing.

Artificial Intelligence

AI has been broadly defined as "the simulation of human intelligence in machines that are programmed to think and act like humans" (**Fig. 1**) (Zhou et al., 2022). It is important to highlight that AI is a term used to describe how machines can complete tasks more intelligently. AI technologies are increasingly being adopted in the food industry to perform a range of tasks, including predicting crop yield, ensuring product quality control, supporting product development, and improving traceability and safety (Sharma et al., 2021).

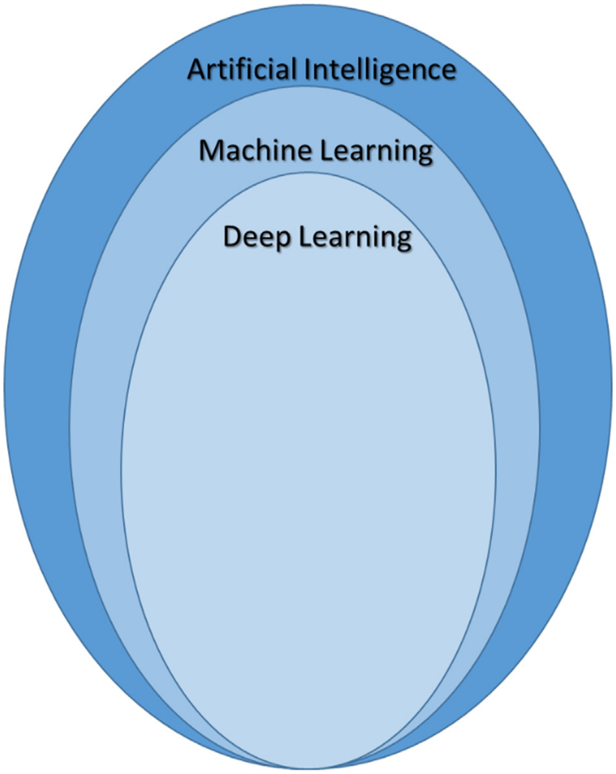

Fig. 1 Representation of the subsets of Artificial Intelligence (AI).

In general, AI applications can be divided into the following groups:

- *Rule-based AI* (also referred to as Expert Systems (ES))—consists of a list of behavioral rules preprogramed based on previous knowledge/experience of the physical food system and are usually determined by expert opinion. It is constantly monitored using machines, the data derived is analyzed using principles. The major disadvantage of this form of AI is its inability to improve itself automatically and adapt to new data. Thus, rule-based AI cannot be utilized in tasks that require accurate decisions produced in real-time.
- *Data-driven AI*—continuous improvement of performance from constant collection of data. Identification of patterns not known to human knowledge determined using algorithms (i.e., machine learning).
- *Combination AI*—systems that can combine elements of both learning strategies above to offer flexibility when handling different data types (Qian et al., 2023).

Machine Learning

Machine learning (ML) refers to a subset of AI techniques covering data modeling, data exploration, and predictive analytics, and has particular relevance in areas such as food safety (Khan and Goodridge, 2022).

The most common form of machine learning, supervised learning, involves a training protocol using labeled input examples to build a model, often using some optimization process. The resulting model can then be used to predict new unseen data (Deng et al., 2021). Classification algorithms, such as Random Forests and Support Vector Machines (SVMs), learn from a labeled training set to make a prediction to assign unseen examples to one of a fixed number of classes (Golden et al., 2019). Regression methods learn from an existing training set to decide the value of a numeric output variable.

The presence of unwanted residues in milk has been discussed for decades. Antibiotics is one example of a residue that has been detected in milk if dosing guidelines or insufficient withdrawal practices are not adhered to. The classical methods used to detect these types of adulterants (e.g., chromatography, mass spectrometry) are expensive, time-consuming and open to human error due to the lengthy protocols involved (de Freitas et al., 2021). One group of researchers used infrared spectroscopy in combination with chemometrics to develop a rapid method for detecting the antibiotic residue tylosin using two algorithms in combination to predict the content of tylosin. First, the Boruta algorithm was used to remove less relevant features that could have a misleading impact when applying supervised learning. Second, a Random Forest classifier was used to develop the prediction model. Overall, the use of this algorithm was found to adequately predict tylosin residues in milk at low concentrations ($0-100\ \mu g\ L^{-1}$). The model resulted in an R^2 of 0.9517 and root mean square error (RMSE) of $0.3145\ \mu g\ L^{-1}$ (de Freitas et al., 2021).

Histamine, an allergen, is one of the main causes of illness in the USA associated with the consumption of seafood. It can be produced in fish by the bacterial enzymatic decarboxylation of histidine to form the biogenic amine histamine. The guidance level for the average concentration of histamine in fish for human consumption must be lower than 100 ppm (European Union) and 50 ppm (US Food and Drug Administration (FDA)). Thin layer chromatography (TLC) in combination with surface-enhanced Raman spectroscopy (SERS) and supervised machine learning have been used to detect and quantitate histamine in spoiled tuna samples. In particular, principal component analysis in combination with Support Vector Regression (SVR) was used to analyze the spectral data. This approach successfully detected the allergen to 10 ppm using the TLC method, which is lower than the guidance level set out by the FDA. The quantitative model developed using SVR resulted in an R^2 of 0.989 for the training set and 0.968 for the testing set.

When a dataset does not contain target labels, unsupervised learning algorithms can be applied to directly identify patterns from the raw data, supporting data exploration and knowledge discovery. Common unsupervised learning tasks include anomaly detection (i.e., identifying anomalous examples that do not fit with the majority of the data) and cluster analysis (i.e., automatically assigning similar examples to groups) (Dal Moro et al., 2021). Widely-adopted approaches for the latter task include k-means and hierarchical agglomerative clustering (Greene et al., 2008).

Temperature abuse in a cold chain reduces the shelf-life of products and contributes to food safety issues and waste. Unsupervised learning models can be beneficial when a real-time cold food chain monitoring system is required to identify parameter changes over time. Parameters of interest in a cold food chain usually include temperature and humidity. An IoT platform is ideal for collecting large amounts of data on the mentioned parameters while transporting perishable food. Using an IoT anomaly detection system, a business owner can be notified about temperature anomalies of refrigerated food products during transport using their mobile device (Gillespie et al., 2023).

Unsupervised clustering algorithms have been used to identify how consumers understand food safety information sources (i.e., credible sources, interpersonal sources and product labels). For instance, consumers have been grouped based on being selective or non-selective in their use of information sources. They also considered the criterion used as part of choosing the source and whether consumers interest in food safety information influences selective or non-selective use. The objective of the study was to help regulators provide consumers with more meaningful and targeted communication strategies. This approach was also utilized in evaluating personality traits and socio-demographic variables. The Ward’s hierarchical clustering method was applied to identify groups of consumers based on individual differences between groups that dominate the individual difference within the groups. The identified groups were further optimized by applying the k-means clustering method. This approach resulted in five distinct consumer groups identified based on the cluster analysis—67% were clustered as selective and 33% were clustered as non-selective. Selective consumer groups were split further into labeled groups “moderate institutional”, “heavy institutional” and “social”, whereas the nonselective cluster was split further into labeled groups “heavy” and “low”.

Other machine learning algorithms are categorized as semi-supervised, since they involve a combination of supervised and unsupervised learning, making use of data that is both labeled and unlabeled. For example, semi-supervised learning of pitch and tone accent, reduces the need for labeled training data in speech recognition. Two datasets were used to predict plasma dosage and to detect foodborne pathogens gathered using spectroscopy-based technologies. It was found that the use of pseudo-labeling methods (e.g., self-training) could greatly improve model accuracy once the underlying samples were well clustered and the number of labeled samples was small (Zhang et al., 2022). Other algorithms fall under reinforcement learning, which depends on a trial and error approach using a learning system that finds the best strategy/path in a given situation. This type of machine learning is mainly used in robotics (e.g., robots learning how to walk) (Deng et al., 2021).

Deep Learning

Deep learning (DL) is a subset of ML algorithms that uses artificial neural networks with multiple layers to model and understand complex patterns in data. The use of DL algorithms is particularly prevalent in computer vision, when performing tasks such as object detection, image segmentation, and image classification. Common models used in DL include recurrent neural networks (RNNs), convolutional neural networks (CNNs), generative adversarial network (GANs), and deep reinforcement learning (DRL) (Zhou et al., 2022).

CNN models in particular have been widely used for food detection and analysis. For example, in the classification and authentication of red meat using snapshot hyperspectral imaging (HSI). 3D-CNN was successfully used to classify the type of meat based on meat source (i.e., lamb, beef or pork), as well as fat, giving an overall accuracy of 98.6% when using spectra derived from a line-scanning HSI (Al-Sarayreh et al., 2020). In several cases, CNNs have been successfully deployed to differentiate between fruit varieties when combined with vision systems. These deep learning methods have also been used to identify defects in fruit to a high accuracy (e.g., defective apples were identified using 2-D CNN and a computer vision system), resulting in an accuracy of 96.5% for the testing set (Liu et al., 2021).

In a food safety context, a Deep Reinforcement learning-based Supply Chain Management (DR-SCM) method has been evaluated as a tool for making data-driven decisions on production and storage of agri-food products and profit optimization. An additional benefit of using DR-SCM was the application of a blockchain-based framework that allowed reliable product traceability (Chen et al., 2021).

Conclusions and Future Perspectives

Test methodologies for food safety that in the past were time-consuming, sometimes taking days, have been reduced to hours or minutes, enabled by the merging of modern biochemistry and digital technologies, including AI. Improved levels of detection and sensitivity in sensing technologies, like SERS, combined with AI has led to the development of advanced data handling and computation protocols, which in the past would not have been possible using classical statistical methodologies. The continuing improvement in the sensitivity and affordability of modern analytical technologies, and when coupled with advancements in AI, provide food processors with the ability to make real-time data driven decisions, thus improving the quality and removing/reducing contaminates during processing.

Implementing and utilizing AI in food safety management systems (e.g., Hazzard Analysis Critical Control Point (HACCP) and Good Manufacturing Practises (GMP)), for monitoring and control, will improve traceability, and remove the requirement for/frequency of time-consuming inspections. Combined with remote sensing technologies and Industrial IoT platforms, AI creates the potential for continuous real-time monitoring and reduction in the risk of foodborne outbreaks.

Everyday devices, such as smartphones, continue to become more advanced and powerful, allowing for the introduction of rapid data recording and collection of food product data for further analysis using machine learning methods. With the aid of AI food labels will become digitalized, allowing for the remote monitoring of time–temperature history of food products, providing real-time food safety information on a smartphone to the consumer (Maskey et al., 2019). Targeted food safety communications will be designed using AI with different consumer types in mind for improved food safety in the home.

Due to the large volumes of data generated, data quality, traceability and cybersecurity of platforms will be important considerations for food processors to ensure the robustness, integrity and accuracy of predictions, and organizational cyber safety.

This overview has provided the reader with a broad perspective of various applications of AI across the food supply chain, including sorting/classification, cold chain monitoring, pathogen detection in food ingredients and finished products, containment and allergen detection, and understanding consumer behavior in relation to food safety. Utilization of AI techniques offers researchers the advantage of improved clarity when visualizing correlations in large data sets, for example, k-means clustering/anomaly detection.

AI continues to progress, possibly at a rate faster than can be disseminated, and so it is vitally important that training is continuously offered to food manufacturers and indeed all participants along the food chain. Adoption of AI will depend on applications and familiarity of terminology and concepts among stakeholders across all food sectors. The requirement for algorithm interpretation and maintenance will become part of food quality and safety management systems. As digital and biological sciences continue to coalesce, many new AI-based applications in food are likely to evolve, ensuring nutrition, safety and health benefits, while maintaining a sustainable food system.

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