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Artificial intelligence for food safety: From predictive models to real-world safeguards

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ABSTRACT

Food safety is no longer just a lab issue; it's a real-world challenge that affects everyone from farmers and vendors to regulators and consumers. With rising concerns about adulteration, spoilage, and contamination in everyday items like milk, oils, fruits, and ready-to-eat meals, traditional testing methods often fall short; they're too slow, too expensive, and not designed for real-time action. This review explores how artificial intelligence (AI) and machine learning (ML) are stepping in as game-changers. We highlight real case studies where AI models, combined with tools like spectroscopy, smart sensors, and computer vision, are detecting food fraud and spoilage quickly and accurately. Beyond the technology, we also discuss challenges like data gaps, model trust, and affordability in rural areas, while offering forward-looking solutions like federated learning and low-cost AI devices. This review will be especially valuable for food scientists, quality assurance professionals, tech developers, policy-makers, and startups looking to build safer, smarter food systems. It's a practical guide for turning AI innovation into real-world food safety solutions.

1. Introduction

Food is one of the most essential elements of life, and yet, ensuring its safety remains one of the most challenging tasks in the modern world. In both developing and developed nations, concerns related to food adulteration, spoilage, contamination, and mislabelling are growing at an alarming rate (Bansal et al., 2017; Deshmukh et al., 2025). The complexity of today's food supply chains, which often span multiple countries and involve diverse storage, transport, and processing conditions, further increases the risk of compromised food safety. Ordinary food commodities such as milk, spices, edible oils, grains, pulses, fruits, vegetables, beverages, and sweeteners are often adulterated with undesirable or non-permitted substances (Anagaw et al., 2024; Machado Nardi et al., 2020). For example, urea or detergents may be blended with milk to raise the viscosity and foaming capacity of the product, while turmeric and chili powder may be added with lead chromate to enhance appearance. Mustard oil, a staple in many households, is sometimes diluted with the highly toxic argemone oil. Grains and pulses may undergo artificial polishing to increase shine, and fruits are often ripened using calcium carbide or coated with waxes to improve visual appeal.

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Similarly, used tea leaves are dyed and reused, while sugar and salt are contaminated with chalk powder or washing soda. Even seemingly natural products like honey may be diluted with glucose or sugar syrup, and fruit juices may contain synthetic colors or preservatives far beyond safe limits (Hoque & Mondal, 2019; Li et al., 2021). In order to provide some clarity, various food adulteration examples have been grouped into examples of dairy, oils, spices, grains, fruits, sweeteners, and miscellaneous. Each example has a summary of common adulterants and their associated health risks (summarized in Table 1). This arrangement aids in comprehending food fraud and demonstrates the broad health risks associated with varying types of food.

These adulterants and contaminants might not only change taste and remove nutritional value, but also present potential health threats ranging from intestinal infection, kidney damage, nervous system impairment, or cancer in extreme situations. The economic costs are substantial, too. This adds up to lost products and damage to brand reputation through loss of product integrity, regulatory fines, or health care costs (Vågsholm et al., 2020). Although traditional methods of food testing, such as chemical testing or culture for specific microbes, may be precise, they take significantly more time, money, and laboratory setup and equipment. In this way, the scalability is also an issue for real-time food protection, or monitoring food from production through consumption. To address these limitations, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools in the domain of food safety. AI has the potential to alter how we detect, monitor, and predict food-related risks. By leveraging large volumes of data, whether from sensors, images, spectral analyses, or even text, AI models can learn patterns that differentiate safe food from unsafe food and can do so in real time (Chhetri, 2024; Karanth et al., 2023; Liu et al., 2023). More importantly, AI systems can scale across locations, adapt to different types of food, and be embedded into smart devices for continuous monitoring. As shown in Fig. 1, traditional food safety workflows consist of time-consuming and sequential tasks, including sample collection, lab testing, and human interpretation, which are inherently reactive and labor-consuming. In contrast, Fig. 1 demonstrates an AI-powered food safety system that is able to streamline food safety workflows with simultaneous data ingestion and predictive analytics to create proactive and scalable solutions (Kakani et al., 2020).

A variety of AI/ML techniques have already shown success in specific food safety applications. In milk adulteration detection, support vector

Table 1
Common food adulterants by category and associated health risks.

Category	Common Food Items	Typical Adulterants	Associated Health Risks
Dairy Products	Milk	Urea, Detergents, Starch	Kidney damage, gastrointestinal issues, metabolic disorders
Edible Oils	Mustard oil, Coconut oil	Argemone oil, Paraffin wax	Glaucoma, liver toxicity, cardiac issues
Spices & Condiments	Turmeric, Chili powder, Coriander	Lead chromate, Sudan dyes, Sawdust	Carcinogenic effects, anemia, and neurological disorders
Grains & Pulses	Wheat, Rice, Lentils	Polished with artificial agents, stone chips, coloring agents	Digestive tract irritation, kidney problems
Fruits & Vegetables	Bananas, Mangoes, Apples	Calcium carbide, Wax coating, Artificial ripening agents	Respiratory issues, neurotoxicity, and potential carcinogenicity
Sweeteners & Beverages	Sugar, Honey, Fruit Juices	Chalk powder, Glucose syrup, Synthetic food colors	Tooth decay, diabetes risk, liver stress, and cancer risk
Miscellaneous	Tea leaves, Salt	Iron fillings, washed/dyed used leaves, Washing soda	Abdominal issues, dental enamel corrosion, and potential poisoning

Fig. 1. A Comparative Overview of Traditional vs AI-Driven Food Safety Workflows: Enhancing Efficiency, Accuracy, and Accessibility.

machines (SVM) trained on near-infrared (NIR) or Fourier transform infrared (FTIR) spectroscopy data can identify the presence of urea, starch, and detergents with accuracy exceeding 95 %. For edible oils, ML models like XGBoost have been effectively used to distinguish between pure and adulterated samples by analyzing their spectral fingerprints. In the domain of fruits and vegetables, convolutional neural networks (CNNs) can analyze images to detect ripeness, bruising, fungal infections, or chemical residues on the surface. These models are not limited to visible contaminants, they can also flag subtle changes that are hard for human eyes to detect (X. Wang et al., 2022; Ben Ayed & Hanana, 2021). AI's applications in this area do not end. In packaged meat and ready-to-eat meals, deep learning models that involve CNN and long short-term memory (LSTM) networks can analyze images and supplemental environmental information (e.g. temperature and humidity) to predict how long a product would be good for sale and the spoiling onset. Blockchain combined with AI is another emerging solution, allowing for traceable, tamper-proof tracking of food products along supply chains (Dhal & Kar, 2025a; Kumar et al., 2021).

AI algorithms can detect anomalies in distributed ledger entries, helping to ensure the authenticity and safety of food items across borders. Despite these advances, several challenges still limit the widespread adoption of AI in food safety. A key issue is data availability. Reliable AI models require large, high-quality datasets that are representative of a wide variety of different geographies, food products, and food adulteration approaches. However, food safety data is typically fragmented, inconsistent, or simply unavailable due to privacy issues or a lack of infrastructure. For example, a model trained on milk samples from India will likely not perform well on samples from Europe because they may have different additives or processing techniques. Also, many of the deep learning and AI models, while accurate, often operate as black boxes, and this lack of interpretability can result in food regulators or quality assurance professionals simply not trusting the predictions enough to act on them. Finally, for many rural and under-resourced areas of the world, there may be a lack of sensors, power supply, or internet infrastructure that would further make AI solutions challenging to deploy or implement (Ennab & Mcheick, 2024; Mu et al., 2024; Salhab et al., 2024).

To address these limitations, researchers and innovators are exploring a number of valuable approaches. One approach is federated learning, which allows several clients to train a common AI model without needing to share raw data, all while also protecting privacy and maintaining diversity. Another is generating synthetic data, which can serve as an alternative when the number of real-world datasets is limited. Multimodal AI models, which can integrate data from cameras, gas sensors, electronic tongues, and olfactory sensors (e-noses), provide a more holistic picture of food quality and safety. These models can detect multiple forms of adulteration simultaneously and adapt to different types of food products (Gbashi & Njobeh, 2024; Yu et al., 2022; Zhang et al., 2024). This review aims to explore the full potential of AI in food safety from a scientific and application-oriented perspective. It begins by introducing different types of machine learning, supervised, unsupervised, and reinforcement learning, and how each type supports various food safety tasks. For example, supervised learning is used for classifying adulterated vs. pure food samples, while unsupervised learning helps detect anomalies in large-scale food processing systems. Reinforcement learning is being explored for real-time decision-making in automated food inspection and smart kitchen environments. Next, we delve into the key machine learning models, including decision trees, random forests, SVMs, CNNs, RNNs, and ensemble models, highlighting their strengths and specific food safety use cases.

Following the technical overview, we analyze important performance metrics such as accuracy, precision, recall, F1-score, and area under the curve (AUC), all of which are critical for evaluating model reliability, especially in real-world settings. We also present real-world case studies to illustrate how these AI techniques are being applied across different food categories, from milk and meat to fruits, juices, and grains. Finally, we examine existing challenges and propose future directions, such as integrating AI with biosensors, using synthetic data generation, and building globally interoperable AI models for food safety. By focusing on practical examples across diverse food categories, milk, spices, oils, grains, fruits, beverages, and more, this review highlights the current landscape, gaps, and future promise of AI in ensuring food safety. The overarching goal is not only to summarize technological progress but to guide future research and development toward making food safer for everyone, everywhere. With the right mix of innovation, collaboration, and regulatory support, AI can serve as a powerful safeguard in the global food system, capable of protecting consumers, improving transparency, and ultimately building a safer food future.

2. Types of ML relevant to food safety

ML is not a one-size-fits-all technology; there are different ways it can learn depending on the type of data and the problem it needs to solve. In the context of food safety, the three most important types of learning are supervised learning, unsupervised learning, and reinforcement learning. Each of these plays a unique role in helping us detect, classify, or even predict problems related to food adulteration, spoilage, and contamination. Choosing the right type of learning method depends on whether we already know what we're looking for, or if we need the system to discover unknown patterns on its own (Morales & Escalante, 2022).

Supervised learning is the most commonly used approach to food safety. It involves training an algorithm on a dataset with labeled examples where the correct answer is already known. For example, if we want a machine to detect adulterated milk, we can use thousands of milk samples that each have labels "pure" or "adulterated" and include the specific adulterant, such as urea, starch, or detergent. Once the model is trained, it can make predictions on new (previously unseen) milk samples with a high degree of accuracy. Methods such as Support Vector Machines (SVM) and Random Forests are particularly effective here and are typically applied to spectroscopy data, for example, near-infrared (NIR) or Fourier-transform infrared (FTIR), to reveal chemical signatures of adulterants. Similarly, for fresh produce like fruits and vegetables, Convolutional Neural Networks (CNNs), a type of deep learning model, can analyze images to spot signs of spoilage, bruising, or overripeness. Because supervised models learn from labeled examples, they are great for classification tasks where we already know what "good" and "bad" food looks like.

At the same time, unsupervised learning is sometimes used when we have unlabeled data or when we don't know exactly what we expect. These models will identify hidden patterns or groupings on their own. In food safety, unsupervised learning is sometimes used to identify unusual behavior or unexpected changes in the process. For instance, in a food processing plant, sensors collect massive amounts of data about temperature, humidity, or gas emissions. Algorithms like K-means clustering can group this data to identify patterns of normal operation and detect when something abnormal, like early spoilage or a machine malfunction, starts to happen. Likewise, hyperspectral imaging, including for spices or edible oils, has also been found to reveal finer differences between pure and adulterated products by using dimensionality reduction methods (e.g., Principal Component Analysis (PCA)). The unsupervised modeling may not provide direct insight into what the issue was, but is useful in marking an area that may warrant further investigation (Haldorai et al., 2020; Rajoub, 2020).

The third category, known as reinforcement learning, is still developing in the area of food safety. However, reinforcement learning offers the potential for advancement, particularly in decision-making scenarios with a real-time approach. Reinforcement learning operates, essentially, like trial-and-error modeling. There is an entity (the "agent") that interacts with its environment, collects data based on the role of the environment when taking an action sequence, just as humans typically do, to learn the task through taking an action and being rewarded or punished for that action. In food processing or storage, reinforcement learning can help maintain ideal conditions by constantly adjusting parameters like temperature, airflow, or conveyor speed based on sensor input. For example, if a sensor detects an increase in humidity that could lead to spoilage, a reinforcement learning system might learn to activate cooling or drying mechanisms to prevent quality loss. Some early experiments have used Reinforcement learning to manage cold-chain logistics, ensuring perishable foods like meat or dairy are stored under optimal conditions while reducing energy usage. Though still in development, reinforcement learning has the potential to make food safety systems more autonomous and responsive in the future (Kish, 2018).

Among these three learning types, supervised learning is currently the most popular and widely adopted in food safety applications. The main reason is that it provides highly accurate results when good-quality labeled data is available, which is often the case for common tasks like detecting adulterants in milk, classifying the quality of fruits, or predicting shelf-life based on environmental data. Models like SVM, Random Forest, and CNN are supported by mature libraries and toolkits, making them easier to implement and integrate into existing food quality monitoring systems. Also, since supervised learning models can give very specific results, like "this honey contains sugar syrup" or "this batch of turmeric contains lead chromate", they are particularly useful for regulatory and compliance checks. That said, both unsupervised and reinforcement learning are gaining ground, especially in situations where labeled data is limited or unavailable. As more food production systems become digitized and connected through IoT sensors, the need for smart, real-time, and adaptable learning systems will grow. In such cases, combining all three learning approaches may offer the most powerful and flexible solution for food safety management (M. Bhaiyya et al., 2024).

3. Key AI/ML models used in food safety

3.1. Decision trees and random forests

DT and RF are among the most widely used ML models in food safety applications. These models are particularly valued for their simplicity, interpretability, and ability to handle both categorical and numerical data. DT mimics the way humans make decisions by asking a series of yes/no or if/else questions and is very effective in classification problems. RF builds on this concept by combining many decision trees to improve prediction accuracy and reduce the risk of overfitting (Refer to Fig. 2(A)). To make this easier to understand, let's walk through a real-world example involving the detection of milk adulteration using spectroscopy data and RF (M. L. Bhaiyya et al., 2023; Manekar et al., 2025). In summary, DT and RF strike a great balance between interpretability and performance when it comes to food safety; this is why these ML approaches are often used. While DT is easy and interpretable by itself, RF adds a significant level of reliability and reproducibility to the original dataset, often reducing the noise in the Dataset. Furthermore, their ability to handle larger amounts of real-world food quality data, whether it be images, sensor data, or spectral data, makes them one of the most used and trusted ML models in the industry.

3.2. Support vector machines (SVM)

Support Vector Machines, or SVMs, are one of the most powerful

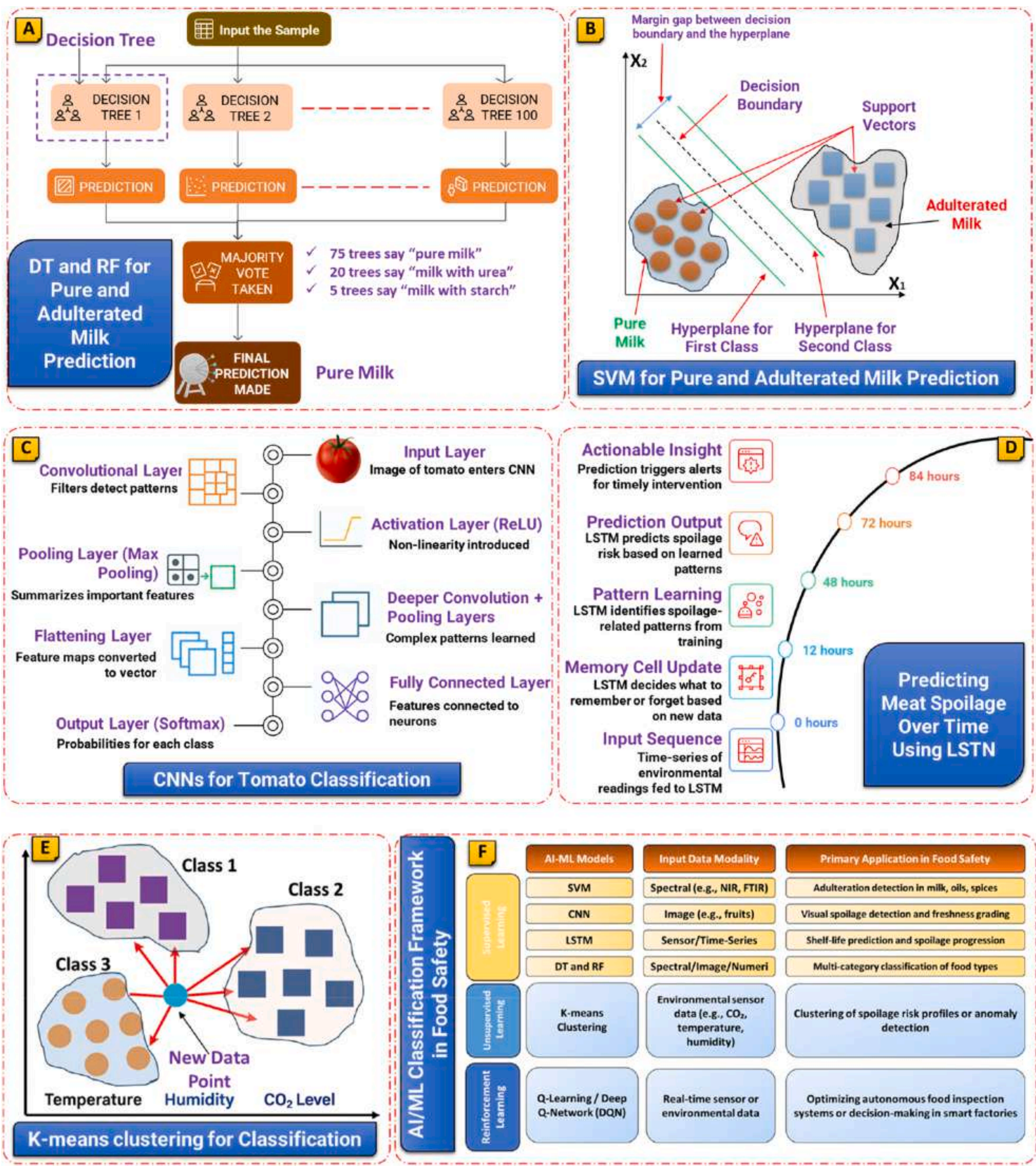

Fig. 2. (A) DT and RF: Ensemble-based prediction of milk purity using 100 decision trees and majority voting to classify samples as pure or adulterated. (B) SVM: SVM model classifying milk samples by finding the optimal hyperplane separating pure and adulterated classes using support vectors. (C) Step-by-step architecture of a CNN used to classify tomatoes based on ripeness using image features. (D) Sequential LSTM model predicting meat spoilage based on time-series sensor data, tracking environmental changes to enable early intervention. (E) K-means clustering groups food samples based on features like temperature, humidity, and gas levels to identify spoilage risk without predefined labels. (F) A unified technical classification framework for AI/ML models used in food safety.

tools in ML, especially when it comes to making decisions based on subtle differences in data. In the context of food safety, SVMs are commonly used to detect food adulteration, particularly in cases where we have chemical or spectral data that can tell us what's inside a food sample. What makes SVMs special is their ability to find a clear dividing line (or boundary) between two categories, for example, "pure milk" and "milk with urea", even when the data is complex and not easily separated. Let's take a practical example. Suppose we want to detect whether milk samples are adulterated with urea, a harmful chemical sometimes added to make the milk look richer in protein. Every milk sample is passed through a near-infrared (NIR) spectrometer, which measures how the milk absorbs light at different wavelengths. Each sample produces a set of numbers that together act like a fingerprint, unique to that sample's chemical composition. These spectral patterns become our input data. For training the model, the lab also adds labels like "pure" or "adulterated," based on confirmatory chemical tests. This labeled data forms the foundation of the supervised learning process (Srivastava et al., 2023).

Now, when we train an SVM model on this data, it essentially looks at all the pure and adulterated samples and tries to find the best possible boundary between them. But it doesn't just pick any random line. Instead, it finds the one that leaves the widest possible gap (or margin) between the two classes, like creating a buffer zone between "safe" and "unsafe." The data points that sit closest to this boundary are called support vectors, and they help define the exact placement of this decision line. To understand this more visually, imagine plotting the spectral values of milk samples on a graph. The SVM draws a line between the two categories in such a way that it doesn't just barely separate them; it gives some breathing room to avoid mistakes when new samples are tested. This makes SVMs especially good at avoiding false alarms while still catching most of the problematic cases (Liang et al., 2024, 2025; Ni et al., 2023).

Once the model is trained, we can use it to predict the status of a new milk sample, shown in Fig. 2 (B). The new sample is scanned by the NIR spectrometer, and its data is fed into the SVM model. If the sample falls on the "pure" side of the boundary, the system classifies it as safe. If it's closer to the side that matches previously adulterated samples, it gets flagged for further testing. This whole process takes just a few seconds and can be automated to work in real-time at collection centers or milk processing units. What makes SVM particularly useful in this kind of problem is its ability to handle complex, high-dimensional data like spectra. Even if the pure and adulterated samples don't follow a clear linear pattern, SVM can use something called the kernel trick to bend the decision boundary into a shape that fits the data better. This flexibility means that SVM can handle real-world complications like noisy data or overlapping features. In conclusion, SVM is akin to a clever filter. It learns the differences between uncontaminated and contaminated food samples by analysing the chemical or spectral fingerprints. Once the training is completed, it makes fast, correct decisions and helps labs and food inspectors to catch dangerous adulterants before they get to the consumer. For any food product where chemical composition tells the story, such as milk, honey, spices, or oils, SVM can be the best, reliable, and efficient option.

3.3. Partial Least Squares (PLS)

Partial Least Squares (PLS) offers a robust regression method specifically designed to analyze complicated high-dimensional data, such as spectra of food samples. PLS methods do not use all of the original variables; some of which may be noisy and share a high correlation. PLS takes the complicated input data (like absorbance values from NIR or FTIR) and throws away those individual (and difficult to interpret) variables in favour of a smaller number of new features called latent variables, that nonetheless capture nearly all of the information that suggests a relevant pattern linking the input to an outcome (like the level of adulteration or microorganisms spoilage). Whereas some approaches consider solely the input data in determining a predictive outcome, PLS supports and identifies meaningful patterns directly available for predicting outcomes. This is particularly relevant in food safety applications, where often the analysis is only the measure of subtle differences in chemistry or the prediction of levels of contamination from sensory input data. Every day, there are articles in the scientific literature discussing the need for quantified predictors of food quality, whether this is an estimation of sugar syrup in honey, gas freshness in a packaged fruit, or food. PLS is a useful approach in all of these contexts, with accuracy and speed vital for the current generation in real-life monitoring of food quality (Liang et al., 2024, 2025; Ni et al., 2023).

3.4. Convolutional neural networks (CNNs)

CNNs (Convolutional Neural Networks) are a type of deep learning model optimized for image applications in food quality assessments, like detecting mold on bread, fruit ripeness grading, and bruising detection in vegetables, as shown in Fig. 2 (C). CNNs automatically learn hierarchical visual features, such as edges, textures, or patterns, directly from raw images without requiring manual feature engineering. In food safety, this enables real-time, non-invasive inspection of surface-level spoilage or visual adulteration. CNNs are appreciated for their scalability to various image datasets and their capacity to manage complicated visual patterns, often beyond the detection capabilities of conventional methods or human inspectors (M. Bhaiyya et al., 2024; Singhal et al., 2025). CNN is like a super-powered visual inspector. They can examine thousands of food items in real-time, pick out the tiniest signs of spoilage or contamination, and make accurate, consistent decisions. Their layered structure, from simple edge detectors to complex classifiers, allows them to "understand" food images much like a trained quality inspector would, but faster and more reliably (Alzahrani, 2025; Ko et al., 2021).

3.5. Recurrent Neural Networks (RNNs) and long short-term memory (LSTM)

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs) are developed for use with sequential or time-series data, making it appropriate to use these algorithms to predict progressions towards spoilage, or to track environmental parameters in a refrigerated environment, such as temperature and gas concentrations. While RNNs track short-term dependencies, LSTMs improve on this by capturing both short- and long-term temporal trends, thanks to their internal memory architecture (Ding et al., 2025; Geng et al., 2022). In the context of food safety, LSTM can predict the possibility of spoilage of a product using past sensor data and make notified decisions in the active cold chain or packaged food supply chain, as shown in Fig. 2 (D). Their predictive ability arises from uncovering data points in time and providing forecasts for degradation of quality trends before they are critical (H. Lu et al., 2025; Sun et al., 2022; G. Wang et al., 2025).

Food doesn't go bad instantly; it follows a process. That process involves many small changes over time. Whether it's the slow rise of temperature in a refrigerator or increasing gas levels in sealed packaging, these changes follow a time-dependent pattern. RNNs and especially LSTM models are great at spotting such patterns. While CNNs are excellent for image-based tasks and RFs are great for classification, they don't handle sequences very well. They can look at one moment and say "this is spoiled" or "this is not", but they don't consider what's been happening over the past few hours or days. RNNs and LSTMs do. They're designed to connect the dots over time and make smarter, context-aware predictions. In conclusion, RNNs and LSTM models are similar to food safety prognosticators. They do not solely respond with the immediate future in mind; they use past information to recognize trends and forecast what will possibly happen next. In an environment where a handful of hours can transform a food item from fresh to spoiled, these models are becoming valuable assets for developing smarter and safer food systems.

3.6. Clustering algorithms (K-means)

K-means is perhaps one of the most popular clustering techniques in ML, especially in the case of clustering data to explore patterns without pre-defined labels. In the context of food safety, K-means could be very handy to find hidden trends for spoilage, cluster similar food batches, or catch early signs of quality issues, without telling the system what to investigate, as shown in Fig. 2 (E). K-means is a kind of unsupervised learning wherein the instruction is based solely on the sample data without supervision, and the model finds clusters based on similarity (Agarwal et al., 2023; Q. Chen, 2024). The reason K-means is so useful in food safety is that it provides early, data-driven insights even before we have ground truth labels. It's fast, simple to implement, and can work on large datasets with multiple variables. And while it doesn't make direct predictions like supervised models, it helps reveal hidden structures in the data, which can then guide decision-making, resource allocation, and further testing.

4. Performance metrics for food safety models

Building an AI model for food safety is only half the job. The other half is measuring how well it performs, because when it comes to detecting adulteration, spoilage, or contamination, even a small error can have serious consequences. That's where performance metrics come in. These metrics help us (shown in Fig. 2 (F)) understand whether the model is just good on paper or actually useful in the real world. Accuracy is the most basic metric; it tells us how often the model is right. But in food safety, accuracy alone can be misleading. Imagine a model that calls everything "safe" in a batch where only 5 out of 100 samples are actually adulterated. It may be 95 % accurate, but it's dangerously useless. That's why we look deeper. Precision shows how many of the items flagged as "unsafe" truly are unsafe. It helps avoid false alarms and food wastage. Recall, on the other hand, tells us how many unsafe items the model actually caught. A high recall is vital when missing even one contaminated product could put lives at risk. F1-score combines both precision and recall, useful when we need a balance between catching real threats and avoiding unnecessary rejections. A confusion matrix gives a complete picture of how many samples were correctly or incorrectly classified, and in what way. It helps identify if the model is being too strict, too lenient, or missing key patterns. For models that make predictions over time, like estimating when food will spoil, we use MAE (Mean Absolute Error) or RMSE (Root Mean Squared Error). These tell us how far off the model's predictions are. Lower values mean better accuracy, which is critical in cold chains or shelf-life forecasting. Another important metric is inference time, how quickly the model makes a decision. In real-time environments like sorting fruits on a conveyor or scanning milk cartons, even a 1-s delay can slow down operations. So, fast and efficient models are preferred here. Lastly, ROC-AUC helps us see how well a model separates safe and unsafe items across different threshold settings. It's especially helpful when we want to compare multiple models before choosing the best one. In short, different tasks need different metrics. A model for allergen detection needs high recall. A model for grading fruits may focus on accuracy and speed. Choosing the right metric isn't just a technical decision; it's about safety, efficiency, and trust (Kahar et al., 2023; Zalke et al., 2024). To make this information more accessible to practitioners and engineers working in food safety, we summarize these metrics in Table 2, along with specific food safety examples and why each metric matters in real-world contexts.

5. Real-world case studies of AI in food safety

5.1. Case-based insights across dairy, oils, spices, and pulse adulteration detection using AI-ML models

The real power of AI and ML in food safety comes to life when we look at how these technologies are being applied across different food categories. From milk and honey to spices and juices, researchers have explored a variety of AI-driven solutions to detect adulterants quickly, accurately, and non-destructively. These case studies not only highlight the potential of AI/ML but also show how each application contributes to safer, more transparent food systems.

In the dairy sector, a 2024 study addressed the problem of real-time detection of milk adulterants such as starch and urea, which are commonly used to manipulate protein content. Using a multi-sensor IoT setup comprising pH, VOC, fat/protein, and conductivity sensors, the system captured detailed chemical signatures of milk samples, as shown in Fig. 3 (A). An ensemble ML model integrated with SHAP explainability achieved 96 % accuracy, enabling both accurate predictions and interpretability. Compared to traditional chemical assays, this system offered real-time operation and portability, making it well-suited for supply chain monitoring (K. Goyal et al., 2024). Building upon the success in dairy, another study focused on detecting adulteration in edible oils, a common practice involving dilution with paraffin or castor oil, as shown in Fig. 3 (B). The researchers used hyperspectral imaging to capture fine spectral differences across oil samples. Preprocessing with Savitzky-Golay filtering enhanced data quality, and models including RF, SVM, and LDA were employed for classification. The LDA model

Table 2
Performance metrics for AI models in food safety applications.

Metric	Definition	Application in Food Safety	Importance
Accuracy	Percentage of total correct predictions	Classifying fruit as "ripe", "overripe", or "spoiled" using CNN	General reliability of the model across all predictions
Precision	TP/(TP + FP): How many predicted positives are actually correct	Identifying contaminated milk samples without wrongly flagging pure ones	Reduces false alarms, prevents unnecessary rejections
Recall (Sensitivity)	TP/(TP + FN): How many actual positives are detected	Detecting all spoiled ready-to-eat meals	Critical as missing unsafe samples can cause health hazards
F1-Score	Harmonic mean of precision and recall	Evaluating model performance in honey adulteration detection	Balanced performance when both FP and FN need to be minimized
Confusion Matrix	Breakdown of true vs. false classifications across all classes	Evaluating model predictions for multi-class food classification (e.g., spices)	Helps diagnose if the model is biased or misclassifying specific classes
ROC-AUC	Measures the ability to separate classes across thresholds	Comparing models in detecting adulteration in edible oils	Helps choose the best model for binary food safety classification
R^2 Score	Proportion of variance in the dependent variable explained by the model	Quantifying adulterant concentration in honey using PLSR or SVR models	Indicates model fit for regression tasks; important in shelf-life prediction and spoilage quantification
MAE/RMSE	Error between predicted and actual values (continuous output models)	Predicting shelf-life of packaged meat using sensor data + LSTM	Evaluates how close model forecasts are to real-world values
Inference Time	Time taken for the model to give output	Real-time fruit grading on conveyor belts	Important for high-speed industrial automation
Confidence Score	Model's probability estimate of prediction correctness	Reporting confidence in detecting sugar syrup in honey	Useful for regulators and QA teams to assess trust in predictions

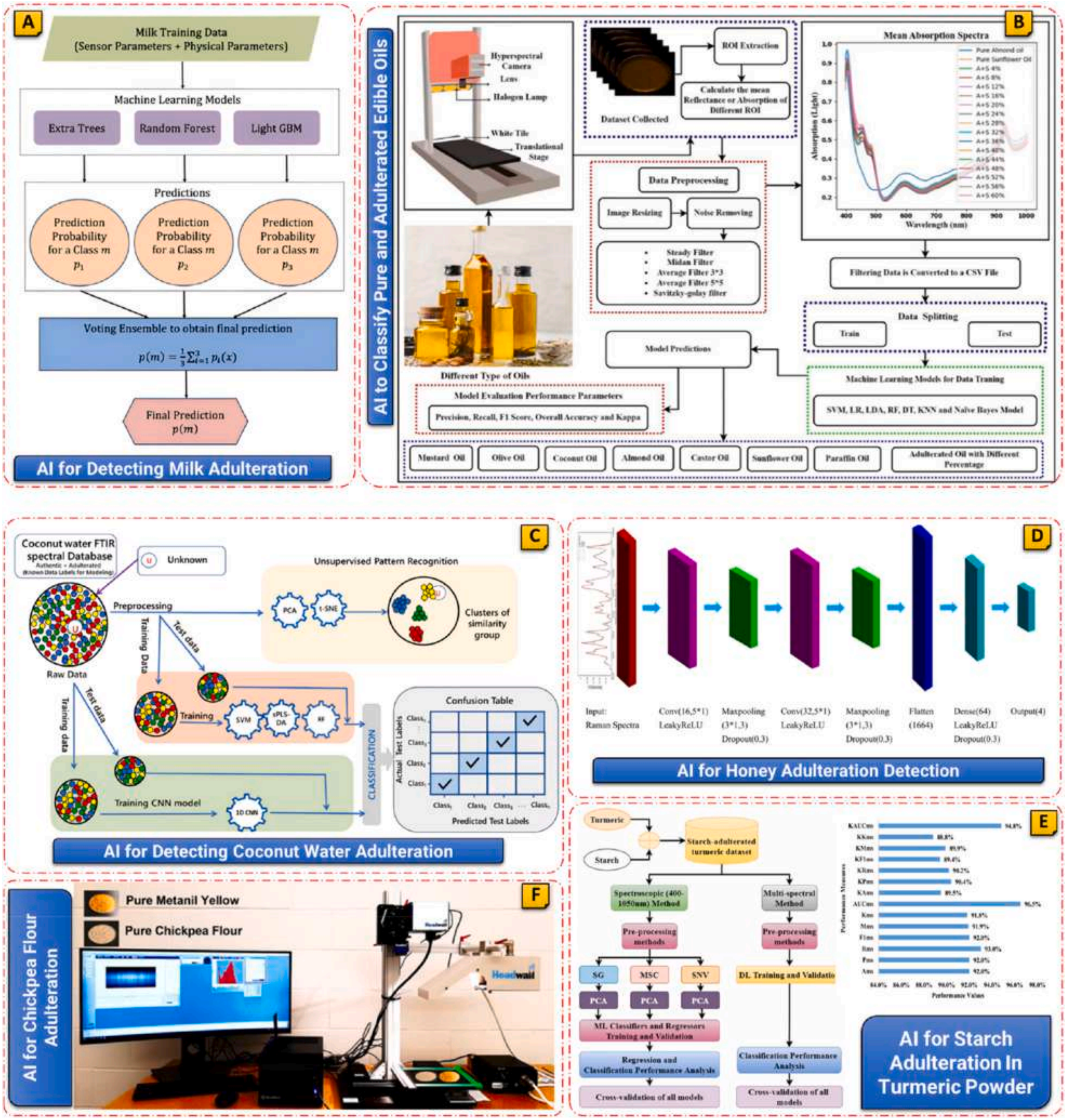

Fig. 3. (A) AI-based milk adulteration detection using ensemble ML models, taken from (K. Goyal et al., 2024), with the permission of Elsevier. (B) Spectral and ML-Based detection of adulteration in Edible Oils, taken from (Aqeel, Sohaib, Iqbal, Rehman, & Rustam, 2024), with the consent of Elsevier. (C) Coconut water adulteration detection using FTIR spectra and ML algorithms, taken from (Teklemariam et al., 2024), with the permission of Elsevier. (D) Deep Learning architecture for honey adulteration detection from Raman Spectra, taken from (X. Wu et al., 2022), with the permission of Elsevier. (E) AI-Driven spectroscopic analysis for starch adulteration in turmeric powder, taken from (Lanjewar, Asolkar, et al., 2024) with the permission of Elsevier. (F) AI-Powered detection system for chickpea flour adulteration, taken from (Saha et al., 2023) with the permission of Elsevier.

achieved 100 % validation accuracy, demonstrating that non-destructive imaging-based approaches can outperform GC-MS or HPLC in speed, cost-efficiency, and ease of use (Aqeel, Sohaib, Iqbal, Rehman, & Rustam, 2024).

Transitioning from oils to beverages, a study investigated the adulteration of coconut water with sugar-based additives. The researchers developed a fingerprint database using ATR-FTIR spectroscopy of 15 adulterants, as shown in Fig. 3 (C). Two models, RF and 1D CNN, were trained on the spectral data, with the CNN achieving 96 % classification accuracy directly from raw spectra. This eliminated the need for manual feature engineering, highlighting the model's efficiency and practicality for real-world deployment (Teklemariam et al., 2024). A similar deep learning framework was applied to detect syrup-based adulterants in honey, a high-value product often diluted with high fructose or rice syrups. The study employed Raman spectroscopy combined with CNN and PLS regression, as shown in Fig. 3 (D). The CNN yielded >97 % classification accuracy, while PLS achieved $R^2 > 0.98$ for quantitative prediction. These results indicate a marked improvement over conventional HPLC or isotope ratio analysis, offering a non-invasive, rapid, and field-deployable solution (X. Wu et al., 2022). Extending the focus to powdered foods, another study tackled starch adulteration in turmeric powder, a common but harmful practice. Using a combination of visible-NIR spectroscopy and multispectral imaging, the researchers applied RF and DenseNet201 architectures to detect adulterants at trace levels, as shown in Fig. 3 (E). With an F1-score exceeding 92 %, the method proved to be both sensitive and scalable. This study also emphasized the benefit of combining multiple imaging modalities to boost detection robustness (Lanjewar, Asolkar, et al., 2024).

Authentication challenges were also tackled in tea and spice products. In one study, UV–Vis spectroscopy combined with PLS-LDA and SVM models successfully distinguished black tea samples based on their narrow geographic origin, with 98 % accuracy. This chemical fingerprinting-based technique provides an affordable and scalable alternative to isotope or metabolomics-based geographic authentication, enhancing traceability and transparency in global tea markets (Mohammadi et al., 2024). To address adulteration in coriander powder, FTIR spectroscopy was merged with ML models such as ANN and SVR. The optimized models predicted sawdust adulteration with R^2 values exceeding 0.96, making the system suitable for both qualitative and quantitative adulteration analysis. This approach not only supports automated, high-throughput monitoring but also demonstrates how spectral-ML frameworks can be tailored for specific species (R. Goyal et al., 2025). Finally, in the domain of pulses, a study explored the adulteration of chickpea flour with metanil yellow, a toxic dye. The researchers employed line-scan NIR hyperspectral imaging, which provided pixel-wise spectral profiles. Using 1D CNN and PLS regression, they achieved an R^2 of 0.992, successfully identifying adulteration down to 0.1 % concentration, as shown in Fig. 3 (F). Compared to traditional

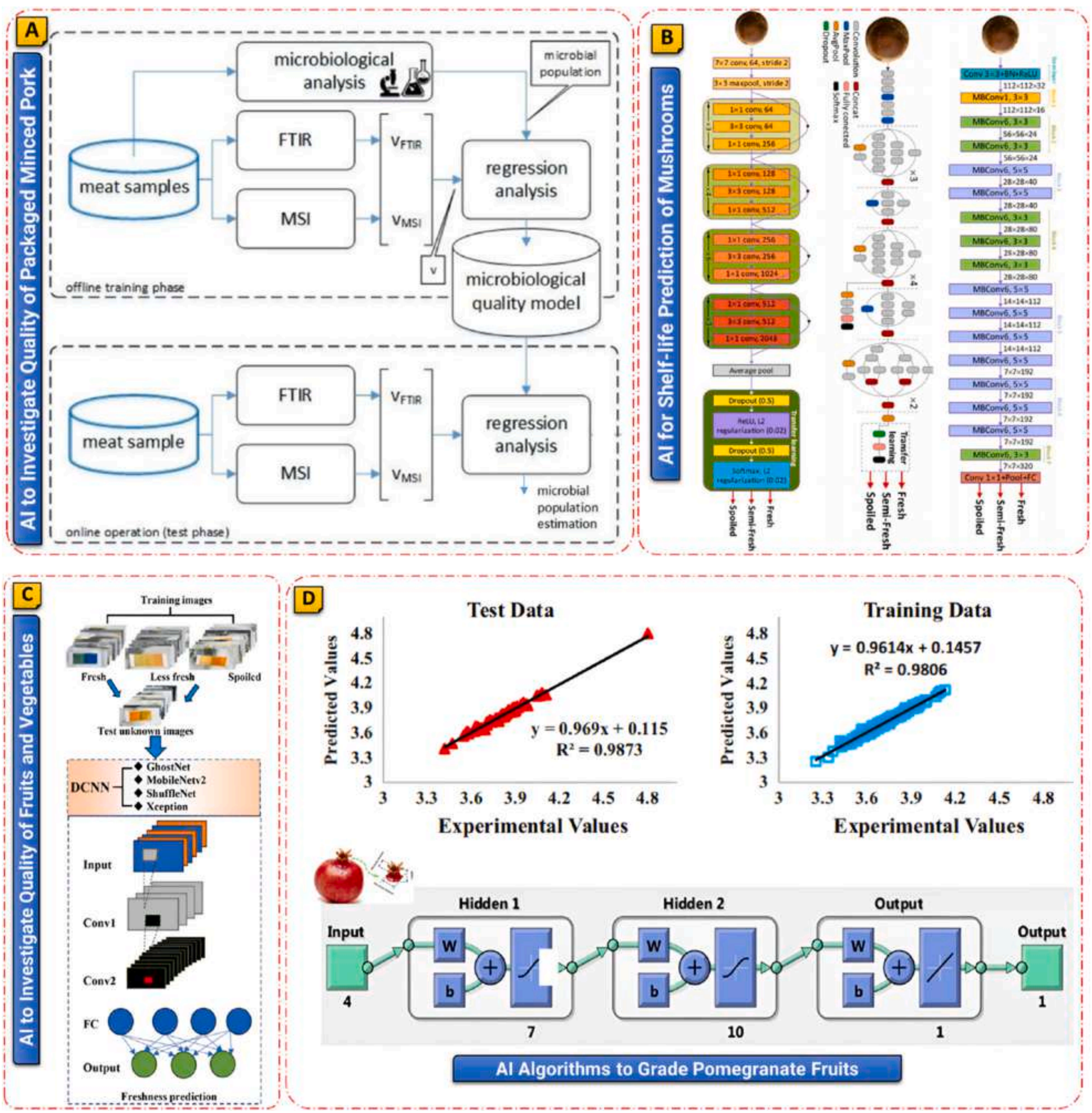

Fig. 4. (A) AI for quality assessment of packaged minced pork using spectroscopy and regression models, taken from (Fengou et al., 2020), with the permission of Elsevier. (B) Deep Learning-Based shelf-life prediction of mushrooms via image classification, taken from (Javanmardi & Ashtiani, 2025) with the permission of Elsevier. (C) AI for assessing the freshness of fruits and vegetables using image-based deep learning models, taken from (T. Tang et al., 2025), with the permission of Elsevier. (D) AI model for automated grading of pomegranate fruits based on experimental correlation, taken from (Fashi et al., 2020), with the permission of Springer.

spot sampling, this approach enabled continuous monitoring of production lines, paving the way for real-time industrial integration (Saha et al., 2023).

Together, the case studies of Section 5.1 reveal the range of AI/ML applications across a broad range of food matrices, such as dairy, edible oils, spices, and pulses. They show how strong the effect is in terms of using spectroscopy/imaging combined with various classification and regression models, such as SVM, RF, CNN, and PLS, for rapid and non-destructive detection of adulteration. But, examining the models more closely exposes additional common limitations: most models are developed assuming a limited dataset or a dataset produced in the lab, and may not be able to fully encapsulate the variability that real-world food supply chains have. It would also be difficult to generalize these models to other arbitrary geographies, variations in raw materials, and complex mixtures of adulterants. Furthermore, the lack of deployment-ready prototypes, especially in low-resource settings, suggests a gap between technological promise and field-level adoption. A more rigorous focus on transfer learning, domain adaptation, and low-cost sensor integration could help bridge this translational divide in future work.

5.2. Predicting shelf-life of packaged meat, smart grading of fruits and vegetables through AI and ML

As the global food industry grapples with issues of waste reduction and consumer safety, AI/ML technologies are emerging as powerful tools for real-time freshness evaluation and smart quality grading of perishable products. In addition to monitoring for adulteration, AI/ML technologies are now being utilized for predictions of shelf-life and freshness assessment across perishable animal- and plant-based food products. These case studies demonstrate how sensor data, in combination with advanced predictive models, can provide non-invasive and real-time measures of quality decline.

A representative example comes from a study that tackled the challenge of predicting microbial spoilage in packaged minced pork. Researchers collected spectral and multispectral imaging data from meat samples stored under varying temperature and packaging conditions, as shown in Fig. 4 (A). Using SVM-based regression models, the system could predict microbial counts with RMSE as low as 0.886, demonstrating excellent quantitative forecasting. This model outperformed conventional microbial plate assays, offering a non-destructive, real-time alternative suitable for inline quality monitoring in meat processing plants (Fengou et al., 2020). Building on this, another study addressed freshness prediction in mushrooms, one of the most perishable food items. By capturing high-resolution images of white button, oyster, and shiitake mushrooms at regular storage intervals, the research team trained multiple deep learning models, including ResNet-50, EfficientNet, and MobileNetV2, as shown in Fig. 4 (B). These models achieved over 94 % accuracy in classifying freshness stages, aided by transfer learning to speed up convergence. The approach bypassed the need for complex chemical tests and offered a rapid, low-cost, and smartphone-compatible method for freshness evaluation (Javanmardi & Ashtiani, 2025).

Moving from fungi to fresh produce, another study introduced a smart packaging system for vegetables and fruits like okra, plums, and jujube using 3D-printed CO_2-sensitive freshness labels, as shown in Fig. 4 (C). These labels used bromothymol blue and methyl red dyes that changed color based on CO_2 accumulation during spoilage. Images of the labels were then analyzed using lightweight CNNs such as GhostNet and MobileNetv2, achieving accuracy above 93 % across multiple freshness levels. This innovation offered a fusion of chemical sensing and AI, presenting an affordable, scalable freshness indicator that can be integrated directly into packaging (T. Tang et al., 2025). Complementing this direction, another study aimed to grade pomegranate fruits based on internal acidity (pH), a critical quality metric. By analyzing image features like crown shape and skin texture, researchers trained ANN and ANFIS models to estimate internal pH values, as shown in Fig. 4 (D). The models reached $R^2 = 0.984$, enabling rapid grading of fruits for juice, dessert, or processing purposes. Compared to conventional titration or destructive testing, this method provided a sensor-free, real-time alternative with high commercial utility (Fashi et al., 2020).

In conclusion, this section illustrates the increasing potential of AI/ML to evaluate freshness and predict shelf-life across perishable food products through multimodal data, spectroscopy, imaging, and smart labels. CNN-based image classifiers and regression models are showing promise for assessing microbial spoilage and texture degradation in meats, mushrooms, and fruits. However, many systems were trained and validated under controlled conditions and with limited, homogeneous sample sizes. Real-world variability, including supply chains, differences in packaging materials, and noise from sensors, is often unexplored. In addition, although both smartphone-based and low-cost freshness indicators show considerable promise, they will still require additional testing for long-term durability and scalability in operational field conditions. Going forward, to facilitate industrial use, the next generation of systems should strive for cross-platform compatibility, real-time inference capabilities, and low calibration requirements. This would enable easier incorporation into cold chains or in-store environments.

5.3. Spoilage detection in ready-to-eat (RTE) meals through AI-ML models

The increasing demand for Ready-to-Eat (RTE) meals, often rich in nutrients and requiring minimal preparation, has led to a growing concern over their spoilage potential, driven by short shelf life and rapid microbial deterioration. In response, AI and ML-based solutions are transforming how spoilage in RTE meals is detected and managed.

One study investigated RTE pineapple spoilage using a combination of FTIR, fluorescence, and visible spectroscopy along with multispectral imaging, as shown in Fig. 5 (A). The goal was to predict microbial quality and sensory degradation (odor, texture). PLSR and SVM models trained on the combined dataset achieved RMSE as low as 0.63 log CFU/g. In particular, FLUO sensor data combined with PLS-DA classification reached >85 % accuracy in odor prediction. Unlike microbial plating, this approach enabled real-time, non-destructive spoilage monitoring with high sensitivity (Manthou et al., 2020). Building on this concept, another study employed Selected-Ion Flow-Tube Mass Spectrometry to capture volatile organic compounds (VOCs) as markers of spoilage in fresh pork. From 37 VOCs, spoilage indicators like ethanol, benzaldehyde, and 3-methyl-1-butanol were extracted. Using ensemble models including ANN and SVR, the system could predict microbial quality across storage durations. The ANN-based bagging ensemble outperformed others, especially when microbial load exceeded safety thresholds (6 log CFU/g). Compared to GC-MS or culture-based techniques, this volatolomic-AI hybrid offered high-throughput, real-time evaluation with no reagents or sample prep (L. Chen et al., 2024). Further emphasizing low-cost, field-ready solutions, researchers developed an Arduino-based e-nose system to assess spoilage in stuffed mussels, a high-risk seafood RTE item. The system incorporated gas sensors (MQ3, MQ135, MQ9) and used image-based CNNs such as ResNet-50 and SqueezeNet to classify spoilage levels, as shown in Fig. 5 (B). The model successfully identified spoilage onset by day three of storage, offering a portable, open-source solution that can empower small-scale vendors or regulatory inspectors (Yavuzer et al., 2024). Lastly, a study on leafy RTE vegetables like baby spinach and rocket utilized FTIR, VIS, and MSI in conjunction with PLSR and SVR models to model microbial degradation. The study highlighted that sensor-model pairings must be optimized per vegetable type, reinforcing the need for product-specific calibration. This case emphasized the importance of tailored AI pipelines for different RTE foods to maintain precision and reduce food waste (Manthou et al., 2022).

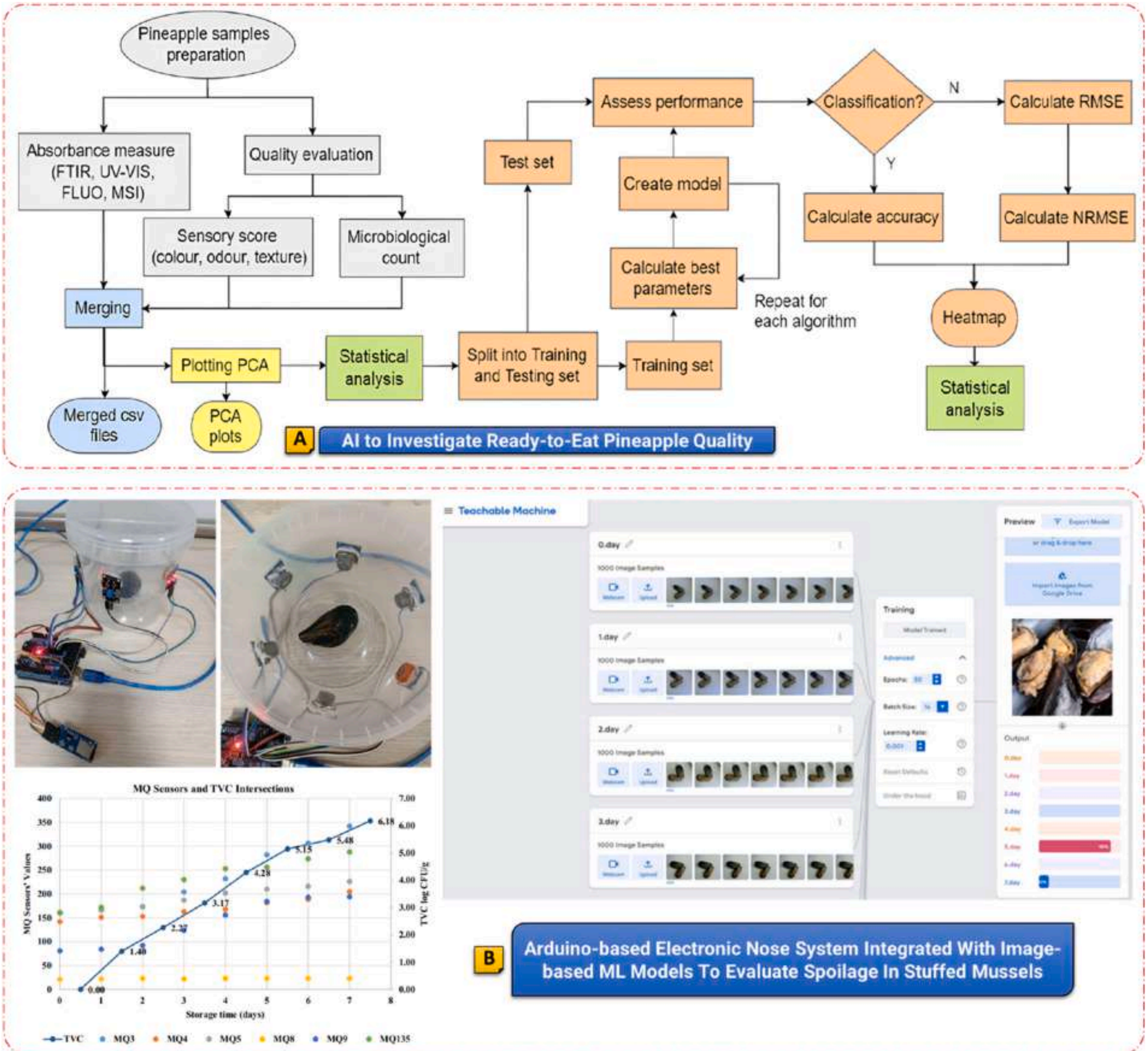

Fig. 5. (A) AI framework for quality assessment of ready-to-eat pineapple using multimodal sensing and statistical modeling, taken from (Manthou et al., 2020), with the permission of Elsevier. (B)Arduino-Based electronic nose coupled with image-based ml models to predict spoilage in stuffed mussels, taken from (Yavuzer et al., 2024), with the permission of Springer.

Overall, AI-based spoilage indicator technology in RTE meals shows great promise due to the high-risk, short-shelf-life nature of these products. The reviewed literature utilizes a variety of approaches to measuring spoilage and understanding microbial kinetics, for example: vibrational spectroscopy, volatolomics, image-based learning, and e-nose systems, coupled with ML models such as SVR, ANN, or ensemble classifiers. Although these technologies generally report high accuracy, scalability and use in field applications is severely limited. Sample sizes are often small, and datasets rarely take into account the cultural influences on regional cuisine, packaging technologies, or ingredient configurations. Additionally, most of the deployments remain prototypes with little acceptance in commercial RTE production environments, despite some authors distributing research to explore portable systems (e.g., Arduino-based e-noses) or microcontroller-based prototypes. Future solutions should focus on the development of standardized protocols, real-time monitoring of quality, and implementation of edge computing technologies. Co-design, with a combination of academic researchers and food industry stakeholders, will be critical for innovative solutions to coincide with relevant regulatory adoption. A comprehensive comparison of AI/ML-based food adulteration detection studies across coffee, milk, edible oils, honey, and turmeric was compiled (see Table 3). This unified dataset highlights diverse models such as SVM, CNN, RF, GA-PLS, and Transfer Learning integrated with various spectral techniques like Raman, FTIR, Vis-NIR, and MSI, showcasing high-performance metrics across multiple food matrices.

6. Challenges and possible solutions

Despite the remarkable potential of AI and machine learning in food spoilage detection, especially for ready-to-eat meals and perishable produce, several real-world challenges persist. These challenges are not merely technical; they reflect deep-rooted infrastructural, environmental, and human-system interactions that must be understood and addressed for AI to truly scale in food safety.

6.1. Data availability and quality

One of the most foundational challenges lies in the availability and reliability of data. AI models thrive on large volumes of diverse, high-quality, and labeled datasets. But in the case of food spoilage, such

Table 3
AI-ML approaches in food adulteration detection.

Ref No	Food Type	Analytical Technique	AI Model	Performance Metrics	Advantages over Conventional Systems
Lee and Rianto (2024)	Coffee	E-nose	DBSCAN	Detected adulteration via aroma profiles	Non-invasive, does not require labeled data or expert supervision
Pradana-López et al. (2021)	Coffee	Image Analysis	CNN + ResNet34	<1 % classification error	No pre-treatment required, highly accurate and fast
Sagita et al. (2025)	Coffee	Spectroscopy	LDA, ANN, RF, SVM	100 % species, 91.7 % origin	Affordable, rapid, and portable solution
Núñez et al. (2021)	Coffee	HPLC-UV-FLD	partial least squares regression	94.4 % classification, 2.9–3.2 % prediction error	Robust fingerprinting without target compounds
Ruttanadech et al. (2023)	Coffee	Spectroscopy	Tree, SVM, KNN, QDA, LDA, NB	Tree: 97.5 % accuracy	Non-destructive, early mold detection
Pinheiro Claro Gomes et al. (2022)	Coffee	Fluorescence Imaging	SVM, RF, XGBoost, CatBoost	SVM: 96 % accuracy	Real-time, non-destructive, high precision
Mohammadi et al. (2024)	Tea	UV–Vis	PLS-LDA, PLS-SVM	LDA: 98 %, SVM: 94 %	Low-cost, simple, no extensive pretreatment
Aqeel et al. (2025)	Milk	HSI	LDA, SVM, Logistic Regression, Decision Tree	Validation Accuracy: 100 %	Non-destructive, high-precision detection for multiple adulterants
K. Goyal et al. (2024)	Milk	IoT Sensors	Ensemble (XAI + SHAP), RF, LightGBM, Extra Trees	Accuracy: 96 %	Portable, real-time, explainable AI for safety assurance
Aqeel, Sohaib, Iqbal, and Ullahd (2024)	Milk	HSI	CNN, ANN, LSTM, GRU	CNN: 97 %, high scores across metrics	High precision, deep spectral learning
Colak et al. (2025)	Milk	FTIR	Ensemble Bagged Trees, SIMCA, DD-SIMCA	Accuracy: 90.38 %	Cost-effective, less preprocessing, highly accurate
Darvishi et al. (2025)	Milk	E-nose	CA, DA, SVM, QDA	QDA: 99.5 %, MDA: 98.5 %	Non-invasive, low-cost, high-precision sensory detection
Lanjewar, Parab, and Kamat (2024)	Milk	NIR	KNN, RF, PCA	KNN: R^2 = 0.999, RF: 100 %	Compact, fast, field-useable system
Yao et al. (2023)	Milk	FT-MIR	LDA, Neural Network	LDA: 100 %, NN limit: 3.27 g/100g	Fast, sensitive, and quantitative spectral detection
Ratnasekhar et al. (2025)	Oils	FT-NIR	FT-NIR + ML	Accuracy >0.98, Sensitivity >98 %	Non-destructive, solvent-free, rapid fingerprinting
Aqeel, Sohaib, Iqbal, Rehman, and Rustam (2024)	Oils	HSI	LDA, SVM, RF, DT, KNN, NB, LR	Validation Accuracy: 100 % (LDA)	Non-destructive, multi-class classification
Bavali et al. (2025)	Oils	LIF	SVM, 1D-CNN, XGBoost	SVM: 99.06 %, LOD: 0.0288 %	Trace-level detection, portable setup
Zhao et al. (2022)	Oils	Raman	9 ML models + PCA	96.7 % classification, R^2 = 0.984	Fast, solvent-free, suitable for high-throughput
Lim et al. (2020)	Oils	Fatty Acid Profiling	End-to-end DL, unsupervised + supervised ML	Error <5.4 % (90th), <1.8 % (median)	Handles complex mixtures, generalizable, real-time, updatable
Aghili et al. (2022)	Oils	E-nose and GC-MS	ANN, SVM, LDA, QDA, PCA	Detected a 25 % fraud level	Rapid, portable, low-cost, odor-based profiling
C. H. Lu et al. (2023)	Oils	Pigment Analysis	SVM	Train: 100 %, Test: 94.44 %	Pigment-based authenticity check, minimal prep
Windarsih et al. (2024)	Oils	FT-IR	SVM, ANN, LR, kNN, Gradient Boosting	SVM: R^2 = 0.993, RMSE = 2.719 %	Sensitive, halal-focused, easy IR-readout
Lanjewar, Panchbhai, and Patle (2024)	Honey	HSI	Stacking Generalization (SG), PCA, SVM, kNN	R^2 = 0.999, RMSE = 0.493 ml	Non-invasive, high-accuracy multi-class classification
Shehata et al. (2024)	Honey	Raman	SORS + PLS-DA, RF, XGBoost	RF: <3.5 % misclassification	Non-invasive, through-container sensing
Razavi and Kenari (2023)	Honey	UV–Vis	SVR, Partial Least Squares Regression	R^2 = 0.98, RMSE = 0.97	Fast, low-cost, non-destructive
Hu et al. (2022)	Honey	Raman	SVM, CNN, PNN	CNN: 99.75 %, SVM/PNN: 100 %	High accuracy, no preprocessing
Phillips and Abdulla (2023)	Honey	HSI	Binary + multi-class	>95 % accuracy (binary & multi-class)	Dataset made public, spatial info + spectrum
Boateng et al. (2022)	Honey	FTIR-HATR	GBDA, SVMDA, GBR	Class: 0.988–0.981, R^2 = 1.000	Feature selection impact studied, low RMSE
Calle et al. (2023)	Honey	Vis-NIR	SVM, RF, SVR	100 % classification, R^2 = 0.991	Non-destructive, botanical origin also detected
Mitra et al. (2023)	Honey	RSM	NN, RF	Correct prediction of simulated adulteration	Low-cost, fast analysis, real-world validation
X. Wu et al. (2022)	Honey	Raman	CNN, PLS	CNN >97 %, PLS R^2 > 0.98	Better than chemometrics; high generalization
Brar et al. (2024)	Honey	Video	2D-CNN	Accuracy = 0.94, Sensitivity = 0.99	No sensors/spectrometers needed, high scalability
Teklemariam (2024)	Spices	Raman + FT-IR	1D-CNN, PCA, etc.	1D-CNN accuracy highest	Minimal preprocessing, handles nonlinear patterns, high accuracy
Lanjewar, Asolkar, et al. (2024)	Spices	MSI + Vis-NIR	RFR, RFC, DenseNet201	R^2 = 0.999, RMSE = 0.391, F1 = 96 %	Combined MSI and spectroscopy for robust detection

datasets are often scarce or fragmented. Collecting data that links microbial spoilage levels (like total viable counts), environmental parameters (temperature, humidity), and sensor outputs (e.g., FTIR, electronic nose, gas chromatography) requires access to expensive laboratory infrastructure and controlled conditions, resources not readily available across all food sectors. Additionally, existing datasets often suffer from inconsistencies in labeling, missing metadata, or low sample diversity, which reduces model robustness. Due to either the absence of clean and comprehensive datasets, AI systems can perform well in controlled experiments and poorly with real-world variance. Poor data quality can contribute to missed classifications, diminished trust in predictions, and increased instances of overfitting. The solution to this problem could be with the use of federated learning, which enables institutions in distinct regions to cooperate on training models without having to share sensitive data. Federated learning approaches have shown a reduction of up to 47 % in privacy leakage compared to traditional centralized training, enabling institutions to collaboratively train models without sharing raw data. Synthetic data generation using tools like Generative Adversarial Networks (GANs) can also expand the data pool. GANs have shown a 30–60 % improvement in model accuracy when real-world data is sparse or unbalanced. Most importantly, establishing collaborative, open-access data repositories backed by government or research consortia can create a standardized baseline for model training and benchmarking (Gbashi & Njobeh, 2024; Rahman et al., 2024).

6.2. Generalizability across geographies and food types

A further important barrier is that models trained for one geography or food product typically do not generalize well to another. This occurs as spoilage signatures, such as microbial profiles or volatile organic compounds, can vary significantly by many factors, including climate zone, industry supply chain practices, and packaging types. Recent evaluations show that ML models trained in temperate environments experienced a 15–30 % drop in classification accuracy when tested in tropical or low-resource settings. Such a lack of generalizability creates barriers to scale and introduces operational risk (Jadhav et al., 2024, pp. 4989–4995). A promising solution is the use of domain adaptation techniques in ML that help models adjust to new data distributions. Additionally, building modular AI architectures that allow partial retraining or localization using small new datasets can enhance flexibility. Developing regionally tuned multi-task learning frameworks that share low-level features across foods while learning high-level differences specific to geography or commodity can also offer a more scalable path forward (Castano-Duque et al., 2022; Q. Tang et al., 2023).

6.3. Interpretability of complex ML models

Although deep learning models (such as CNNs) or ensemble methods (like RF) provide better performance in spoilage detection tasks, they typically operate as "black boxes." In other words, they predict spoilage correctly without providing a transparent explanation for classifying a food sample as spoiled. This lack of interpretability poses a serious barrier in food safety applications, where decisions must be explainable to regulators, auditors, and even consumers. When a prediction cannot be explained, especially a false positive that leads to product rejection or recall, it becomes difficult to build trust in AI-driven decisions. To improve transparency, explainable AI (XAI) frameworks such as SHAP and LIME should be integrated. For instance, SHAP-based interpretability added to ML pipelines in recent food adulteration studies improved user trust by approximately 28 %, as reported in user feedback surveys. Reporting uncertainty estimates and confidence scores alongside predictions further enhances decision-making and reduces the risk of false positives (ElShawi et al., 2021; Gambo et al., 2024; Oldroyd et al., 2021).

6.4. Cost and infrastructure constraints in rural or developing regions

Finally, one of the most practical limitations is the high cost and infrastructural requirements for deploying AI solutions in rural or resource-limited settings. Advanced models often rely on high-resolution imaging systems, cloud computing for real-time analytics, and stable power and internet, conditions that may not be met in many parts of the world, particularly in small-scale farms or food markets. This severely limits the democratization of AI-driven food safety. The consequence is a growing digital divide where only industrial players can benefit from predictive food quality systems, while smallholders and informal vendors continue to rely on manual inspection or unverified shelf-life labels. To bridge this gap, lightweight AI models deployed on edge devices (e.g., smartphones, Raspberry Pi, or Arduino-based systems) have been shown to reduce costs by over 80 % while maintaining above 92 % accuracy for tasks such as spoilage detection in stuffed mussels. Encouraging public-private partnerships to subsidize these tools, along with training programs for local vendors, can enable widespread deployment. Integration of AI with existing rural supply chain programs (e.g., via cooperatives or government food safety missions) will be key to achieving scale and equity (Yavuzer et al., 2024; Lins et al., 2021; C. Wu et al., 2023).

6.5. Regulatory and standardization challenges

A considerable hurdle faced in AI implementation for food safety is compliance with existing regulatory requirements. AI-based decisions must conform to food safety regulations set forth by regulatory organizations such as EFSA and FDA. Currently, the absence of standardized validation protocols for AI models across jurisdictions creates uncertainty and legal barriers. The necessity for global cooperation to standardize testing protocols, performance expectations, and audit processes cannot be overstated. This would facilitate the adoption of AI and foster trust in all actors in the food system (Abid et al., 2024; Dhal & Kar, 2025b).

6.6. Human-system integration and capacity building

While there are technological obstacles, we still need to address human factors in more depth. Even with the technologies available, we are still left with the training of the intended end-users/first responders (food handlers, inspectors, quality control personnel, etc.) in how to use the technology, which must be done within the context of already existing inspection systems. Recent deployments of AI-powered food safety systems have demonstrated that capacity-building initiatives can increase the likelihood of making accurate interpretations from AI outputs by 35–40 %, which can increase compliance and enable fewer recall events [97]. Encouragement of training programs should necessarily include training on the operation of AI tools, along with interpreting confidence scores and being able to circumvent these outputs, at times, doing so is vital. Embedding these educational programs within national food safety missions can ensure long-term success. Together, these multifaceted challenges and their corresponding solutions lay the groundwork for scalable, explainable, and human-aligned AI systems in global food safety applications (Nazaretsky et al., 2022).

7. Conclusion and future direction

AI and ML are moving from futuristic tools to practical tools. They are now changing the ways we detect and prevent food adulteration, spoilage, and contamination. AI-enabled systems have shown the potential to provide real-time, noninvasive, and scalable solutions to food safety problems, whether it be milk, spices, meat, or prepared meals. However, as emphasized in Section 6, several core challenges must be addressed to fully realize the potential of AI in food safety:

- **Data availability and quality**: Quality and availability of data: Future research should focus on developing high-quality, open-access, and representative datasets from different geographic regions. Initiatives could include frameworks for collaborative data-sharing using federated learning and synthetic data production methods.
- **Model generalizability across regions and food types**: The creation of adaptive and modular AI systems will be beneficial in supporting fine-tuning with local datasets of limited sizes. Research into the development of multi-task learning and domain adaptation approaches will increase transferability.

- **Interpretability and trust**: Incorporation of explainable AI techniques (ex: SHAP, LIME) into prediction pipelines and demonstrating their value through user-centered research may help to improve trust from regulators and stakeholders. In the future, it would be useful for tools to provide uncertainty estimates to enable decision-making.
- **Infrastructure and cost constraints**: Affordable edge-AI options suitable for rural or under-resourced areas deserve study and prototyping. AI-enabled food safety should be made accessible to anyone via the combination of featherweight models and inexpensive sensors, mobile applications, or IoT devices.

Moreover, adopting long-term favourable implementation of these solutions will require regulatory coordination and human-system interface integration, as mentioned previously. Future work will need to work with regulatory agencies such as EFSA and the FDA to develop standards for AI validation. In addition to these, several emerging trends hold strong potential for future research and real-world deployment:

- **AI for Pathogen Detection**: AI is developing rapidly in the use of biosensors and imaging for the detection of microbial pathogens in food. ML models can facilitate the detection/classification of bacterial colonies and predict the occurrence of pathogenic organisms through time series data from the sensor or predicted by measured spectroscopic features.
- **Zero-Shot and Few-Shot Learning**: Zero-Shot and Few-Shot Learning: supervised models require large, labeled datasets; however, zero-shot and few-shot learning methods can generalize to new food types or contaminants with little beforehand data. These methods could alleviate the burden of data collection and increase flexibility in changing environments in food.
- **Blockchain + AI for Traceability**: Blockchain + Artificial Intelligence (AI) for Traceability: Utilizing blockchain's immutable ledger in conjunction with AI's predictive capabilities would enable end-to-end traceability and fraud detection in food supply chains. AI could detect anomalies, substantiate the authenticity of products, and disclose previously distributed data from the chains found on a distributed ledger.

By systematically addressing current barriers and exploring these future directions, AI can become a more trusted, inclusive, and adaptive technology for safeguarding food systems worldwide. Strategic partnerships between academia, regulatory agencies, and industry will be critical in transforming these innovations into operational food safety safeguards.

CRediT authorship contribution statement

B.P.: Writing – original draft, Software, **A.L.A.:** Resources, Project administration, Methodology, **J.N.:** Investigation, Formal analysis, Data curation, **P.J.A., K.S.:** Conceptualization, Validation, Visualization. **M.B.K., M.B.:** Visualization, Supervision, Writing-editing and reviewing.

Availability of data and material

Data will be made available based on a reasonable request.

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Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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