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AI-Powered Advancements in Food Analysis and Safety: Ensuring Quality, Protection, and Precision in Modern Food Systems: A Review

Ammar B. Altemimi[1,2] | Farhang Hameed Awlqadr[3] | Raqad R. Al-Hatim[1] | Syamand Ahmed Qadir[4] | Mohammed N. Saeed[5] | Aryan Mahmood Faraj[6] | Tablo H. Salih[3] | Hala S. Mahmood[7] | Mohammad Ali Hesarinejad[8] | Francesco Cacciola[9]

[1]Food Science Department, College of Agriculture, University of Basrah, Basrah, Iraq | [2]College of Medicine, University of Warith Al-Anbiyaa, Karbala, Iraq | [3]Food Science and Quality Control, Halabja Technical College, Sulaimani Polytechnic University, Sulaymaniyah, Iraq | [4]Medical Laboratory Techniques Department, Halabja Technical Institute, Research Center, Sulaimani Polytechnic University, Sulaymaniyah, Iraq | [5]Department of Nutritional Analysis and Health, Kifri Technical College, Garmian Polytechnic University, Kalar, Iraq | [6]Medical Laboratory Science Department, Halabja Technical College, Sulaimani Polytechnic University, Sulaymaniyah, Iraq | [7]Department of Management Information Systems, College of Administration and Economics, University of Basrah, Basrah, Iraq | [8]Department of Food Sensory and Cognitive Science, Research Institute of Food Science and Technology (RIFST), Mashhad, Iran | [9]Messina Institute of Technology c/o Department of Chemical, Biological, Pharmaceutical and Environmental Sciences, Former Veterinary School, University of Messina, Messina, Italy

Correspondence: Ammar B. Altemimi (ammar.ramddan@uobasrah.edu.iq) | Mohammad Ali Hesarinejad (ma.hesarinejad@rifst.ac.ir; ma.hesarinejad@gmail.com)

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ABSTRACT

The review paper is about the amazing influence that artificial intelligence (AI) has brought to the food production industry, as it gives much importance to food safety and quality assurance. It introduces the connection of AI technologies, including machine learning, deep learning, and computer vision, to enhancing food safety, control, and analysis. The role of AI in contaminant detection and spoilage prediction is underlined. One of the applications is using near-infrared spectroscopy on a machine learning algorithm sample to determine if it contains any adulterants in olive oil. Also, trying to develop computer vision techniques that can soon be widely deployed to detect defects in the automated visual inspection of produce. Real-time monitoring sensors incorporated in smart packaging solutions are among the AI that protects and manages the freshness and safety of perishable goods. The review, through analyzing up-to-date AI techniques in the food sector, also proposes potential remedies to the ongoing food issues that can lead to unhealthy and unsafe products. Furthermore, it sheds light on AI's role in food science and its function as a safeguarding agent of the youth sector in the food industry.

Abbreviations: AE, autoencoder; AI, artificial intelligence; ANFIS, Adaptive neuro-fuzzy inference system; ANN, artificial neural networks; CNN, convolutional neural networks; DL, deep learning; DLT, distributed ledger technologies; ELM, extreme learning machine; e-nose, electronic nose; FL, Fuzzy Logic; FTIR, fourier transform infrared spectroscopy; F-LDA, fisher linear discriminant analysis; GAN, generative adversarial network; HFCS, high fructose corn syrup; HSI, hyperspectral imaging; IoT, internet of things; KNN, K-nearest neighbors; LDA, linear discriminant analysis; LIBS, laser-induced breakdown spectroscopy; ML, machine learning; MOS, olfactory machine system; MVR, multiple variable regression; NLP, natural language processing; OENS, e-nose system; PCA, principal component analysis; PLS-DA, partial least squares discriminant analysis; RF, random forest; RNN, recurrent neural network; SVM, support vector machines; VAE, variational autoencoders; Vis-NIR, visible near-infrared.

1 | Introduction

Artificial Intelligence (AI) has rapidly transformed various industries, including healthcare, logistics, and distribution. Among these, the food industry has significantly benefited from AI advancements, particularly in food analysis, safety, and quality assurance (Bendre et al. 2022). Ensuring food safety and quality is increasingly critical due to the growing global population and more complex supply chains. AI technologies like machine learning (ML), deep learning (DL), and computer vision have emerged as powerful tools in managing extensive datasets, forecasting outcomes, and automating processes (Kumperščak et al. 2019). AI has extensive applications in the food industry, significantly influencing food chemistry, analysis, and safety. In food chemistry, AI technologies facilitate detailed examination of chemical constituents, monitoring of heating curves, and tracking of phase transitions during food processing. Furthermore, advanced AI-driven spectroscopy has substantially enhanced the precision in identifying and differentiating chemical components and contaminants in food products. Such technological advancements enable precise detection of contaminants down to individual pollutant particles, accurate characterization of ingredients, and comprehensive quality assurance. Consequently, AI is profoundly transforming food analysis methods, allowing companies to ensure higher quality and safer food products (Mavani et al. 2021). In addition, AI is becoming increasingly vital in ensuring food safety, addressing common threats such as microbial contamination, spoilage, and food fraud. Advanced AI tools enable accurate forecasting and real-time monitoring, significantly improving early detection and response to potential hazards. For example, AI effectively identifies microbial contaminants, predicts spoilage timelines, optimizes packaging materials to enhance shelf life, and reduces food waste (Kudashkina et al. 2022). Another important AI application is multimodal learning, which integrates various data types such as spectrometry, imaging, and omics analyses. By synthesizing these diverse datasets, multimodal learning offers comprehensive insights into food safety and quality parameters. Although this method faces challenges related to data complexity and computational demands, it holds significant potential for innovation in food analytics (Temilade Abass et al. 2024; Chhetri 2024). AI is becoming increasingly important in evaluating food quality without damaging the product through non-destructive testing methods, which in turn helps achieve real-time quality control and safety assurance. AI can upgrade these methods by providing accurate and fast analysis, which helps the manufacturer identify and solve problems earlier (Liu et al. 2023). In terms of food safety, AI-based microbial assessment techniques have transformed how contaminant detection is performed. Common microbial detection methods are usually time-consuming and require a lot of manpower. In this context, AI-based technologies can quickly analyze huge amounts of data, hence facilitating quicker and accurate detection of pathogens. Consequently, food safety is improved, and at the same time, the probability of broader contamination and corresponding health hazards is lowered (Qian et al. 2023). Predictive modeling is another impactful area of AI application in food safety. By analyzing historical data alongside environmental factors, AI models predict potential food spoilage and contamination risks before they occur. This proactive approach helps prevent foodborne illnesses and improves food quality, strengthening consumer confidence and industry practices (Kumar et al. 2024). This review paper explores how AI technologies have transformed food analysis and safety, highlighting current integrations within modern food production systems. It discusses both the promising opportunities presented by AI and the challenges that must be addressed to realize its full potential in ensuring safer food supplies.

2 | Types of AI-Based Technologies in Food Analysis and Food Safety

Nowadays, AI has become a critical tool in the food industry, presenting creative ideas for optimizing food analysis and food safety. Among the different types of AI, one of them is ML technology; the latter emerged as a core technology that can calculate the probabilities of different classes in making a prediction. Figure 1 provides a visual overview of the key ML models employed in detecting contaminants. This visual aids in understanding the theoretical benefits outlined in the previous sections, as it categorizes the models based on their application areas and success rates. In addition, ML algorithms can analyze data, process it, and then develop algorithms that assist in recognizing patterns and make predictions, resulting in smart and efficient decision-making systems. Regarding food analysis, ML is a critical tool in translating traditional methods, for example, spectroscopic techniques, by magnifying the accuracy of chemical composition predictions and adulterant identification in food products. For example, the ML models have significantly improved the abilities of Near-Infrared (NIR) and Raman spectroscopy, giving those devices more reliability in food quality testing (Hefei et al. 2021). Similarly, in food safety, ML is used in predicting modeling, for example, to estimate possible safety issues, such as change or pollution, according to the data and environmental conditions found in the past. These strategies make food producers better prepared; therefore, the incident of food poisoning becomes scarce (Taiwo et al. 2024). In addition, predictive models using ML have been successfully implemented to identify contaminants such as *Salmonella* in various food products. Researchers in a study validated the core of an ML model that, through the data of several sources, has proven to be a highly accurate predictor for *Salmonella* contamination in poultry, demonstrating accuracy of over 90%. Moreover, a research project successfully used ML algorithms to anticipate the aflatoxin contamination in maize, encouraging farmers to make prompt decisions, thereby giving them the chance of almost zero contamination.

One of the top AI trends that blew up so fast was DL, which is the newer version of the ML method, aided by neural networks, to the point where the neural networks are of multiple layers, making the data easier than ever. The DL process is designed exclusively to handle unstructured data, for instance, images and outputs of sensors, that are used to analyze a move in safety mode. The photo is captured and analyzed with the help of a DL tool layer to distinguish the goods based on their appearance and identify existing faults. The artificial intelligence (AI) and computer vision allows for automated visual inspection to define and detect errors visually. The system setup, which uses DL, a machine intelligence domain, is valuable in the discovery and judgment of food quality with sensory equipment. Using the

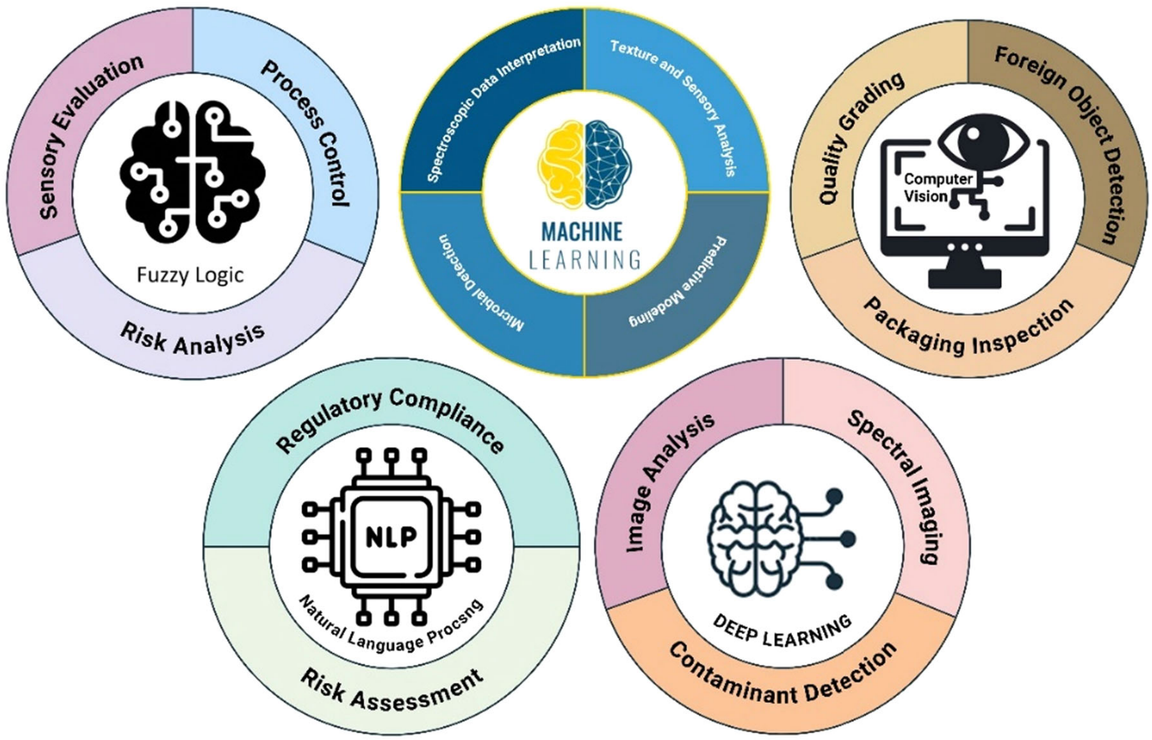

FIGURE 1 | Types AI used for food analysis and food safety.

human eye, this technique is necessary to distinguish between different characteristics of fruits and vegetables. Achieving the desired quality attributes for a complete and flawless grading process of fruits and vegetables is one of the major steps in food safety (Shah et al. 2023). In food safety domain, DL techniques were used to improve disease detection systems, for example, electronic noses (e-noses; Wang et al. 2024). An example of ML implementation is seen at Pfeiffer Vacuum, a leader in vacuum technology, which employs AI for non-destructive quality control of food products using advanced spectroscopy techniques. Additionally, Zest Labs utilizes AI for real-time freshness monitoring in its products, employing predictive analytics to extend product shelf life.

Computer vision involving AI is also useful for the food industry by automating inspection and quality control. This specific technology teaches machines to perceive and analyze visual data, thus, akin to human vision. The visual technology used in food analysis, for example, computer vision systems, is a must for activities such as inspection and sorting of products based on their visual characteristics, like hues, shapes, and sizes. This form of technology is mainly used in the fruit and vegetable sector, where the appeal of these products becomes very important to the consumers (Chopde et al. 2017). In the field of food safety, computer vision makes use of packaging inspection for separator protection and eliminates any sort of inclusion of contaminants that are thus lost in quality when played.

Natural Language Processing (NLP) is a subfield of AI that focuses on the interface between machines and human language and its application in the food industry, especially in processing large volumes of text data. In terms of food safety, NLP tools are particularly helpful for extracting important information from scientific reports, regulatory documents, and inspection records. This attribute is really important for product safety as well as the product of a non-compliance state with food safety regulations and production risks identification by the analysis of written consumer feedback and other textual data sources (Ricketts et al. 2023).

Fuzzy logic, at last, is termed the type of AI that stands for reasoning in the absence of certainty and is often applied to cases in which the data is imprecise or missing, as in the food industry. To sum up, fuzzy logic, a kind of model on human perceptions such as the taste and texture of food, is mainly used in the sensory evaluation of food. In a more nuanced manner, this model gives a way to understand food quality better. These directions are the propellers towards adopting the more flexible and adaptive quality control processes, which correspondingly to the complexity of human sensory experience (Guillaume and Charnomordic 2004). The use of fuzzy logic in food safety is a method for risk assessment that helps to evaluate food safety risks when the available data has uncertainty and covers the full range of variability, thus supporting more efficient decision-making processes. Among AI technologies, the food industry is gaining many of its advantages with the precision, efficacy, and reliability of food analysis and safety protocols that are significantly enhanced. As AI moves forward, the technology will be anticipated to bring life into the food industry and quality control without a doubt. Table 1 summarizes the types of AI used in food applications.

3 | AI-Based Technologies in Food Analysis and Adulteration Detection

The use of AI in the food industry has redefined food quality assessment by combining technologically advanced methods

TABLE 1 | AI-based technologies in food analysis and safety: An overview of technologies.

Type of AI	Applications in food analysis	Applications in food safety	References
Machine Learning (ML)	• Enhances spectroscopic techniques (e.g., NIR, Raman) for accurate chemical composition predictions and adulterant detection.	• Predictive modeling to forecast spoilage and contamination risks.	Goyal et al. (2024); Teklemariam (2024)
Deep Learning (DL)	• Image analysis for quality assessment, including defect detection and product classification.	• Enhances contaminant detection systems, such as electronic noses.	Hu et al. (2023); Lien and Zhao (2018)
Computer Vision	• Automated inspection and grading based on visual attributes like color, size, and shape.	• Packaging inspection to ensure seal integrity and detect contaminants.	Savakar and Anami (2015); Sivaranjani et al. (2021)
Natural Language Processing (NLP)	• N/A	• Extracts information from reports and documents for regulatory compliance and risk identification.	Zhang and El-Gohary (2011)
Fuzzy Logic	• Sensory evaluation to model human perceptions and provide nuanced quality assessments.	• Risk assessment when data is uncertain or incomplete.	Guillaume and Charnomordic (2004)

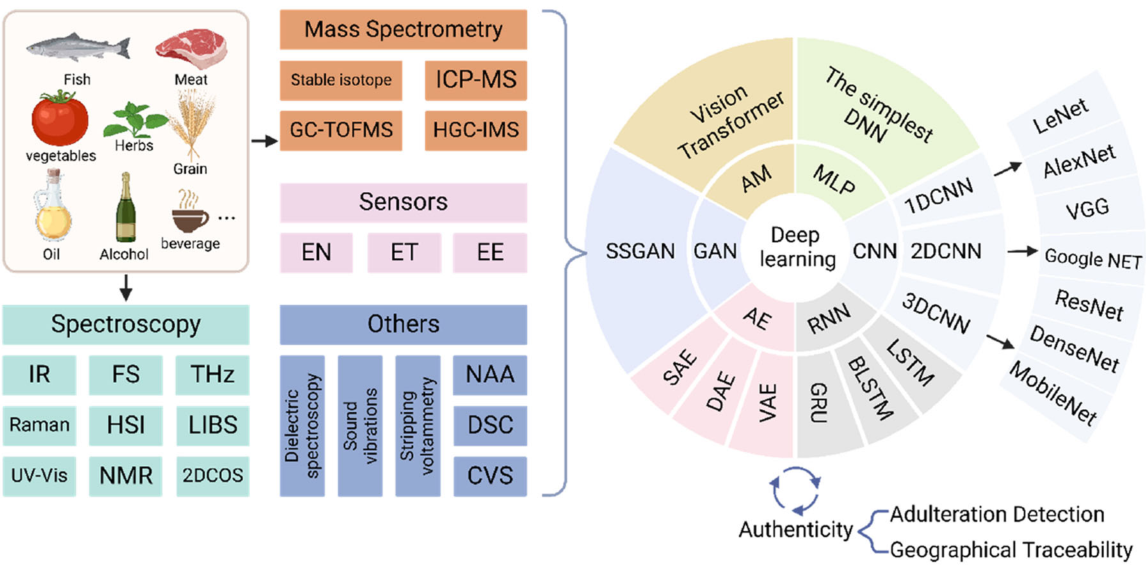

FIGURE 2 | Overview of different detection technologies along with deep learning models for food authenticity.

with traditional ones like spectroscopy and non-destructive testing. ML models are known to increase the precision of the chemical composition forecast, while DL allows for quality grading of an image with more details. Transparency becomes part of the process of food authentication with some applications based on DL technology. Several detection technologies and DL models have been utilized in food authenticity, as depicted in Figure 2. Also, AI tools such as computer vision and fuzzy logic facilitate object quality assessments by offering a more uniform and finer thread of the quality outline of food. The developments as mentioned above illustrate the necessity of AI in the current food analysis, thus guaranteeing better precision and reliability in food quality control.

3.1 | Spectroscopic Techniques Enhanced by AI-Based Technologies

NIR, MIR, and Raman spectroscopies are techniques used to analyze food, providing information about the molecular structure through interaction with light molecules. This is key in assessing the presence of contaminants, nutritional content, and food quality. While spectroscopic techniques offer valuable benefits such as rapid analysis and non-destructive testing, they do have certain limitations. For example, environmental factors can impact these methods, and the calibration of different matrices may be very long, which is a limiting factor in the accuracy of these methods in complex food samples. Trained personnel are vital to the calibration and interpretation of the results, though they are the methods that consume more time and are the most error-prone (Kharbach et al. 2023). Figure 3 demonstrates the systematic method for detecting alterations in spectroscopy through ML. In this scenario, tech-driven AI can timely and accurately scan through huge spectroscopic data, which humans would be very unlikely to do, and therefore make more accurate guesses of the constituents of the food sample (Meza Ramirez et al. 2020). For example, one of the impressive innovations in the AI-aided NIR spectroscopy process is the ability to accurately determine the amount of moisture, fat, and protein in the products at any production stage by means of new quality control systems.

In the same way, AI-supported Raman spectroscopy has been regularly used to determine the presence of impurities in food components precisely, which results in obtaining a very effective device to ensure food safety (Yan et al. 2023). Similarly, in the dairy industry, AI-assisted MIR spectroscopy has been one of the applications in which the instrument is utilized through the monitoring of the composition of milk and the detection of such problems as the presence of adulteration, thus, it makes the quality control in the dairy industry highly efficient (Hayes et al. 2023). da Silva Medeiros et al.'s study showed that NIR was appropriate and well-used for analyzing butter oil blends. They applied ML, support vector machines (SVM), and partial least squares discriminant analysis (PLS-DA) methods to the NIR spectra to ensure the models could classify correctly.

SVM and PLS-DA did a good job in spotting contaminated samples (da Silva Medeiros et al. 2023). Furthermore, Spectroscopy on the Visible Near-Infrared (Vis-NIR) spectrum using AI was used to make recognition of olive oil fraud, actually the NIR section acting as a marker or an identity of the olive oil seeded with others, easier. With the help of ANN, the research was completely processed and classified using Vis-NIR spectra with an accuracy of 100%. The use of AI and NIR spectroscopy appears to be one of the effective methods of high-quality product assurance, showing genuine and excellent products such as olive oil (Violino et al. 2021).

NIR spectroscopy is another effective method of analyzing food that was used to predict and classify the adulteration in fruit juices; for example, it tested the presence of grape juice in other fruit liquids such as pineapple, orange, and apple. To analyze the NIR spectral data, a number of AI models (RF, LDA, and SVM) were used. The study found that both LDA and RF had a correct separation rate of 97.7%. On the other hand, SVM demonstrated very good regression results, namely $R^2 > 0.98$ and RMSE values < 0.001, were obtained. In their research, Calle et al. (2022) demonstrated an approach that integrates NIR spectroscopy with AI; this coupling can be accurately utilized for identifying and quantifying the components in complex juice blends. Honey may actually be mixed with other substances, which is to say, through NIR spectroscopy, the presence of glucose syrup in honey can be determined. The AI models, such as Random Forest (RF) and Logistic Regression, were deployed to analyze spectral data. The RF had an accuracy rate of 90.2%, showing that it could isolate pure honey from the false ones. AI method enhanced the detection accuracy and became the main tool in verifying the authenticity of honey products (Woeng et al. 2022).

NIR spectroscopy can detect the existence of high fructose corn syrup (HFCS) in honey with Logistic Regression, with a reliability rating reaching 98%. As for food testing, AI-elevated NIR spectroscopy can detect a lesser extent of adulteration, hence being trustworthy for the high-quality foods (Tan et al. 2021). Additionally, Raman instruments gave some information that helped to reveal the fake honey. AI manipulations make it possible to track down maltose syrup that the counterfeiters added to the honey through the use of PNN and convolutional

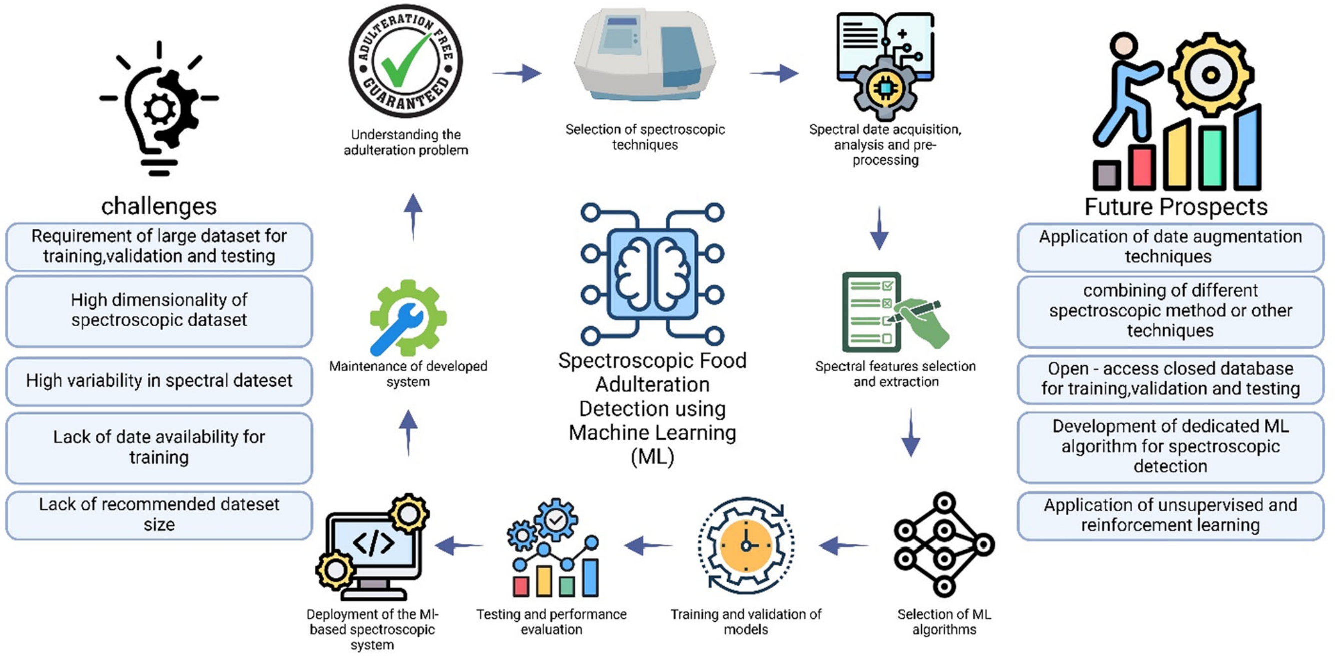

FIGURE 3 | Step-by-step process of using machine learning in spectroscopy to detect adulteration.

neural network (CNN) technologies (Hu et al. 2022). Raman spectroscopes were also used to check if avocado and olive oils were mixed with cheaper oils like canola or soybean. AI examined the Raman data using L2 linear regression, getting a reliable $R^2 > 0.99$. This indicated that Raman spectroscopes combined with AI can confirm whether these oils are pure or adulterated, showing they are essential for checking food quality (Zhao et al. 2022). Raman spectroscopy was utilized to identify adulteration in edible oils, such as sunflower oil, with less expensive alternatives like soybean oil and rapeseed oil. The Raman spectrum data was subjected to AI models such as SVM and PLS to improve the sensitivity and accuracy of the analysis. Although background noise and weak Raman signals present some obstacles, the application of AI greatly enhanced the identification of adulterants in edible oils (Duraipandian et al. 2019). Raman spectroscopy can detect if cassava starch contains any additives, such as talcum powder, aspirin, baking soda, and flour.

The OC-SVM and SIMCA types were employed with sensitivity and specificity values of 87%. As a consequence, Raman spectroscopy with AI is useful for ensuring cassava starch is pure (Kelis Cardoso and Poppi 2021). Some research demonstrates how AI can significantly enhance near-infrared spectroscopy to detect adulterants in various food products. It is important to note that integrating AI algorithms can enhance the accuracy and efficiency of spectroscopic analyses. By analyzing large datasets and identifying patterns that traditional methods might miss, AI can improve the detection of subtle spectral variations indicative of contamination. Table 2 shows selected applications of AI-enhanced spectroscopic techniques in food analysis.

DL has significantly advanced the field of food analysis, offering new ways to ensure food authenticity, detect adulteration, and assess food quality. For instance, CNNs have been used to form food items based on their visible properties. A previous research employed them to create images of extra virgin olive oil, which led to a 96.7% accuracy in the two aspects of the wine-based color (intensity) (Pradana-Lopez et al. 2022). In recent times, CNNs have been utilized to spot fake saffron. For instance, the VGG11 and ResNet50 models achieved an impressive accuracy of 99.67%. This shows how well CNNs can classify food accurately (Alighaleh et al. 2022). Additionally, Innovate Nature's Generative Adversarial Networks (GANs) have even proved to be very effective in the aspect of food adulteration detection. For example, a study that efficiently applied a GAN model in tandem with near-infrared (NIR) spectroscopy to tell apart the cumin and fennel with different origins resulted in a 100% classification accuracy.

This fact alone informs us about the GANs' ability to fix the issue of data scarcity and give us genuine food warranties (Yang et al. 2021). Recurrent neural networks (RNNs) perform well using series data. There was a certain case in which RNNs were used for Vis/NIR hyperspectral images of Radix Glycyrrhizae origins, resulting in an accuracy value of 90%. Despite its complexity, this can be seen as a strong point of RNNs in food data manipulation (Yan et al. 2020). Multi-layer perceptrons are used to analyze NMR data and are effective for food analysis (Rachineni et al. 2022). Autoencoders (AEs), especially variational AEs (VAEs), have been growing in importance given their application as a tool to extract features and develop image data augmentation for food authenticity. Through a study where VAE and hyperspectral imaging (HSI) were combined, honey counterfeiting was identified using the method of high-dimensional data mapping into a lower space and precise classification by adding these particular ingredients (Phillips and Abdulla 2023). In meat analysis, CNNs are used to classify pork freshness based on hyperspectral images. They can detect pork freshness where human judgment is not always reliable, with an accuracy value up to 97.4%, to ensure safe and high-quality food (Al-Sarayreh et al. 2020).

Additionally, CNNs' use in conjunction with Raman spectroscopy made it possible to identify the adulteration of honey with maltose syrup with a value of 100% in sensitivity and specificity (Hu et al. 2022). DL is also widely employed in food chemical composition analysis. Using NIR spectroscopy and a DL model, the moisture content in wheat flour was effectively forecasted, resulting in a correlation coefficient of 0.98, confirming its high predictive accuracy (Zhang et al. 2023).

3.2 | E-Nose Techniques Enhanced by AI

The cooperation of e-nose systems with ML models has revolutionized food quality assessment, especially in detecting adulteration and freshness evaluation. This method is especially predictive of the future in fields such as meat, dairy, seafood, edible oils, coffee, and tea, where quickly, non-infringing, and precise methods are used as alternatives. For example, in the meat industry, e-nose systems integrated with top-level ML techniques, for example, 1DCNN-RFR, have demonstrated high accuracy in the detection of adulterations, such as beef mixed with pork, with an R^2 of 0.9977, RMSE of 0.9491, and MSE of 0.4619 (Huang and Gu 2022).

Similarly, another research involved a digital nose system that depends on colorimetric sensor array to identify pork adulteration with beef. Fisher linear discriminant analysis (F-LDA) and the extreme learning machine (ELM) were employed to discern pure beef from a combination of beef and pork and pure pork. The ELM model was able to outmatch the F-LDA model with an identification accuracy of 91.3% at the time of training and 87.5% at the prediction set, indicating the possibility of this low-cost e-nose system in rapid detection of meat adulteration (Han et al. 2020). Besides, the researchers have also designed a tailor-made e-nose system (OENS) to assay exactly the pork mixing in beef. Beef samples were analyzed using a number of MQ series sensors. In the end, the e-nose was programmed to detect and figure out the volatile organic components in each sample. The prominent result of the classification process can be summarized as follows: the mentioned method has exhibited 98.1% accuracy in detecting pork food fraud cases using the best SVM model. An e-nose system is proposed to authenticate meat as halal. To detect pork adulteration, the OENS device is also a suitable tool for authenticating halal (Sarno et al. 2020).

In addition, using e-noses in dairy farming has enabled the detection of contaminants in milk, such as formalin and hydrogen peroxide gas, using a MOS gas sensor array. This thorough system, combined with the utilization of SVM, yields

TABLE 2 | Applications of AI-enhanced spectroscopic techniques in food analysis.

Type of food	AI technique	Application	Result and accuracy	Original research reference
Olive oil	FTIR + PLS-DA, ANN	Detection of adulteration with soybean oil	100% classification accuracy	Meng et al. (2023)
Butter oil	FTIR + SVM, PLS-DA	Detection of adulteration with lard, vegetable oil	High accuracy in classifying adulterated samples	da Silva Medeiros et al. (2023)
Fruit juices	FTIR + Gaussian SVM, LDA, RF	Detection of adulteration with grape juice	100% classification accuracy	Calle et al. (2022)
Coffee	FTIR + CNN, PLS	Detection of adulteration with chicory, barley, maize	RMSE < 0.82, $R^2 > 0.98$	Nallan Chakravartula et al. (2022)
Honey	FTIR + SVM, PLS-DA	Detection of adulteration with syrups (e.g., HFCS)	High sensitivity, specificity, and accuracy	Ciursă et al. (2021)
Coconut milk	FTIR + KNN, SVM	Detection of adulteration with water	93.33% balanced accuracy	Al-Awadhi and Deshmukh (2021)
Milk powder	LIBS + CNN	Detection of exogenous protein	97.8% accuracy	Huang et al. (2022)
Honey	NIR + Random Forest	Detection of adulteration with glucose syrup	90.2% accuracy	Woeng et al. (2022)
Avocado and olive oil	Raman + CNN, PLS	Detection of adulteration with soybean and canola oils	$R^2 > 0.99$	Zhao et al. (2022)
Chicken	NIR + SVM	Classification (moisture, lipid, protein content)	91.8% accuracy	Geronimo et al. (2019)
Pork	NIR + BP-AdaBoost	Freshness detection	Correlation coefficient of 0.8325	Huang et al. (2015)
Beef, chicken, and lard	NIR + SVM	Authentication and classification	98.33% accuracy	Alfar et al. (2016)
Beef	Raman + PLSR	Tenderness prediction	70%–88% accuracy	Bauer et al. (2016)
Bovine serum albumin	Raman + PCA	Detection of Norfloxacin orientation	High correlation, effectiveness	Lian et al. (2019)
Fish	Raman + PCA, PLS-DA	Detection of cooked meat endpoint temperature	97.87% accuracy	Berhe et al. (2015)

the accuracy of formalin detection in sensitive milk samples with a classification accuracy as high as 94.64% (Tohidi, Ghasemi-Varnamkhasti, Ghafarinia, Bonyadian, et al. 2018). Detection of adulteration in ghee with sunflower oil and cow body fat leads to reasonable accuracy. In this case, 91.3% and 82.5% were achieved by using artificial neural networks (ANNs) (Ayari et al. 2018a). In another research paper, the e-nose was also used to identify detergents in milk, which are normally used for protein-fortified milk. This sensor, composed of an array using MOS, outperformed its competitive systems by reaching 90% accuracy with the aid of an SVM model.

This study draws attention to the possibility of e-noses detecting the presence of an added substance that could potentially harm human health (Tohidi, Ghasemi-Varnamkhasti, Ghafarinia, Saeid Mohtasebi, et al. 2018). However, the alternative to this is an e-nose that is made up of various different types of sensors, such as MQ136 and MQ137, that is applied to assess the quality and spoilage of milk. The fresh, sour, and spoiled milk samples were separated, and the neural network was fed by the sensor data for which a human recognition rate of 83% was achieved for milk quality classification. In this study, the main focus of the study is that e-noses could be live-monitored for the milk quality, a non-destructive way of providing security by guaranteeing dairy products (Putra et al. 2018).

One major field where e-nose technology has been extremely helpful is detecting fish freshness. For instance, the utilization of an e-nose system combined with K-Nearest Neighbors (KNN) and PLS-DA was a successful means of monitoring the freshness of various kinds of seafood, with the result that the spoilage stage classification had an accuracy as high as 100% (Grassi et al. 2022). In a study, an e-nose with GGS sensors classified salmon and plaice fish freshness. The KNN classifier was 83.3% accurate, and the PLS-DA result was 84%. This shows the e-nose can tell fish freshness levels well (Grassi et al. 2019). In addition, a smart e-nose equipped with seven sensors (e.g., TGS813, TGS822) was created to identify fish spoilage during the cold storage period. The authors performed total viable count and total volatile base nitrogen analysis to assess fish health. The data from the e-nose were treated with principal component analysis, and the samples were grouped into fresh, semi-fresh, and overripe categories. The classification of fish spoilage was successfully done using the backpropagation neural network and the hyper disk model maximum margin optimum classifier with accuracies of 96.87% and 100%, respectively, which outlined the application of e-noses for the seafood industry (Vajdi et al. 2019).

Researchers made a new device called an e-nose that sniffed out stinky bits in fish, keeping the latter at different temperatures. The e-nose was capable to catch signs of spoilage fast and sort fish by freshness (Wang et al. 2019). Edible oil assessment by e-nose seems to be implemented effectively in the perusal of adulteration. A survey has shown that a Gradient Boosting Classifier in tandem with an e-nose has been able to detect the fraudulent practice of cuttings in extra virgin olive oil at a rate of 97.75% (Zarezadeh et al. 2021). The technology specialized in e-noses (E-noses) was very successful in detecting spoilage agents in top-quality oils in a short period of time and with maximal accuracy. The coffee industry is also a happy sector in the e-nose technology, with the differentiation of coffee fineness and the grill flavor being the main application, 98% of which is achieved using ANN models (Gonzalez Viejo et al. 2021). Moreover, evidence of its potential use in fighting fake products is the high precision of the e-nose, which distinguishes civet and non-civet coffee with 97% accuracy (Wakhid et al. 2020). The tea sector is among the subjects that e-noses have been used to recognize the fragrance quality of the black tea infusions while applying F-LDA with a high success rate of 95.2% (Chen et al. 2022).

In addition, SVM and LR for the tea quality grades classification achieved a maximum accuracy of 88%, which underscores the effectiveness of e-noses in the tea's quality evaluation (Xu et al. 2021). Being significant noxious pollution sources, power plants need to go green. While promising, the practical implementation of e-noses is faced with problems that need to be addressed. One of them is calibration, which is a significant issue; e-noses need to be calibrated regularly to keep their accuracy, since the instruments may be influenced by climatic conditions, namely temperature and humidity. Moreover, e-nose systems might involve the problem of expensive pricing; smaller producers or farms might be afraid of them and may consider their cost to be very high. The need to invest in the system, cover maintenance costs, find a specialized workforce to run the machine, and interpret the data can act as barriers. That is why e-noses are a great idea for improving food quality and safety assessments, but these practical adversities must be given more thought when inserting e-nose technology in the food industry. Drawing attention to these problems would make them more efficient and more cost-effective.

In this regard, Alpha MOS integrates e-nose technology with AI for rapid quality assessment of products such as coffee and seafood, showcasing effective applications of AI in food analysis. Figure 4 shows the detection methods involving quality and classification by integrating e-nose with AI, whereas Table 3 summarizes the e-nose systems combined with AI for food quality assessment across various sectors, including meat, dairy, seafood, edible oils, coffee, and tea.

3.3 | Mass Spectrometry (MS) Enhanced by AI-Based Technologies

MS has long been a foundational tool in food analysis and safety, providing precise chemical characterization of food matrices, detecting contaminants, verifying authenticity, and monitoring quality. However, with the recent integration of AI into MS workflows, the capabilities of this powerful technique have expanded significantly. Today, the fusion of MS and AI technologies marks a transformative leap toward achieving unparalleled quality, protection, and precision in modern food systems. Traditionally, food safety relied heavily on classical methods such as visual inspection and basic chemical assays. While effective to a degree, these methods were limited in sensitivity, speed, and objectivity. With MS, particularly high-resolution MS, food scientists were able to quantify trace-level contaminants such as pesticides, mycotoxins, heavy metals, and unauthorized additives with extraordinary accuracy (Lehotay and Chen 2018). However, MS generates highly complex and voluminous data that can be

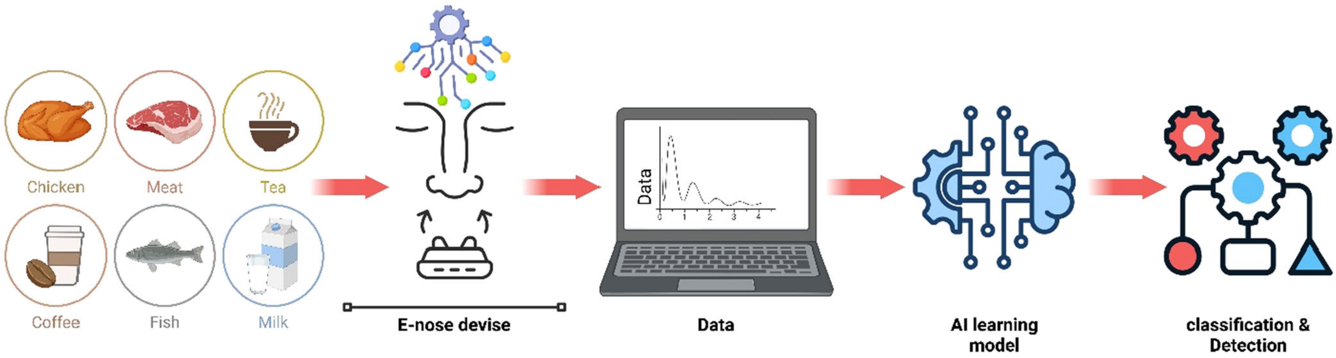

FIGURE 4 | Detection methods for quality and classification by E-nose with AI.

challenging to interpret manually, often requiring expert analysts and time-consuming processes. This bottleneck posed challenges for real-time decision-making, an essential need in a globally interconnected food supply chain.

AI has entered the scene as a powerful ally, providing solutions for these challenges. ML algorithms, DL models, and neural networks are increasingly deployed to enhance MS data analysis. They assist in automatic pattern recognition, anomaly detection, classification, and even predictive analytics, making MS not just faster but significantly smarter. One prominent study highlighted that AI-assisted MS imaging (AI-SMSI) allowed researchers to achieve subcellular metabolomics analysis, resolving complex chemical environments inside cells, an achievement previously unattainable with conventional MS alone (Zhao et al. 2024). In food analysis, AI-enhanced MS drives innovations that directly impact consumer safety. For instance, AI-based pattern recognition can differentiate authentic food products from adulterated ones, such as distinguishing wheat cultivars and their derived products like bread, an application demonstrated through high-resolution non-targeted MS combined with ANNs (Nichani et al. 2020). In another example, researchers applied AI to optimize ambient ionization MS to rapidly detect trace volatiles in food matrices, enhancing sensitivity without laborious sample preparation (Gazeli et al. 2024). A study by Shang et al. (2022) compared the lipid profiles of goat milk from Guangdong, Shaanxi, and Inner Mongolia using untargeted lipidomics. They identified 16 lipid subclasses and 638 lipid molecules, with significant differences in lipids like DG, TG, PC, PE, PI, SM, GlcCer, and LacCer among the groups. Thirteen lipid molecules were proposed as potential markers for geographic origin identification. Additionally, key metabolic pathways were mapped, supporting the development of a traceability system for Saanen goat milk and providing comprehensive lipid data across different regions. In addition, a study by Nichani et al. (2020) investigated the use of non-target high-resolution MS combined with AI algorithms for detecting food fraud and geographical traceability. Using a data-independent acquisition (DIA) approach, they analyzed the complex proteomic profiles of several wheat and spelt cultivars. An ANN was trained to classify different cultivars, as well as processed flour and bread samples, demonstrating the model's robustness in distinguishing closely related varieties. The study also introduced a novel validation framework to calculate precision parameters, enabling reliable evaluation of the discriminatory power of the DIA-AI method and supporting the development of accurate decision rules for food authentication and traceability. On the other hand, a study by Gao et al. (2025) demonstrated that DIA-based QC metrics are more sensitive than traditional DDA-based metrics for monitoring LC-MS/MS performance. An AI model was developed using 2754 DIA files and 2638 DDA files collected across nine laboratories, achieving high AUC values for LC and MS quality prediction. The study also introduced iDIA-QC software to easily implement DIA-based quality control in proteomics (Gao et al. 2025). Looking ahead, the convergence of AI and MS is expected to reshape food systems further, making them more resilient, transparent, and responsive. As AI models continue to evolve, incorporating real-time data streams from Internet of Things (IoT)-enabled food production systems, MS will serve not just as a diagnostic tool but as an intelligent sentinel across the food supply chain.

In conclusion, MS enhanced by AI-based technologies is redefining food analysis and safety, enabling the food industry to achieve unprecedented levels of quality assurance, protection, and operational precision. The fusion of these powerful technologies not only helps protect public health but also fosters consumer trust, promotes sustainable practices, and safeguards the integrity of modern food systems.

4 | AI in Food Safety

Nowadays, the food safety sector frequently operates using AI, providing new kinds of applications for the identification, follow-up, and treatment of diseases caused by foodborne pathogens, contaminants, and other sources of security. One area that stands out the most is the development of ML algorithms that can detect pathogens in food. For example, DL models have gone through many selections on vast sets to recognize different types of microbes on agar plates, by which the time used for the correct detection was reduced significantly, compared to the traditional methods (Krizhevsky et al. 2012). Another approach is the coupling of AI and HSI to screen for contaminants and dilutants in food products. The innovation uses the AI model to read the light spectrum pattern of the products, therefore identifying even the tiniest unwanted materials or toxic elements that are not visible to the naked eye. This device is the outright killer in sectors such as meat product manufacturing, where no contaminants mean safe and satisfied consumers (Sun 2010).

The use of AI in predictive modeling can be a lever for food safety, as well. Typically, ML algorithms with the help of

TABLE 3 | Summary of e-nose systems and AI applications for food quality assessment in meat, dairy, seafood, edible oils, coffee, and tea.

Nose type	AI type	Type of food	Application	Result	Original references
PEN3 E-nose	1DCNN-RFR	Beef	Adulteration detection	R^2 of 0.9977, RMSE of 0.9491, MSE of 0.4619	Huang and Gu (2022)
Colorimetric sensor-based E-nose	F-LDA and ELM	Beef	Adulteration detection	91.27% accuracy	Han et al. (2020)
Optimized E-nose system	SVM	Beef	Adulteration detection	98.10% accuracy	Sarno et al. (2020)
MOS-based E-nose	SVM	Milk	Adulteration detection	94.64% accuracy	Tohidi, Ghasemi-Varnamkhasti, Ghafarinia, Bonyadian, et al. (2018)
E-nose with MOS sensors	ANN	Ghee	Adulteration detection	91.3% for sunflower oil and 82.5% for cow body fat	Ayari et al. (2018a)
E-nose with MQ and TGS sensors	PCA and ANN	Ghee	Adulteration detection	85.6% accuracy	Ayari et al. (2018b)
E-nose with multiple sensors	Hyper disk model	Fish	Spoilage detection	100% accuracy	Vajdi et al. (2019)
E-nose with MQ and TGS sensors	PCA and SVM	Milk	Adulteration detection	95% accuracy for milk fat, RÂ^2 of 0.9399	Mu et al. (2020)
E-nose with TGS sensors	PCA and ANN	Milk	Freshness detection	83% accuracy	Putra et al. (2018)
E-nose with multiple sensors	MLP	Fish	Spoilage detection	100% accuracy	Grassi et al. (2022)
E-nose with MOS sensors	ANN	Coffee	Aroma classification	71% accuracy	Magfira and Sarno (2018)
E-nose with multiple sensors	Decision tree	Coffee	Aroma classification	97% accuracy	Wakhid et al. (2020)
E-nose with MOS and TGS sensors	PCA and LDA	Tea	Aroma quality	95.2% accuracy	Xu et al. (2021)
E-nose with FOXÎ ± 4000, Alpha MOS	PCA	Coffee	Composition analysis	97.3% variance in roasted coffee	Cui et al. (2020)
E-nose (Alpha M.O.S.)	F-LDA	Tea	Quality grade classification	99% accuracy	Liu et al. (2019)

historical data and environmental factors predict the possibility of food spoilage or contamination. This predicting ability lets manufacturers harness the advantage of choosing the lowest cost to avoid potential foodborne illness causes; thus, this technology is one of the methods to overcome the food safety problem (Zhang et al. 2020). The field of smart packaging has AI to keep a check on the standard of food products in actual time. The sensors that are coded into packaging materials are soundly capable of detecting the flickering of the temperature–humidity–lever as well as a change in gas composition on the way. AI algorithms are processing the data *via* predictions that provide details on the product's remaining shelf life or the onset of spoilage. This technology is highly used for perishable goods like dairy products and other fresh produce (Meyers et al. 2015).

AI application is an important aspect of supply chain management, specifically, in the distribution process, whereby ML or models are used to find out the entire food supply chain. With the help of data from different digital sources, AI applications can target numbers and the stage where unsafe or potential disasters arise, such as bacterial pollution during transportation or storage. This feature is a major support for transparency and quick action to any food safety incidents (Ni et al. 2019). In the present situation, AI is highly involved in the struggle against food fraud, which is a very grave issue. AI, through ML and NLP, is applied to the product labels, ingredient lists, and the supply chain documentation to recognize any inconsistencies that might point to fraudulent activities. The software is of great value in consumer safety, protecting them from the food that has been mislabeled or tampered with (Ponce et al. 2019). In addition, the use of AI in diagnosing allergens in food is already a reality. With the help of the molecular compositions of food, AI can easily detect allergens with a precision level almost above average. Such a detection procedure then leads to manufacturing companies creating allergy-free products (Adedeji et al. 2024).

AI application in food safety to automate quality control processes is another major one. These robots, equipped with vision technology and driven by AI, can now conduct very fast visual examination of the food products to see if there is any harm or contamination. This has greatly increased the efficiency and accuracy of the quality control process in food processing plants (Chen and Yu 2021). The detection of chemical contaminants involves using AI models to analyze spectroscopic data, which is used to report the presence of such substances as pesticides, heavy metals, and the residues of antibiotics in food products. This field is of key importance for making sure that such products comply with the safety rules even before they are put on the shelves for the consumers (Teklemariam 2024).

AI infrastructure is obviously used in food safety compliance monitoring as well. ML algorithms go over inspection reports, regulatory documents, and other data sources so that food production processes comply with safety regulations. It ensures the prevention of safety incidents because potential violations are identified and corrective actions are taken (Esteki et al. 2018). AI has made its way through the agricultural sector and more specifically through the utilization of crop health monitoring and environmental factors to predict the diseases and pests that can affect both the food and the farming table. Software programmed with the capability to detect early symptoms of illness and pests on crops via AI on the data collected from drones, sensors, and satellite imagery enables farmers to take action in time to stop their crops from being infected and to provide us with safe food (Susheel and Rajkumar 2023). Systems for food processing run by predictive maintenance systems help to identify potential equipment failures that might lead to contamination. By analyzing data from sensors installed on machinery, AI can predict when maintenance is needed, reducing the risk of breakdowns that could compromise food safety (Kharbach et al. 2023). In testing for mycotoxins,

AI is being used to process information obtained from biosensors and chemical assays. For example, in an evaluation process, ML-based systems can correctly indicate or recognize the existence of mycotoxins in food products or agricultural products, which is of utmost importance in cutting down on food contamination (Inglis et al. 2024). The AI of the future purposes to aid food processing to diminish the chances of any unintentional yet perilous occurrences. To make the point, ML models could be used to scan data about the food products that are being heated in a thermal process and to make sure that the temperature measurement is sufficient to kill the pathogens without the loss of quality (Chidinma-Mary Agbai 2020). AI is a technique that is used to detect shellfish poisoning that algal blooms may cause, which can potentially be a food safety hazard. By carefully monitoring the environmental data and using satellite images, AI predictive models can predict the appearance of algal blooms, thus helping the prevention work of transporting spoiled seafood from the marketplace (Mu et al. 2024).

AI technology has also been instrumental in ensuring water quality in food production facilities. Water tracing sensors are being implemented via ML algorithms that make it easier to spot toxic substances in water as well as to collect and analyze all the data. Water is used for the production of food (Czyczula Rudjord et al. 2022). The dairy industry is yet another sector in which AI now makes its presence felt. In the dairy sector, AI now helps monitor milk quality and identify adulterants. Through spectroscopic techniques, AI models can spot water, starch, or any other impurity in the milk, which at the end guarantees that the consumers only get pure milk (Mhapsekar et al. 2022).

Also, AI technology is being utilized in the identification of antibiotic residues in meat products. The ML models analyze MS data to find the antibiotics present to the extent of making it the goal, and meat products are thus guaranteed to be harmless. The final stage before selling meat to consumers should be checked to be sure it is free of any hazardous substances (Cheng and Sun 2015). In food packaging, AI-driven systems are utilized to detect leaks and ensure that the packaging seals are secure. Through the evaluation of the sensor and camera data, AIs can find defects that are very small and could cause contamination, thereby offering protection to food products (Wang et al. 2018). A notable example is Nestlé, which has adopted AI and ML technologies to monitor food safety and quality throughout its global operations, reflecting the industry's commitment to innovation in food safety. Table 4 summarizes the key applications of AI in food safety, including the type of food, the type of AI used, and the specific application.

TABLE 4 | Applications of AI in food safety.

Type of food	Type of AI	Application	Result	Accurate and original
Meat (beef, fish)	Support Vector Machine (SVM)	Determination of microbiological quality and freshness	Improved accuracy in predicting spoilage and contamination in meat products	Nayak et al. (2020)
Fruits	SVM	Detection of ripeness, spoilage, and contamination	Enhanced detection of fruit ripeness and early spoilage using spectral data	Hashim et al. (2018)
Strawberries	SVM	Differentiating between fresh and processed juice	Accurate categorization of fresh versus processed strawberry juice	Qiu et al. (2014)
Ginger	Random Forest (RF)	Identification of origin and type	Effective classification of ginger origin and type based on chemical composition	Yu et al. (2022)
Winter jujube	Multiple Variable Regression (MVR)	Predicting quality	Accurate prediction of quality parameters in winter jujube fruits	Hui et al. (2015)
Beer	Principal Component Analysis (PCA), LDA, ANN	Olfactory and quality assessment	Enhanced sensory evaluation of beer quality and classification	Ghasemi-Varnamkhasti et al. (2012)
Sesame oil	PCA, LDA, ANN	Detection of fraud	Improved detection of fraudulent sesame oil based on chemical analysis	Soltani Firouz et al. (2022)
Maize	K-Nearest Neighbors (KNN), SVM	Detection of aflatoxins	High accuracy in distinguishing between natural and artificially introduced aflatoxins	Machungo et al. (2023)
Black tea	Partial Least Squares Discriminant Analysis (PLS-DA)	Aroma detection	Effective origin-related characteristics identification in black tea	Kanaga Raj et al. (2023)
Walnut	Convolutional Neural Network (CNN)	Categorization of nut quality	Accurate quality categorization of walnut samples	Nayak et al. (2020)
Olive oil	SVM	Geographic origin detection	Enhanced identification of the geographical origin of olive oil using AI	Tan and Xu (2020)
Dairy (milk)	PCA, SVM, PLS	Quality and shelf-life assessment	Improved predictions of milk shelf-life and quality, reducing wastage	Tan and Xu (2020)
Cocoa beans	Random Decision Forest (RDF)	Classification of fermentation levels	Accurate classification of cocoa beans' fermentation levels for quality control	Oliveira et al. (2021)
Cereal products	Machine Vision (MV), Fuzzy Logic (FL)	Automated control in processing	Enhanced efficiency in processing cereal products by automating control systems	Rawat et al. (2023)
Rice	MV, FL	Whitening process control	Improvement in rice whitening process through intelligent control systems	Zhou et al. (2017)
Packaged foods	Fuzzy Logic (FL)	Detection of defects	Accurate detection of packaging defects to ensure food safety	Davies et al. (2022)
Beer and wine	K-Mean Clustering	Quality assessment	Enhanced classification and quality assessment in alcoholic beverages	Addanki et al. (2022)

(Continues)

TABLE 4 | (Continued)

Type of food	Type of AI	Application	Result	Accurate and original
Saffron	CNN, BDT1, BDT2, KNN, SVM	Detection of adulteration	Effective identification of saffron adulteration using a combination of AI techniques	Momeny et al. (2023)
Dairy products	Adaptive Neuro-Fuzzy Inference System (ANFIS)	Quality control measures	Improved prediction of microbial growth and control measures in dairy products	Goli et al. (2019)
Processed foods	Machine Learning (ML)	Monitoring cleaning and sanitation processes	Enhanced monitoring and optimization of sanitation in food processing plants	Crandall et al. (2024)
Frozen foods	AI-based IoT integration	Cold chain monitoring	Improved monitoring of cold chain conditions, ensuring food safety during transport	Lu and Wang (2016)
Leafy greens	SVM, RF	Environmental monitoring and Listeria detection	Enhanced persistence detection of Listeria in retail environments	Yang et al. (2013)

5 | AI in Food Quality Assurance

Technology has become the foundation of food quality assurance by inventing new methods for defining, testing, and distributing food products. In this regard, the use of AI provides advantages such as accuracy, efficiency, and stability, which are important ingredients for both food security and customer satisfaction. Food quality assurance systems are switching to AI technologies, such as ML, computer vision, and DL, to automate operations, decrease human error, and increase productivity. AI has been the key player in these advancements in sensory attribute prediction and quality rating of foods. The conventional quality evaluation methods that depend on human perception are time-consuming, subjective, and sometimes misleading. ML systems using massive sensory attribute datasets can accurately predict food quality. Hany et al. (2023) showed that ML through sensory-related variables and image processing could predict yogurt quality more accurately than before. Additionally, AI-powered systems are especially beneficial in settings where the evaluation of human beings is difficult or sometimes impossible. For instance, CNNs have been used to rank the quality of chili depending on various attributes like taste, aroma, and color, and in this way achieving the highest precision rates by distinguishing between the quality grades (Adam and Niswar 2023). Moreover, it is also important to let you in on the fact that AI has been used to replace the destructive surfactometry approach and non-destructively determine the composition of the gel by means of the moisture and starch content, with a precision exceeding 90% (Yoon et al. 2023). The use of AI extends beyond simple classification and grading. In the processing and manufacturing stages, AI monitors and controls quality by analyzing real-time data from sensors and other monitoring devices. For example, ML has been applied to the chemical composition of the sound to predict sensory characteristics in vineyards. It also lets the winemaker adjust the juice density quite accurately and thus enhances the final product to the desired level (Armstrong et al. 2023). AI is a technology that allows, inter alia, wine production to benefit through the analysis of subtle differences in sensory attributes to produce the product with the best quality and satisfy customers. AI also ensures that food quality assurance activities are performed better through the assistance of computer vision technology, which reduces the time spent on manual labor and thus minimizes the perils of human error. Employing active and semi-supervised learning techniques, such as the example with the cotton quality assessment, is one representation of the existing practice; thus, it has been successful in making the procedure of image labeling shorter by 60% while still keeping the accuracy of the classification high (Fisher et al. 2023). The grading process, which is now both more efficient and cheaper, is how labor is being trimmed from the quality assurance department, thus making the quality assurance process more efficient and scalable. AI is not only a way to enhance the current quality control methods, but it also has the potential to create new ones that would otherwise be beyond our reach. For example, using a combination of near-infrared spectroscopy and ML models for predicting the sensory attributes of dry-cured loins has been successful and is an alternative to traditional sensory panels (Vasconcelos et al. 2023). This approach is advantageous in a number of ways. It is precise and allows for establishing a general standard that can be applied to the production of different items to assure that the food in the industry is of high quality. On the brighter side of AI in food quality assurance, the ability to mitigate risk and make better decisions is achieved. With the use of smart algorithms to track and receive essential insights about potential risks, companies can minimize the potential dangers and cater for the feasible shortcomings. For instance, by using AI automation to forecast potential dangers in a definite part of the food supply chain, the result will be enlightening since the risks will be timely identified and resolved (Temilade Abass et al. 2024). Being proactive about risks is vital for food safety and quality assurance from production to consumption. AI technologies such as those used by companies like Tetra Pak help enable food processing equipment to conduct quality assurance checks, enhancing efficiency and setting new safety standards for the industry.

6 | AI in Food Industry

AI is now the main focus of the food industry when we look at its advantages: food safety issues, quality control, and supply chain optimization. The rapid increase in the world population and the constant need for food have led to the rise in the usage of AI technologies. AI uses sophisticated algorithms and computing models to handle food production and supply, which in turn helps make processes more efficient and sustainable. AI's most vital part in the food industry is the quality control and product classification. Systems such as computer vision and near-infrared spectroscopy (NIRS) are applied in the process to separate and grade food products very precisely. These systems easily recognize the defects and variances in real time; therefore, only the quality goods are delivered to the consumers. The ability of AI to go through large data volumes for the right decision-making is a big plus point for the food-making sector. It generates lots of data very fast, and the food manufacturers can stop problems early, thus, they will have less waste and better efficiency (Mavani et al. 2021).

Moreover, knowledge-based expert systems have been created to handle hazards, spot dangers, and ensure compliance with safety standards. Smart packaging systems, which are AI-driven, check the freshness and the quality of food products during their transport or storage. These technologies are not only decreasing the possibilities of foodborne illnesses, but they are also extending the shelf life of perishable goods, which is beneficial to the consumers and the industry stakeholders as well (Drago et al. 2020). Among the top priorities of quality and safety, AI technologies have been significantly improved by using unconventional techniques to automate production. By way of illustration, using fuzzy logic systems, a canning food production environment can successfully achieve sterilization temperature control, producing the common quality of a product more efficiently.

AI-enabled predictive maintenance tools inspect the equipment and outperform it, and additionally predict failures, which, in turn, allow immediate interventions to be provided and, in the end, reduce the operational downtime. All these technological breakthroughs are contributed by cost-saving and improving production line reliability (Okuyelu and Adaji 2024). ANNs have played a big role in the food industry. Modeled after the human brain, ANNs learn and respond to new data. These are systems that are mostly used for pattern recognition, predictive modeling, and decision-making tasks. Heat and mass transfer processes optimization, food product classification, and quality affect parameter prediction are some of the uses of ANNs.

Their adaptability and precision make them the best option to tackle complicated challenges in the production of food (Kujawa and Niedbała 2021). ML is a part of AI that, like other advancements before, has brought brilliant possibilities in the food industry. The ML models look at big data to spot trends, predict results, and aid in decision-making. From a future perspective, solutions are being rapidly developed to simplify the food distribution chain, such as smart forecasting of waste and demand, accurate inventory, and optimized supply chain logistics. Long short-term memory networks are one type of neural network, a type of RNN, and a special case, a network that uses time series data, like the example presented here, which regulates pH. These inventions bring out in practice how adaptable MLs are to differing industrial necessities (Kler et al. 2022).

Adaptive Neuro-Fuzzy Inference System (ANFIS), a hybrid of Fuzzy Logic and ANNs, shows some additional efficiency while facilitating uncertainty and results in accurate estimates/outputs. These methodologies are very popular in systems requiring human-inspired inherent reasoning parallel with deterministic progress. For example, ANFIS models have been used in the production parameter optimization problem to guarantee product quality and increase workflow efficiency. Their feature of the ability to deal with useful data even if they occur and change over time, for instance, is what makes dynamic industrial locations always in crucial need of them with respect to the development process (Ankit Reddy and Padmavathi 2024).

While all these developments will help, adding AI to the food industry also has some issues. The main obstacles are the price of making it practical, worries connected to users' personal data, and the necessity of trained personnel to implement an AI system. Table 5 summarizes the general application of AI in the food industry.

7 | Ethical Considerations in AI for Food Safety

The integration of AI into food safety processes offers many benefits and, at the same time, poses several risks related to the ethical dimension that require the development of a suitable ethical framework. This model should be helpful in the course of dialog regarding the digital cooperation of the food chain while also keeping a devoted innovation approach. Ethics should be seen as a complex and interdisciplinary subject, so it is vital not to oversimplify it and consider that there are no "silver bullet" solutions. Unconditionally, the collective attention of the parties involved is to be concentrated on the adequate solution to the issue through the creation of the right framework, thus the responsible identity of the digital ecosystem of the food supply chain will be maintained (Craigon et al. 2023). While delving into the intersection of AI and food

TABLE 5 | AI applications in the food industry.

Application	Objective	AI technique	Outcome	References
Food sorting	Efficient sorting of food items	Machine Learning (ML)	Improved speed and accuracy in food categorization	Khollam and Mane (2019)
Quality grading	Assessing food quality	ANN	High accuracy in grading fruits and vegetables	Tata et al. (2022)
Intelligent packaging	Monitoring freshness	Smart sensors	Extended shelf life through real-time quality monitoring	Dodero et al. (2021)
Process optimization	Optimizing food production	FL and ANN	Reduced energy consumption and improved output quality	Guiné (2019)
Supply chain management	Efficient logistics	Reinforcement learning	Reduced costs and environmental impact	Sun and Zhao (2012)
Predicting food demand	Forecasting consumption trends	ML	Minimized surplus and wastage	Yang (2024)
Coffee roasting control	Consistency in roasting	Fuzzy logic	Consistent coffee quality	Falah et al. (2019)
Dairy production	Optimizing milk yield	ANN	Maximized yield through optimal feed and conditions	Gamlath (2020)
Waste reduction	Reducing food wastage	ML	Efficient prediction and reduction of food waste	Ifham et al. (2023)
Wine quality control	Measuring wine aroma	Sensory evaluation	Precise aroma profiling without human olfactory intervention	Nicolotti et al. (2019)
Fermentation monitoring	Alcoholic fermentation supervision	ANN and expert systems	Improved process efficiency in wine production	Șipoș (2020)
Predictive maintenance	Equipment monitoring	IoT and ML	Reduced downtime and maintenance costs	Suthar et al. (2024)
Nutritional analysis	Personalized diet planning	Expert systems	Real-time nutritional insights for tailored food products	Han et al. (2024)
Grain classification	Barley and rice quality assessment	ANN	Efficient classification and sorting with over 90% accuracy	Hamzah and Mohamed (2020)
Food additives analysis	Ensuring Halal compliance	Fuzzy logic	Enhanced transparency in food additive certification	Zakaria et al. (2019)
Beverage industry	pH monitoring in cheese fermentation	Long short-term memory	Real-time process monitoring	Li et al. (2020)
Energy efficiency	Reducing processing energy consumption	ML and sensors	Significant reduction in electricity use	Brehler et al. (2023)

safety, it is evident that the ethically sound use of such technologies is the primary concern. AI and distributed ledger technologies (DLT) have the potential to revolutionize the food sector via innovative technologies such as AI and DLT.

Nevertheless, the efficient implementation of these new technologies requires the establishment of systems that secure data and simultaneously stimulate collaboration and data sharing among the stakeholders. This kind of situation raises the issues of trust, openness, and the responsible deployment of AI (Sharma et al. 2023). The ethical predicament of AI covers bias, accountability, privacy distortions, and the urgency for transparent decision-making processes. They are heightened when unmanned AI makes a complex steered system, where the consequences of the ethically wrong business may result in heavyweight materials. With the increase in the use of technology in the food industry, it is mandatory to create systems that bring the highest priority to human well-being and conform to the principles of RRI (Kulaklıoğlu 2024).

The increase in the use of AI in food supply chains emphasizes the need for handling its ethical concerns in every respectful way. In this field, the trust between the parties that use the technology and the one who purchases the product from them increases when responsible AI practices underpin this trust, and transparency in the world of AI and its application in the food supply chains becomes business as usual. The same can be the role of a comprehensive ethical framework that involves the following seven dimensions: transparency, traceability, explainability, interpretability, accessibility, accountability, and responsibility (Manning et al. 2022). To be transparent means to keep an eye on and acquire correct information about how food is produced and distributed. With traceability, it is possible to follow the path of the supply chain elements, hence creating consumer trust. Explainability and interpretability improve users' understanding of AI decisions by explaining and clarifying data and decision-making processes behind models.

Accessibility is mainly about ensuring that information is available, as various social and commercial factors can hinder data sharing. Accountability guarantees that the persons responsible for AI-driven decisions can justify their actions and bear the responsibilities when needed. Responsibility, finally, is the ethical and social duty of all the participants in the food supply chain. It means standard and consequently unbiased decision-making via norms. Ethical issues in AI are a major obstacle to effectively implementing food safety, and these are closely related to data privacy, transparency, and algorithmic bias. The collection and management of sensitive data must comply with the regulatory frameworks, and consumer trust and privacy must be preserved. It is indispensable to confront data bias and secure the algorithmic fairness to avoid unintended negative influences of decision-support systems. A cross-industry effort is a must to combine the knowledge and experience of industry partners, policymakers, and researchers to develop the most comprehensive guidelines, standards, and best practices of AI use in food safety. With transparency, accountability, and the promise of continuous improvement of AI technology, there is an unequivocal need to earn and maintain consumers' trust and simultaneously innovate food systems for environmental benefits. However, the stakeholders, through the conscious tackling of these challenges, can gain the competitive edge of AI for the safe and resilient global food systems (Shukla 2024).

AI sustainability primarily revolves around establishing ethical AI considerations and governance approaches to produce food in the supply chain. Moreover, AI deployment in food safety is a technology-driven sustainable development that results from the increased societal and ethical challenges sectors are confronted with when trying to innovate in a responsible manner. Ethical AI actually requires that we continually reflect on its implications and put joint effort into the development of practical solutions that will benefit humanity while safeguarding data integrity and fair practices in the supply chain. The advantages of a future in which AI models favor food safety that are consistent with fairness and ethical standards can be obtained using rigorous and well-structured research.

8 | Challenges and Limitations of AI-Based Food Safety Systems

The effective usage of AI in food safety systems has many new opportunities, but it still has to cope with certain challenges and limitations that may not allow it to be fully efficient. Main difficulties are data quality, model interpretability, and computational costs. The efficiency of AI models is very much influenced by the fact that the data on which they are trained is of good quality, and there is enough of it. In a lot of cases, the data could be incomplete or inconsistent, or it is in a certain part of the food supply chain, and it has very little representativeness. Bad data is one of the reasons why models become biased, and they cannot be generalized well to real-life situations (Bortnyk et al. 2023). Different food products, sources, and environmental conditions may display quite different food safety data. This difference can sometimes cause much noise to enter the picture and make AI model training more difficult (Tajkarimi 2020). For example, the contamination of different products worldwide can create multiple image patterns, hence the challenge for AI to accurately predict the potential risks. The main issue with sensitive data collected and stored is the issue of its security and accuracy. Making sure that the data is not touched, corrupted, or changed in any other way is what gives the model its personality, that, in turn, builds trust with customers if their personal data is not jeopardized (Gbashi and Njobeh 2024). AI models are often described as "black boxes," which can be difficult to understand for non-IT professionals. Even if they might be very efficient in terms of accuracy, the decision processes can be hard to understand, thus resulting in a situation where stakeholders cannot comprehend how the conclusions have been reached. Due to this matter, AI technology can have a very short lifespan in the IT industry if a company cannot build devices with which they can be held accountable or which they can validate (Franzoni 2023). A lot of times, food security programs have the obligation to adhere to very strict rules and regulations. It is the duty of regulators and stakeholders to give a crystal clear understanding of their decisions concerning food safety, for example, when there are alerts about contamination or audits for compliance. The inability to satisfactorily interpret AI models can present obstacles to fulfilling these responsibilities and attesting to the documentation required (Gilpin et al. 2018). Food safety workers and end-users may become incredulous about this function's "black box" nature. Irrespective of a high-quality model, users are likely to be reluctant to adopt its decisions, the reason for this is that if they cannot comprehend the method a given AI model uses to trigger a response, the AI model is supposed to help in real-world applications. In other words, this will lead to an AI model being powerless in cases when there is a real need to help (Ranasinghe et al. 2022). Deploying AI-operated food safety technologies often implies the necessity of enormous investments in hardware infrastructure. It implies updating the hardware, purchasing data storage solutions, and networking capabilities. These costs can become a real obstacle to smaller businesses and producers. Creating and training AI models also requires considerable resources, as they need vast computational power and consume a lot of time. This is particularly true for real-time analysis and response, which can drive high operational costs. Scaling AI engineering and AI solutions to meet the skyrocketing amount of data and the types of analysis can be incomplete, and sometimes it could lead to a lack of computational resources due to the system's complexity. The development of a model personalized for a particular task can be a technological challenge while maintaining the required accuracy (Nachiappan 2024).

Even though the use of AI-based food safety systems is seen as a way to make huge strides in food safety and quality assurance, this field faces multifaceted obstacles involving the quality of data, the interpretability of models, and computational costs. It is a must to overcome these when AI is discussed in food safety. It is essential that these be done by continually improving the data collection protocols, increasing model transparency, and managing computational resources. Through the use of AI, the current food industry is moving towards innovative, more trustworthy, and more efficient modes of production. The relationship between the food industry and AI technology is a new type of collaboration requiring efforts from regulators, end-users, and solution providers to create mutual dependence.

9 | Conclusions and Outlook

The AI's usage in food safety, by creating automated product accuracy, efficiency, and reliability in food products, caused a constant revolution. In the food sector, ML, DL, and computer vision technology are extremely vital tools in the detection of pollutants and food quality inspection. The aim of AI has been to utilize these advanced technologies to deal with the food industry's supply chain complexity and the rising demand for safe food. AI can change the course of food safety policies and product quality in a big way; however, more studies and tests should be conducted to fully optimize its potential. These AI

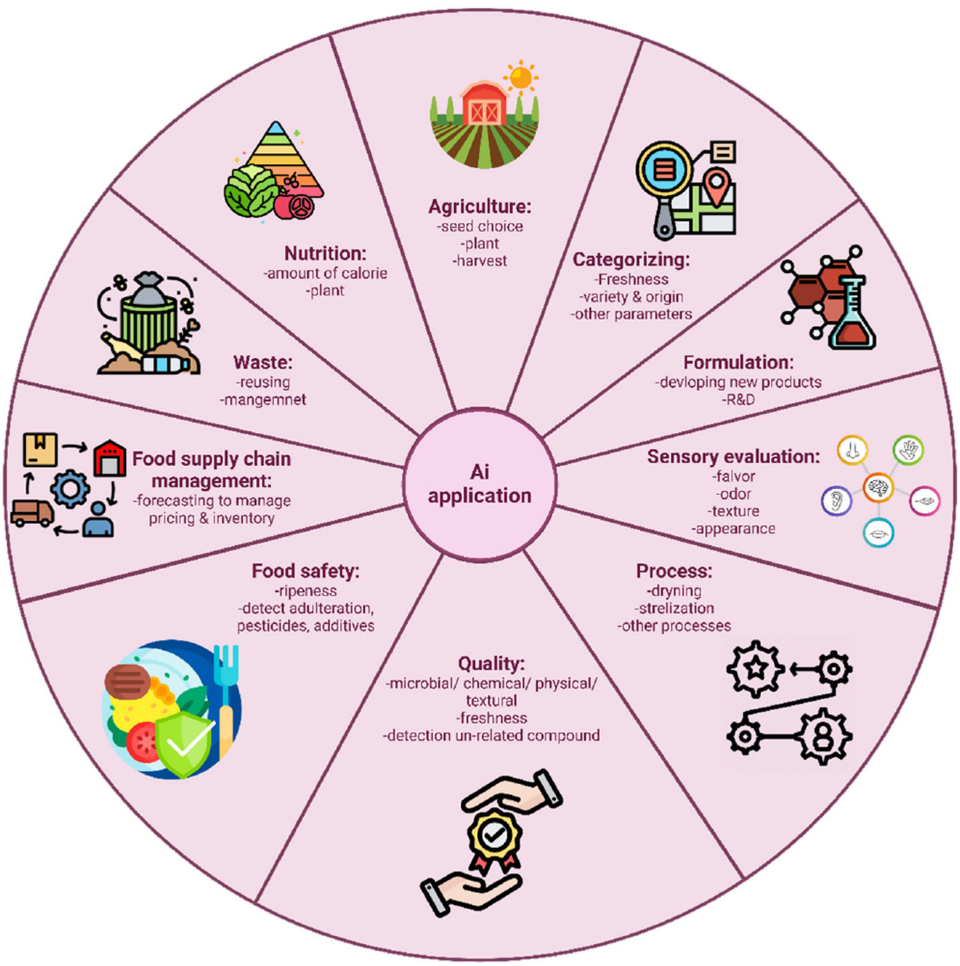

FIGURE 5 | Areas of agriculture, food science and technology, and nutrition that have undergone evaluation on the implementation of artificial intelligence.

notions have the prospect of developing trend analysis by analyzing additional data and integrating more heterogeneous data sources to achieve real-time decision-making in the food supply chain. AI has smart packaging, maintenance predicting systems, and automation technology to address all trends, which is definitely beneficial to secure the food industry, both according to regulations and consumers. The development of such technologies cannot happen without the input of industry people, researchers, and regulatory agencies who are to ensure AI applications are safe and efficient. Food safety and quality assurance have a future that suggests AI will become a part of this revolution. AI technologies are sure to change the global food system's safety and sustainability. A blooming future for AI technology in food science is forecasted, but more research is required to tackle modern food problems. Figure 5 shows the fields of agriculture, food science and technology, and nutrition that have been tested for the use of AI. With the rise of AI technology, next to its role in food safety, waste reduction, and process efficiency, food production technology will also be an essential factor. The given examples allow for appreciating the fruitful usage of AI technologies in firms like IBM, Zest Labs, Nestlé, and Tetra Pak, which stress the transformative power of AI in modern food systems.

Future research should concentrate on developing a hybrid AI model that utilizes various technologies such as ML and DL to improve the performance of the food safety system. Furthermore, research on the interactions between AI and the latest technological advancements like blockchain and the IoT should be the top of the list; the synergies of AI and blockchain can be found in many possible ways one of which is the AI with blockchain which can help to have a clear and transparent record of the food supply chain meaning the producers are able to verify the originality and the quality of the product through immutable records. Such an approach with various technological aspects could be a very promising method to overcome such major food safety issues. The standardized operating procedures for AI activations in food safety should be activated without further delay, and the guidelines should be set with the proper explanation of data collection, algorithm transparency, ethical considerations, etc. These guidelines will speed up the good transformation of AI by considering the terms of the safety regulations and consumers' well-being. Long-term observations are indispensable for the continuous use and functionality of AI applications in food safety, and carry out investigations to find out how society reacts to their use, among other things, which positions and policies to advocate for. Besides this, the ethical AI elements in the area of AI should be reflected, considering the bias issue and the need for discernible and transparent decision-making. The stakeholder involvement in formulating a framework that includes their views is a significant progression in cultivating trust in the ethical use of AI technologies. Through involving both food producers and consumers in AI solutions innovation, the necessary element of the fulfillment of their needs, along with the implementation of these technologies, can be accomplished. The combination studies will improve the comprehension of different points of view and will help the AI-controlled sustainable food safety standards to be more accepted. In doing this, we will be able to improve the safety of the food, increase consumer and stakeholder trust, and ensure that AI systems in the food industry are dependable and just. This holistic way of implementing food security allows society to have a safe and robust food system by finding the right balance between safety and quality.

Author Contributions

Ammar B. Altemimi: conceptualization, writing – review and editing. **Farhang Hameed Awlqadr:** conceptualization, visualization, writing – original draft. **Raqad R. Al-Hatim:** writing – review and editing. **Syamand Ahmed Qadir:** conceptualization, writing – original draft. **Mohammed N. Saeed:** conceptualization, writing – original draft. **Aryan Mahmood Faraj:** writing – original draft. **Tablo H. Salih:** writing – original draft. **Hala S. Mahmood:** writing – original draft. **Mohammad Ali Hesarinejad:** conceptualization, writing – original draft, writing – review and editing. **Francesco Cacciola:** conceptualization, writing – review and editing. All authors discussed the results and contributed to the final manuscript.

Ethics Statement

The authors have nothing to report.

Consent

All authors have read and agreed to the published version of the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are contained within the article.

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