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# Application of Artificial Intelligence in Food Science and Nutrition: Challenges and Future Perspectives

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## ABSTRACT

The Artificial intelligence (AI) and Machine Learning (ML) advent has proclaimed unparalleled knowledge transformation across several sectors, including food science and nutrition. This advancement can aid in a deeper understanding of the insights of both fields and their subfields. A systematic search was conducted across literature resources in many databases, including Web of Science, Scopus, and PubMed, according to PRISMA guidelines. The possible eligible study data were retrieved to assess eligibility and inclusion criteria. This research comprehensively explores the use AI applications in food science, such as the food industry and processing, food safety and packaging, and nutrition, including food and nutrient intake, supplements, clinical nutrition, gut microbiota, and trace elements intake. AI applications can be very helpful in addressing various issues, developing novel techniques in food production, food safety, and quality, and aiding in planning nutrition and nutrient intake for better health with high accuracy and precision. Despite these advancements in the application of AI and ML in both food science and nutrition, more improvement is needed for more efficient, precise, and accurate application in some fields.

## 1 | Introduction

Artificial intelligence (AI), as a broad concept of enabling machine learning (ML) and ML as a more specific subset of AI, are relatively recent technologies that are finally entering every part of human life (Amore and Philip 2023). AI has been defined as an MK that combines different themes, including convex optimization, statistics, and probabilities, to effectively solve various issues (Jordan and Mitchell 2015). Furthermore, other AI algorithms include test-based, logic programming, expert systems, and reinforcement learning (Borana 2016). This is to enable a system to process information in a manner that mimics or is similar to biological and human systems. This might eventually dominate all aspects of human life (Amore and Philip 2023).

Among many fields that apply AI, algorithms of AI have been used effectively in the field of food science in analyzing and mapping various areas, including environmental impact on food commonly named “food desert” (Sigalo et al. 2022). On a larger scale, AI and, more specifically, ML empowered us to monitor the global food supply chain and ensure the safety of food products. Moreover, it helps predict potential risks arising from global climate change (Dora et al. 2022). For food safety, AI used analytical tools to generate and assemble complex datasets, drawing on available data resources to provide insights and address food safety issues (Friedlander and Zoellner 2020). AI has also been used in the sensory assessment of foods. This is through a system composed of cardiac pulse, facial emotion recognition, and galvanic skin responses (Álvarez-Pato et al. 2020). AI has been used in many other fields of food science and technology, including food enzymology, food biotechnology, food microbiology, food safety, and toxicology. This will be further explained in the upcoming sections.

On the other hand, nutrition is one of the fields of study that uses AI and/or ML. This is to more accurately inform and guide nutritionists and food scientists to improve food and health quality (Eetemadi et al. 2020). AI creates an opportunity to accelerate the data synthesis process, generating data that enables scientists to obtain more recent data, make precise, timely decisions, and save costs. Furthermore, AI can provide computational data in different ways, potentially generating a complex etiology of diet-related diseases. Last but not least, it can measure individual responses to a diet plan (Bailey et al. 2024). On the other hand, having a large amount of data ranging from agricultural areas and satellite images, AI provides a cost-effective and timely process to generate powerful evidence to develop food and nutrition interventions that can avert or manage chronic health issues, like data related to medical records and recent wearable personal and individual data (Kirk et al. 2022; Colmenarejo 2020). Furthermore, AI have also been utilized to predict or structure policy interventions, unhealthy dietary habit taxation, drinking soda taxation, for instance (An et al. 2023).

Therefore, the aim of this review is to understand and comprehensively review the application of AI in different areas of food sciences and technology. It is also aimed at understanding the impact of AI in the field of nutrition. Finally, the paper will address the ethical challenges encountering the AI in both field food and nutrition.

## 2 | Methods

### 2.1 | Study Selection

A systematic search was conducted across literature resources in multiple databases, including Web of Science, Scopus, and PubMed, according to PRISMA guidelines. "AI" was defined as the combination of technologies, including probability, optimization, and statistics, to solve problems. ML is defined as a subset of the wider category of AI. The researchers searched for titles and abstracts to be evaluated for selection during the period from 01//11/2024 to 01/08/2025. The possible eligible study data were retrieved to assess eligibility and inclusion criteria.

### 2.2 | Eligibility Criteria

For the eligible criteria, all publications written in English were included. A number of keywords were used for search, including "artificial intelligence", "AI", "machine learning" and "ML". The study included reviews, meta-analyses, and case reports focusing on 'Food science and technology' AND nutrition. The studies were evaluated to determine whether they could be duplicated or yield similar results.

### 2.3 | Data Extraction

After assessing the eligibility data, the studies were then submitted for data extraction. The interesting selected criteria were determined. This includes publication year, study population, study models (human or non-human model, and area of application (nutrition or food science).

## 3 | Application of AI in Food Science and Nutrition

AI has numerous applications across both food science and nutrition. Here are some examples of the application (Figure 1).

### 3.1 | Application of AI in Food Science

The development of food science technology paved the way for the integration of AI into this field. Various fields of food science have adopted AI. The following section presents insights into the use of AI in food science.

#### *3.1.1 | Food Industry and Processing*

The application of AI and ML in the food industry is summarized in Table 1. Many machine-based systems have been used in the food industry for various purposes. This includes k-nearest neighbors' regression (kNN-R), support vector regression (SVM-R partial least square regression (PLS-R), ordinary least square regression (OLS-R), stepwise linear regression (SL-R), and random forest regression (RF-R)(Estelles-Lopez et al. 2017). Research has shown that AI is used in the food industry for quality decision-making, sensory assessment, cost analysis, and business establishment based on customer requirements (N. V. Lu et al. 2020). Additionally, a Long Short-Term Memory (LSTM) neural network was utilized to detect acidity in the dairy industry (Bing Li et al. 2021). Other AI systems have been developed to determine optimal process control parameters and to predict end-product fault percentage (Kim et al. 2020). It was reported that AI-based techniques were beneficial in security prediction in the UK. AI was also employed SVM PCA regression model to classify lamb meat based on the fat percentage (Table 1) (Alaiz-Rodriguez and Parnell 2020). On the other hand, AI and ML have been used to pattern food industry sales rates (Tsoumakas 2019). To predict waste management and its generation, AI was employed (Garre et al. 2020).

#### *3.1.2 | Food Quality and Safety*

The papers presented extensively demonstrate the growing dominance of AI in revolutionizing food quality inspection, smart sorting, and storage safety management. Among the most important results is that AI-enabled computer vision and hyperspectral imaging systems, coupled with machine learning methods like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Vision Transformers (ViTs), can recognize food external and internal defects, contamination, and spoilage with great accuracy, typically over 95%. For instance, DenseNet-based models correctly classified the fruit quality with 99.67% accuracy (Ananda et al. 2025) and ViT models correctly classified pork belly contamination based on hyperspectral data (Ghimpeteanu et al. 2025). The models outperform conventional

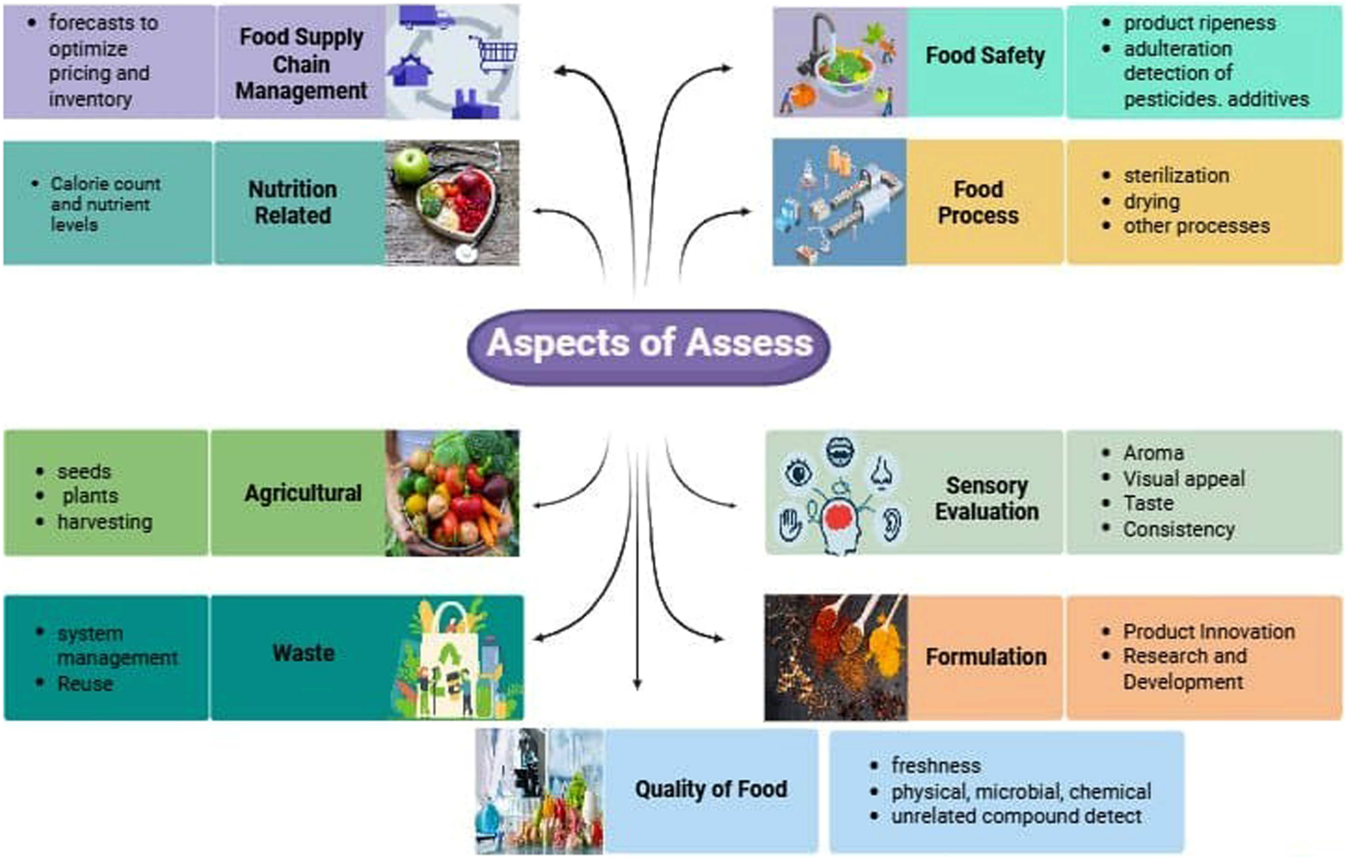


**FIGURE 1** | Different applications of AI in food science and nutrition (Friedlander and Zoellner 2020).

inspection methods in accuracy and speed, enabling real-time, high-throughput inspection in industry. Automated sensor-based and optical sorting equipment for potatoes, nuts, and fruits has also been shown to achieve high sorting accuracy, with AI enabling sophisticated defect detection that is not consistently possible with human labor (Sharif et al. 2020; Maier et al. 2024).

AI-enabled food safety storage and monitoring systems, particularly those integrating IoT sensors and big data analytics, also significantly enhance traceability, early spoilage detection, and food safety. For example, NIR spectroscopy and ANNs have been successful in tracing meat and cheese and evaluating storage-induced quality changes (Curto et al. 2020). Additionally, AI-driven predictive models used to forecast mycotoxin contamination or microbial growth from environmental and spectral data play a leading role in preventive safety (Naseem and Rizwan 2025). It is clear from literature reviews that intelligent inspection systems, in combination with robotics and automation, bring objectivity, reduce reliance on labor, and facilitate standardized grading parameters throughout the food supply chain. In total, these reviews position AI as a disruptive technology in the agri-food sector, with the potential to improve efficiency, accuracy, and safety in preprocessing and postharvest handling operations. Table 2 delineates the use of artificial intelligence in ensuring food quality at the point of origin, intelligent sorting optimization, and storage safety.

### *3.1.3 | Food Packaging*

One of the decisive parameters affecting food quality and shelf life in the food supply chain is food packaging (Table 3). Furthermore, alongside its communication properties like ingredient, nutritional value, shelf life information, packaging also contributes to preservation from external bodies and pollutants, as it keeps its freshness (K. Yu et al. 2021; Z. Zhang et al. 2021).

In modern food packaging, several modern techniques have been used, including AI, deep learning, more specifically, ML. These techniques identify potential inconsistencies and imperfections in packaging by employing data from images and detection sensors. ML and AI enable the automatic analysis of packaging quality, such as reliability and consistency. Furthermore, ML and AI have been used to reduce problems and enhance productivity through and inspect packaging misaligned, breaks, and creases (Goyal et al. 2024).

Studies have shown that ANN has been used to predict packaging protocols by developing models from available data patterns. It was also employed to expect the design composition of active packaging to prolong product shelf life. The ANN was imbued by the neural network of biological structure and proved its efficacy in detecting antioxidant and microbial compounds within the model of active packaging (Gorde et al. 2024).

The application of AI is very wide, and various sections have been studied (Figure 2). These sections include analytical assessment to analyze the risks of the sensory aspects of food. Furthermore, it was also used in food safety in order to assure safe products for clients and consumers. Moreover, AI is used in food packaging to optimize processes. Additionally, using AI in interactive management to engage with the supply chain and

**TABLE 1** | The Application of AI in Food Industry and Processing.

| Source | Country | Type of food | Type of technique | Aim | Outcome |
|---|---|---|---|---|---|
| (Sabater et al. (2019)) | Spain | Artichoke | MLP, RF, BLR | AI models were developed to identify ion patterns specific to each enzyme, achieving prediction accuracies exceeding 95%. | artichoke pectic-oligosaccharides mixes can be used for numerous ions using an AI model |
| (M. Li et al. (2018)) | USA | Apple | adaptive boosting and Linear discriminant analysis, | The model was created to classify apples and manifest codling moth incidence | The model aided high classification percentage rate and fast signal collection were obtained |
| (de Sousa Silva et al. (2020)) | Brazil | Biscuits | CNN | Classify and assess variety of biscuits quality | The AI model managed to produce a more accurate quality assessment by 99% |
| (Bing Li et al. (2021)) | New Zealand | Cheese | ANN, LSTM | A hybrid model combining an LSTM with mechanical modeling was developed to accurately describe lactic acid modification. Furthermore, the model used to predict the pH of cheese. | The hybrid system can reasonably predict pH and cheese fermentation. |
| (Younis et al. (2019)) | India | Sweet lime | SVM–ANN and SVM–GPR | The model was developed to anticipate total antioxidant and polyphenol characteristics. | AI-based modeling aided in maintaining maximum polyphenol without compromising the taste. |
| (Estelles-Lopez et al. (2017)) | UK and Greece | Meat | OLS-R, SL-R, PC-R, PLS-R, SVM-R, RF-R, and kNN-R | ML was utilized to detect the spillage microorganism of beef meat from different methods. | All the methods were accurate. But, RF-R was the highest, and SVM-R was the least accurate. |
| (Alaiz-Rodriguez and Parnell (2020)) | Spain and Ireland | Lamb meat | SVM compared to Principal Component Analysis (PCA) regression | Evaluate the efficacy of ML in classifying meat according to fat percentage accurately | The model significantly increased accuracy. The accuracy of PAC and SVM were 93.89% and 91.80, respectively. |
| (Pise and Upadhye (2018)) | India | Mangoes | SVM and Naive Bayes | Grading Mango types according to their maturity level | The system improved accuracy in determining maturity over the conventional method |
| (Gutiérrez et al. (2020)) | Chile | Milk | SVM | Determination of antibiotic level in cow milk | The model determined the level of antibiotics with higher accuracy than the conventional analytical method in terms of sensitivity and speed. |
| (Xu and Sun (2017)) | Ireland | Salmon | HSI | The model used develop to distinguish between normal and freeze-burnt types | The model was able to distinguish between the two categories of normal and freeze-burnt accurately |

Abbreviations: ANN, artificial neural network; BLR, boosted logistic regression; CNN, convolutional neural network; GPR, Gaussian process regression; HIS, hyperspectral imaging; kNN-R, k-nearest neighbors regression; LSTM, long-short term memory network; ML, machine learning; MLP, multilayer perceptron; OLS-R, ordinary least square regression; PCA, principal component analysis; PC-R, principal component regression; PLS-R, partial least square regression; RF, random forests; RF-R, random forests regressions; SL-R, stepwise linear regression; SVM, support vector machine; SVM-R, support vector machines regression.

**TABLE 2** | Applications of AI in Food Quality and Safety.

| No | Food | Detection method | ML algorithm | Model performance | Reference |
|---|---|---|---|---|---|
| 1 | Walnut foreign object detection | Visual/multispectral | CNN | 95% accuracy | (Rong et al. (2019)) |
| 2 | Storage insect detection | Elytra micrographs | VGG16 CNN | 83.8% classification accuracy | (Shi et al. (2020)) |
| 3 | Fresh food distribution | Expert system + visual inspection | LP | Better than manual cost-minimization | (Nguyen et al. (2021)) |
| 4 | Banana grading system | Mobile vision (edge + cloud) | SVM + YOLOv3 | Layer-1: 98.5%, Layer-2: 85.7%, overall 96.4% | (Zhu and Spachos (2021)) |
| 5 | Food and Cheese quality | NIR spectral analysis + cloud-based system | ANN (C4.5, PLS, etc.) | High predictive reliability in organoleptic attributes | (Bhatt (2023)) |
| 6 | Date defect detection | High-resolution visual + segmentation | Deep CNN | Low-latency, industrial-grade precision | (Tulbure et al. (2022)) |
| 7 | Wheat and rice storage | Temp and humidity sensor data | BP neural network, SVM | correlation coefficient ($R^2$) | (Liu et al. (2024)) |
| 8 | Soft drink classification | Image classification of package & labels | DCNN (transfer learning) | 98.51% accuracy | (Hafiz et al. (2022)) |
| 9 | Date defect detection | High-res conveyor images | Deep CNN + segmentation | High precision, industrial-ready | (Azimi and Rezaei (2024)) |
| 10 | Poultry foreign object detection | High-speed NIR-HSI inline scanning | Semi-supervised GAN + DL | High detection accuracy, real-time capable | (Kim and Byoung-Kwan (2024)) |
| 11 | Mycotoxin contamination | Chemical/spectral features from food | CNNs | High accuracy | (Inglis et al. (2024)) |
| 12 | Food fraud (beeswax, herbs) | Media text and batch records | Bayesian networks, LDA | 85%–91% predictive accuracy | (Gbashi and Njobeh (2024)) |
| 13 | Salmon freshness in cold storage | IoT sensors (temp/humidity) + spectral imaging | CNN-SVM hybrid | High classification of freshness levels | (B.; Wang et al. (2024)) |
| 14 | Grain quality assessment | Hyperspectral imaging (grains) with limited labels | Few-Shot Learning CNN | Comparable to fully-trained models | (Karmakar et al. (2024)) |
| 15 | Walnuts | Multispectral + reflection & fluorescence | SVM, Extreme Learning Machine | 98% correct classification | (Guimarães et al. (2023)) |
| 16 | Pork belly contamination detection | Hyperspectral NIR imaging + segmentation | Lightweight ViT | High detection accuracy | (Ghimpeteanu et al. (2025)) |
| 17 | Pork and beef freshness | Hyperspectral imaging | PLSR, LSSVM, RF | $R^2 \approx 0.99$ for the freshness index | (B. Li et al. (2025)) |
| 18 | General food safety review | Literature review | Various ML methods | Summarizes performance trends | (Dhal and Kar (2025)) |
| 19 | Fish fillet quality assessment | Computer vision, multispectral imaging | ML algorithms, deep learning architectures | Achieving high accuracy, uniformity, and efficiency | (Sagar Naik et al. (2025)) |
| 20 | Black tea | Gas Chromatography Electronic Nose (GC-E-Nose) + multivariate statistical analysis | Discriminant Analysis (PLS-DA), FDA, Stepwise Multiple Linear Regression | FDA accuracy = 95.2%, PLS-DA accuracy = 78.6%, Sensory score model Rp = 0.94 | (J. Chen et al. (2022)) |

(Continues)

**TABLE 2** | (Continued)

| No | Food | Detection method | ML algorithm | Model performance | Reference |
|---|---|---|---|---|---|
| 21 | Mango and tomato defect grading and sorting | Image processing + machine vision + deep learning | CNN and image processing algorithms (pre-processing, thresholding, morphological, bitwise ops) | Detection accuracy: Mango = 89%, Tomato = 92% (image processing); CNN validation accuracy: Mango = 95%, Tomato = 94% | (Akram et al. (2025)) |
| 22 | Mushroom classification | Image classification using CNNs | DenseNet-121 and Modified DenseNet-121 (with frozen layers, dropout, weight decay, Keras Tuner) | Standard DenseNet-121: Accuracy = 0.90, Precision/Recall/F1 = ~0.90–0.91 Modified DenseNet-121: Accuracy, Precision, Recall, F1 = 0.97 | (Singh et al. (2025)) |
| 23 | Animal-Source Foods (ASFs)/Food safety & HACCP monitoring | Non-destructive techniques including: spectroscopy, smartphone sensors, chromogenic arrays, machine vision, and hyperspectral imaging | General ML algorithms, feature extraction/selection techniques, hybrid AI models, and computer vision | Performance details not quantified; noted as capable of real-time monitoring, predictive analytics, and reduction in food safety risks | (Revelou et al. (2025)) |

Abbreviations: ANN, artificial neural network; BP, back-propagation; CNN, convolutional neural network; DCNN, deep convolutional neural networks; DL, deep learning; FDA, Fisher discriminant analysis; GAN, generative adversarial networks; HACCP, hazard analysis and critical control points; HIS, hyperspectral imaging; LDA, linear discriminant analysis; LP, linear programming; LSSVM, least square support vector machine; ML, machine learning; NIR, near-infrared; PLS, partial least squares; PLS-DA, partial least squares discriminant analysis; PLSR, Partial Least Squares Regression; RF, random forest regression; SVM, support vector machine; ViT, vision transformer; YOLOv3, you only look once v3.

client and consumer interaction has been well-documented. On the other hand, AI and ML were used in packaging quality control to maintain food quality standards, as we all use in visual inspection and store and environmental management.

## 3.2 | The Application of AI in Nutrition

Several studies in different countries have been conducted in different areas of nutrition that used AI. We have summarized the aim of the study, location, area of study in nutrition, and the main findings in Figure 3. AI has proven to be fast in response and can be a milestone and revolutionize the field of nutrition. According to the studies conducted, AI can be used effectively in dietary intake. Research included in this study stated that using AI can be very useful since most dieticians and nutritionists depend on paper questionnaires to document patients' information. This can be consuming and has accuracy limits. However, with the use of AI, this problem is mostly resolved. Furthermore, AI has demonstrated utility and can provide accurate, precise results in dietary assessment. This could avoid bias related to the self-data entry and report by the clients and patients (Table 4).

According to the literature, AI systems in nutrition rely on data collection and technical analysis and mostly focus on diet assessment and comparing to predicting lifestyle intervention and malnutrition prediction. Another issue with AI is the accuracy and precision of results, which can be resolved in the future to avoid biases resulting from self-report information and foster the data and guidelines to be available in a better form. Furthermore, AI can help with faster physical and dietary adherence and may offer significant benefits; however, it also raises a range of potential integrity, safety, and ethical issues.

### 3.2.1 | *AI in Gut Microbiota*

AI techniques have been applied to the macrobiota in subsequent years. A few researchers studied the differentiation of thirty-six strains of *Bifidobacteria* using metabolic models of genome scale (Devika and Raman 2019). Furthermore, a specific analysis related to gut microbiota was conducted, relying on a collection of visualizations of networks as well as ML (Shima et al. 2017). AI was also used to investigate microbial enzymes produced by gut microbes. The study used a specific approach for enzyme identification as well as human pathways of gut metabolic. The AI techniques were utilized to identify and classify enzyme types. The study found that there are 48 pathways that bacteria can encode enzymes to metabolize nutrients(Mohammed and Guda 2015). AI was also used to analyze the gut microbiota and its use in intervention (Abavisani et al. 2024). A very recent study found that AI can foster microbiome-related treatments through modifying the microbial community in the gut to treat different gut syndromes. Furthermore, AI can aid in identifying microbial footprints that are connected to specific diseases (Patil et al. 2025).

### 3.2.2 | *AI in Clinical Nutrients*

In clinical nutrition, AI and its techniques were used to develop tools to support supplementation and dietary planning. Furthermore, it was intended to support disease prediction and control (Table 5).

**TABLE 3** | The Application of AI in Food Packaging.

| NO. | Application | Technique methods | Description/specific application | Impact/outcome | References |
|---|---|---|---|---|---|
| 1. | Intelligent food packaging. Real-time freshness monitoring systems. | ANN and SVM | Food freshness detection and monitoring across various food products. | – Current limitations in processing speed and accuracy.<br>– Challenges with 3D/multidimensional data handling.<br>– Dependence on large training datasets.<br>– Potential for future integration with advanced sensors. | (X. Li et al. (2023)) |
| 2. | Product packaging design and industrial design. | ML, DL and NLP | Product innovation packaging design system that extracts design-related information from big data generated throughout product lifecycle for intelligent design decision-making. | Demonstrated capability to translate heterogeneous life-cycle data into actionable packaging insights; prototype system achieved encouraging accuracy and user-rated superiority in esthetics, recognition, innovation, and information transmission. | (Gan et al. (2022)) |
| 3. | Food Packaging labeling and Nutritional research. | KNN algorithm. | Predict the added-sugar content of packaged foods and beverages using readily available nutrient, ingredient, and food-category information. | – Achieved $R^2 = 0.96$ and Spearman $\rho = 0.91$, demonstrating high validity and reliability.<br>– Enables fully automated, large-scale predictions without manual steps. | (Davies et al. (2022)) |
| 4. | Packaged food inspection and quality control. | Supervised-learning YOLOv4 network with X-ray data augmentation. | Anomaly detection for packaged food X-ray images to identify defective food products and foreign objects. | – At least 94% accuracy for all foods; improved performance with post-processing.<br>– Realistic defective food images augmented. | (K. Kim et al. (2021)) |
| 5. | Food packed product evaluation. | ML-based prediction system. | Healthiness assessment of food products through Barcode scanning and nutritional data analysis. | – Enables informed food choices through health score prediction.<br>– Real-time scanning and information retrieval.<br>– Enhanced user literacy through apps and online tools. | (Nakhate (2025)) |
| 6. | Packaged food nutrient estimation. Automated food label analysis. | Fine-tuned DistilBERT transformer-based language model for regression. | Predict five nutrient values (fat, sugar, protein, carbohydrates, salt) of packaged foods using only their ingredient lists from Mintel's GNPD European market dataset. | – DistilBERT achieved an overall $R^2 = 0.81$, outperforming Linear Regressor ($R^2 = 0.57$), XGBoost ($R^2 = 0.69$) and LightGBM ($R^2 = 0.63$) without requiring prior feature engineering.<br>– Demonstrated prediction of all essential nutrient values possible. | (Murtaza and Yigin (2022)) |

(Continues)

**TABLE 3** | (Continued)

| NO. | Application | Technique methods | Description/specific application | Impact/outcome | References |
|---|---|---|---|---|---|
| 7. | Food packaging monitoring of fiber levels. public health nutrition. | KNN algorithm. | Prediction of fiber content in Australian packaged foods and beverages based on commonly available nutrient information. | – More accurate than manual prediction.<br>– Similar performance to neural networks but with greater interpretability.<br>– Enables monitoring of fiber in Australian packaged food supply.<br>– Can inform interventions aimed at increasing fiber intake. | (Davies et al. (2021)) |
| 8. | Pre-packaged sauces. Nutritional analysis of food products. | ANN and SVM | Predicting nutritional content of pre-packaged food sauces. | – SVM achieved 85% accuracy vs. ANN's 82% accuracy.<br>– Demonstrated that advanced AI algorithms can reliably ascertain dietary content of foods. | (Kusuma and Varadarajan (2025)) |
| 9. | Product packaging design. | Computer virtual technology. | Design and visualization of product packaging structure, style, and form. | Greatly promotes development and broadens prospects of the product packaging design industry. | (Zong (2021)) |
| 10. | Food packaging label. | ML algorithms ML analysis. | Categorizing micronutrients (Low/Medium/High). Estimating vitamin and mineral content. | Addresses micronutrient deficiencies through informed choices. | (Razavi and Xue (2023)) |
| 11. | Efficient packaging plans. Logistics optimization. | Mathematical optimization model for load-balanced 3D-BPP. | Efficient loading of boxes into bins with orientation flexibility and product-family constraints. | Reduced logistics and transportation costs. Increased customer satisfaction through effective packaging plans. | (Erbayrak et al. (2021)) |
| 12. | Food safety and quality control in the meat product packaging. | Deep learning-based approach. | Detection of adulteration in red-meat products using hyperspectral imaging. | – CNN model achieved 94.4% average overall accuracy, outperformed state-of-the-art models.<br>– Demonstrated stability and invariance to meat status (fresh, packed, frozen, or thawed). | (Al-Sarayreh et al. (2018)) |
| 13. | Quality control of packaging meat products. Real-time beef cut recognition tool for consumers in meat industry. | Deep learning-based approach; CNN | Classification of seven different types of beef cut images. | VGG16 achieved 98.6% classification accuracy, Inception ResNet V2 achieved 95.7% accuracy, both models correctly identified beef cuts over 96% of the time, and demonstrated higher classification accuracy through a pretrained CNN with image augmentation. | (GC et al. (2021)) |
| 14. | Shelf-life monitoring of dairy products. | ANN and MLR | Prediction of overall desirability of spreadable Gouda cheese during storage. | – Both models achieved good adjustment and fits between 0.99 and 0.87; ANN model demonstrated slightly better performance than MLR models in predicting cheese quality. | (Stangierski et al. (2019)) |

(Continues)

**TABLE 3** | (Continued)

| NO. | Application | Technique methods | Description/specific application | Impact/outcome | References |
|---|---|---|---|---|---|
| | Risk assessment process, food safety/quality assessment. | | | – Demonstrated capability for quality prediction during storage. | |
| 15. | Quality assurance in food packaging systems.<br>Dairy industry fouling detection and monitoring, manufacturing. | ANN | Detection of dairy fouling presence and absence using ultrasonic measurements combined with neural network analysis. | – Achieved 98.58% correct identification of fouling presence and absence in tested samples (350 samples tested after training with 400 samples).<br>– Demonstrated stable and efficient pattern recognition with decreased error proneness compared to single acoustic parameters. | (Wallhäußer et al. (2011)) |
| 16. | Monitoring of shrimp freshness during storage and transport in the seafood supply chain. | Deep learning algorithm (Stacked Autoencoders with Logistic Regression - SAEs-LR).<br>Compared with traditional PLS-DA method. | Detection of shrimp freshness (distinguishing fresh vs stale) during cold storage using hyperspectral imaging. | Achieved 96.55% accuracy for calibration set.<br>– 93.97% accuracy for prediction set (outperforming PLS-DA).<br>– 98.28% accuracy when applied to all ROI pixels.<br>– Enabled visual freshness evaluation through hyperspectral imaging. | (X. Yu et al. (2018)) |
| 17. | Eco-friendly food packaging design.<br>Consumer product selection guidance. | ANN | Development of carbon-neutral and environmentally friendly food packaging solutions. | – Achieved 97.6% accuracy in smart energy-saving packaging selection.<br>– Enabled identification and avoidance of 6 non-eco-friendly packaging types.<br>– Improved product utilization and production efficiency. | (Dai (2023)) |
| 18. | Food packaging optimization.<br>Shelf-life prediction for perishable crops. | ANN | Predicting the maximum shelf-life of cauliflower crops under Modified Atmosphere Packaging based on color changes. | – ANN model achieved prediction accuracy (MSE: 0.00953, $R^2$: 0.99008).<br>– Predicted 50-day marketing capability for MAP1-packaged cauliflower.<br>– Identified polypropylene pouches as unsuitable due to water vapor permeability. | (Mohi Alden et al. (2019)) |
| 19. | Internet-famous food packaging design.<br>Visual communication innovation. Digital media art integration in packaging. | Conjunction-disjunction double arithmetic weighted fusion rules. | Innovative identification in interactive packaging visual communication design for Internet-famous foods. | – Solves evidence contradiction problems in classical evidence theory.<br>– Provides more accurate results for packaging design innovation identification. | (L. Wang (2022)) |

(Continues)

**TABLE 3** | (Continued)

| NO. | Application | Technique methods | Description/specific application | Impact/outcome | References |
|---|---|---|---|---|---|
| | | | | – Enables better handling of conflicting design evidence. | |
| 20. | Shelf-life monitoring of shrimp quality.<br>Seafood safety detection. | Deep Learning: (SAEs, LS-SVM). | Non-destructive prediction of Total Volatile Basic Nitrogen (content in Pacific white shrimp during cold storage. | – Achieved high prediction accuracy ($R^2 = 0.921$).<br>– Low error rate (RMSEP = 6.22 mg N/100 g).<br>– Demonstrated effectiveness of deep hyperspectral features (RPD = 3.58).<br>– Enabled non-destructive quality assessment. | (X. Yu et al. (2019)) |
| 21. | Real-time, non-destructive quality inspection and sorting of blueberries on packing lines and in cold-chain logistics. | CNN, Traditional ML algorithms (SMO, LR, RF, Bagging, MLP). | Detection of internal mechanical damage in blueberries using hyperspectral transmittance data. | – ResNet: 88.44% accuracy, 89.52% F1-score, 93.25% recall.<br>– ResNeXt: 0.8784 accuracy and 0.8905 F1-score with 0.8944 recalls.<br>– Superior to traditional ML (max 80.82% accuracy).<br>– Fast processing (5.2–6.5 ms per sample).<br>– High damage detection recall minimizes false negatives. | (Z. Wang et al. (2018)) |
| 22. | Food safety inspection of leafy greens during packing and processing for pathogen-risk mitigation. | Hyperspectral fluorescence image processing algorithm. | Detection of bovine fecal contamination spots on the adaxial and abaxial leaf surfaces of fresh romaine lettuce and spinach. | – 100% spot-level detection accuracy; all contaminated spots were correctly identified.<br>– Effective on both leaf surfaces (adaxial/abaxial). | (Yang et al. (2010)) |
| 23. | Preservation of food quality and nutritional value. Food drying process optimization. | ANN with topologies compared to MLR and the Midilli mathematical model. | Predicting drying characteristics of edible-coated pineapple cubes under various temperature conditions. | – ANN provided higher accuracy than MLR and mathematical models.<br>– Successfully predicted MR and DR under various drying temperatures and edible coating applications with satisfactory accuracy.<br>– The MR network achieved a satisfactory nonlinear regression fit. | (Meerasri and Sothornvit (2022)) |

Abbreviations: ANN, artificial neural network; CNN, conventional neural networks models; DL, deep learning; GNPD, global new product database; KNN, k-nearest neighbors; LR, logistic regression; LS-SVM, least-squares support-vector machines; ML, machine learning; MLP, multi-layer perceptron; MLR, multiple linear regression; NLP, natural language processing; PLS-DA, partial least squares discriminant analysis; RF, Random Forest Regression; SAEs, stacked autoencoders; SAEs-LR, stacked autoencoders with logistic regression; SMO, sequential minimal optimization; SVM, support-vector machines; YOLOv4, you only look once v4.

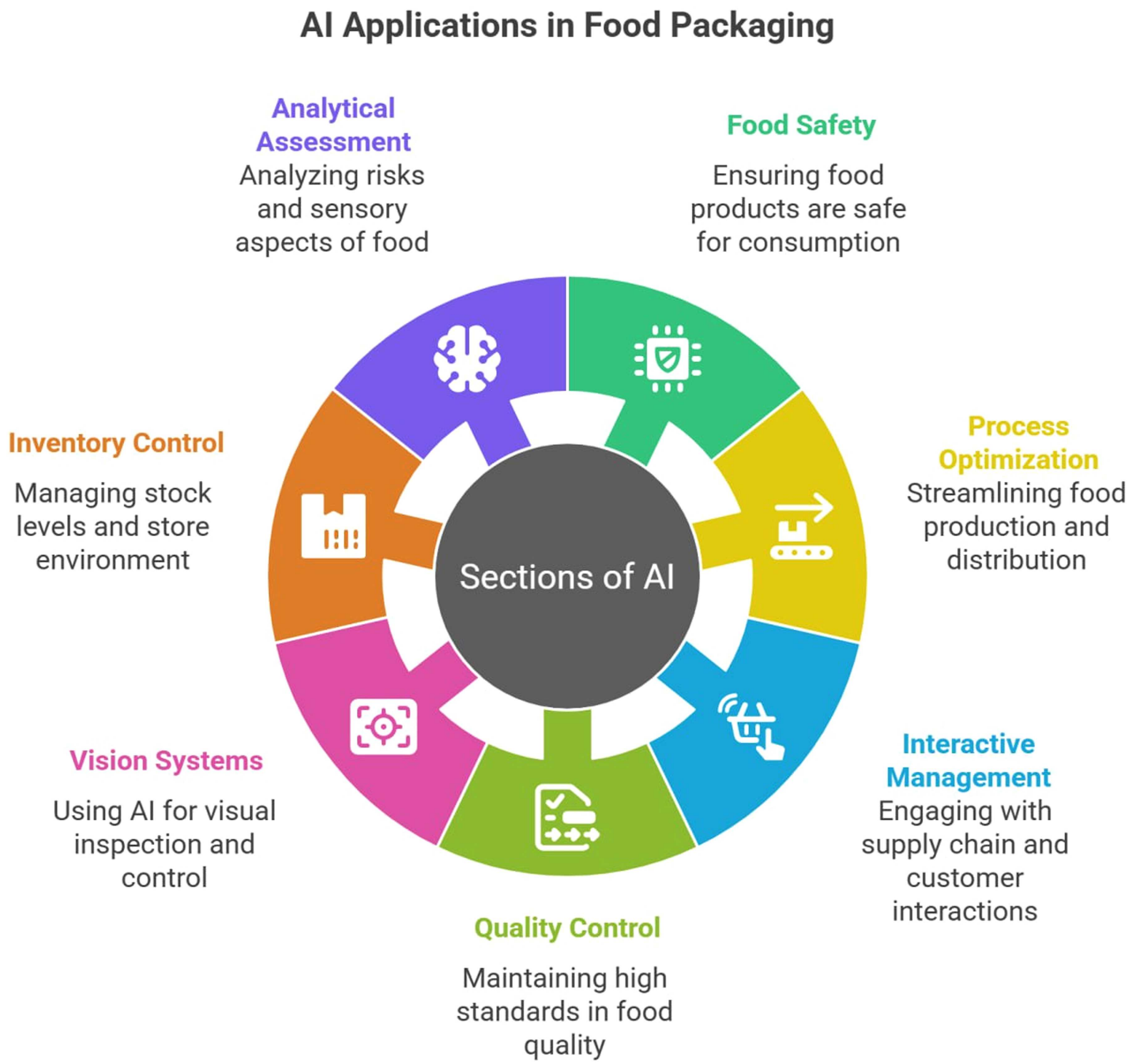


**FIGURE 2** | Application of food packaging in different sections.

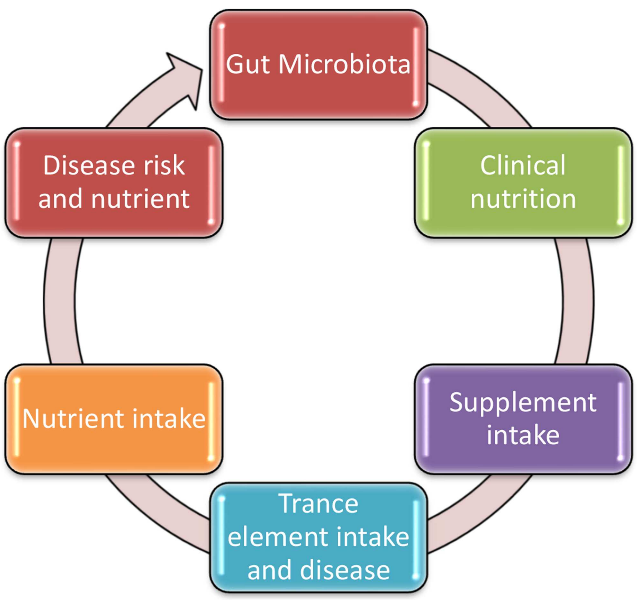


**FIGURE 3** | The Application of AI in Nutrition.

**TABLE 4** | The Application of AI in Nutrition, Modified from (Sosa-Holwerda et al. 2024).

| | | Area of nutrition | AI | Aim of use | Outcome |
|---|---|---|---|---|---|
| (Maharjan et al. (2019)) | United states | Diabetes dietary assessment | NLP | AI was used in order to help management of diabetes using participants voice | Volunteer's satisfaction and health state development using this technology are not fully met. |
| (Davis et al. (2020)) | Australia | Lifestyle intervention | NLP | AI assistance assessment and volunteers adherence to diet and physical activity | The virtual health assistant significantly changed behaviors, but its knowledge was limited to its training |
| (Maher et al. (2020)) | Australia | Lifestyle intervention | NLP | To assess the recruitment and sustain physical ability program derived based on the Mediterranean diet. A virtual AI coach presented the program. | Paola, the virtual health assistant, effectively delivered a lifestyle intervention program, helping participants lose weight and increase their physical activity. However, the AI virtual coach ability could be improved to better emotionally connect with people. |
| (Oh et al. (2021)) | United states | Lifestyle intervention | NLP | To evaluate the properties of function and conversation of chabtbots and its ability to change (eating behavior, weight management and exercise and health issues. | Chatbots has the possible ability to improve lifestyle behavior and access to effectively improve nutrition based personal programs. |
| (Beyeler et al. (2023)) | Switzerland | The assessment of health bot to understand its effectiveness in treating patients with bariatric | NLP | Dietary assessment | The Health Bot (HB) was favorably accepted by patients, for its comprehensiveness and easy to navigate. Participants indicated that the HB provided access to valuable information. Nevertheless, concerns were expressed regarding the potential for the HB to replace dietetic professionals, as well as concerns related to the security of personal information and the confidentiality of submitted inquiries. |
| (Limketkai et al. (2021)) | United states | The integration of advanced technologies, such as health apps, wearable sensors, and AI-powered remote nutritional assessment, into clinical nutrition and patient care is examined in this review. | ML | Dietary assessment | Some of the apps that record sleeping patterns and heart rate need a monthly upgrade and subscription. They are at the infancy stage and need a lot of improvement. |

(Continues)

**TABLE 4** | (Continued)

| | | Area of nutrition | AI | Aim of use | Outcome |
|---|---|---|---|---|---|
| (Morgenstern et al. (2022)) | Canada | The aim was to develop a machine learning tool and evaluate its potential to anticipate the relationship between food and CVD | ML | Nutritional epidemiology | The finding showed that the most significant nutritional factors were supplements, alcohol, caffeine, and sodium. |
| (Murumkar et al. (2023)) | India | The create an AI related tool dietitian that acts real, it provides individual based diet plant | ML | Dietary assessment | No real dietician intervention is needed |
| (Fujihara et al. (2023)) | Japan | The aim was to develop a machine learning tool to predict body based variation for medical examination over 3 years of period | ML | Weight management | The tool managed to create three different formulas for body change anticipation. The tool successfully managed to predict factors related to weight modification in three years. |
| (Z. Yang et al. (2021)) | China | Developing an AI tool to mimic dietetion congnitive processing to estimate food size | DL | Food estimation | The machine can be used in portable devices for food size estimation |
| (Taylor et al. (2021)) | China | To create an AI app to figure out food and place it on a national database to count calories and preferred procedures. | DL | Weight management and dietary assessment | An intelligent app using NLP and national databases predicted energy intake as precisely as the 24 h recall method (the gold standard). This could help with weight management. Interestingly, users preferred typing their food intake instead of talking to a nutritionist. |
| (Papathanail et al. (2021)) | Switzerland | Developing and evaluating AI based system that utilizes inserted image for nutrient intake before and after in patients | DL | Dietary system | The system proved to be more sufficient than health professionals in the estimation. It also provided better and instant results of meal component estimation |
| (X. Chen et al. (2021)) | United states | To assess the nutrition of restaurants at a wider scale using crowded food images and offering calorie-based quality of food | DL | Dietary assessment and food environment detection | The system is unable to determine images of crowded foods a part of one image The results cannot be generalized people who assessed were youngsters that night affected the reviewing and assessing |

(Continues)

**TABLE 4** | (Continued)

| | | Area of nutrition | AI | Aim of use | Outcome |
|---|---|---|---|---|---|
| (Van Wymelbeke-Delannoy et al. (2022)) | France | To evaluate food intake using a system that would not need human intervention to quantify food leftover in the hospital. | DL | Dietary assessment | The system deems to be beneficial in collecting images and determining food consumption through analyzing leftover of food. Having sufficient pictures, the AI based system can understand and recognize novel foods |
| (Jin et al. (2022)) | United states | The potential of AI system to predict malnutrition based on patient records. | DL | Prediction of Malnutrition | Using patient's data, the system can be beneficial. The system relied on information of multiple visits rather than the last visit. No anthropometric and/or lab test was utilized for prediction. |
| (Sefa-Yeboah et al. (2021)) | China | Creating an app for mobile to manage obesity as well as proving individual based diet planning with sufficient micronutrient and calories. | GA | Obesity management | AI system can be used to planning meals and presume calorie intake. It can use food recall to predict energy estimation. It also determines the amount of calories needed to meet the daily goal. |
| (Niszczota and Rybicka (2023)) | Poland | To evaluate the ability of diet generation of ChatGPT and confirming its safety and accuracy of a number of diets | GPT | Dietary assessment | The menu was generated, but it is not safe, as it includes allergens and repeats the same menu. The portion size was calculated incorrectly. The system may misguide consumers with wrong dietary suggestions. But it was following guidance from various diets. |
| (Arslan (2023)) | Turkey | Assess ChatGPT capacity for treating malnutrition and obesity, ChatPGT can modify its guide based on progress. | GPT | Obesity management | AI information can be biased according to the data that the system was trained on. The system lacks emotional skills like humans and not supporting emotional eating. Providing wrong information might lead to confusion and not find the responsible and who to blame and when guide is given by the system |
| (Sun et al. (2023)) | China | To create and validate AI based nutritionist specialized in diabetes | GPT | Diabetes dietary assessment | GPT4 and ChatGPT are able to answer expert dietitian assessment. However for endocrinology related food information was not very precise. The system is able to provide dietary assessment and is an alternative to dietitians. |

(Continues)

**TABLE 4** | (Continued)

| | | Area of nutrition | AI | Aim of use | Outcome |
|---|---|---|---|---|---|
| (Chatelan et al. (2023)) | Not stated | To offer recommendations based on the usefulness and side-effects of ChatGPT in clinics public health and academics. | GPT | dietary assessment | AI based system has both risks and benefits. It is not necessarily precise and accurate and might offer risky materials. However, it is useful in terms of providing materials for education including food, nutrition, and healthy eating. The system is better to be supervised and because of not having soft skills, it might perform like a real dietitian. |
| (Bond et al. (2023)) | United Kingdom | Assess the space for using AI in nutrition | deep learning, machine learning and natural language processing | Dietary assessment | AI might provide healthcare information through translating photos, and generating prescriptions and nutritional recommendations in nutrition-related places. Using this AI might be faster to get guidance instead of waiting for dietitians. |

Abbreviations: DL, deep learning; GA, genetic algorithm; GPT, generative pre-trained transformer; ML, machine learning; NLP, natural language processing.

**TABLE 5** | Summary of Studies Conducted the Infield of Clinical Nutrition.

| Scope | AI scope | Types of nutrients | Type of algorithm | Reference |
|---|---|---|---|---|
| Nutrients Supplementations | ML | Herbs, spice, and vitamin | Clustering algorithms. | (L. Chen et al. (2020); R. Li et al. (2020); Fan et al. (2020)) |
| Disease and trace elements levels | ML | Trace minerals | Support vector machines, naive Bayes, decision tree algorithm, support vector machines | (Berry et al. (2020); Panaretos et al. (2018)) |
| Diseases risks to food and nutrients patterns | ML and ANN | Micro and macro nutrients | k-nearest neighbor, decision tree algorithm, linear regression, random forest | (H. Chen et al. (2014); H. Chen and Tan (2012)) |
| Clinical nutrients Intake | ML, DL and ANN | Micro and macro nutrients | feed forward neural network, least absolute shrinkage & selection operator, support vector machines, k-NN | (H. Chen and Tan (2012); Baek et al. (2019); Konstantinidis et al. (2020); Sanjith et al. (2024)) |

Abbreviations: ANN, artificial neural network; DL, deep learning; *k-NN*: k-nearest neighbor; ML: machine learning.

Several studies have examined the application of AI in clinical nutrition, aiming to support and enhance monitoring, and to help and modify the diets of people with diseases. A study documented an AI-based novel technique to precisely measure nutrient intake by processing RGB/depth image pairs taken before and after daily meals (Y. Lu et al. 2019). Furthermore, another study compared the therapy program of a mobile application and a human. It was concluded that the findings of this randomized controlled trial will bridge the gap between the need for AI support in nutritional interventions and the scientific evidence regarding its effectiveness (Oka et al. 2019). Furthermore, a study used an AI technique to help type 1 diabetic patients control carbohydrate intake. The authors used GoCARB system to determine the carbohydrate content of the meals. In the study, 54 plate meals were generated by GoCARB, compared with the estimated carbohydrate content provided by experts. The results indicated that the AI-based tool was as accurate as experts' determinations (Vasiloglou et al. 2018). Moreover, another study reported 24 h. dietary assessment self-administered tool, focusing on lactose in the nutrition system for research (Chin et al. 2019).

The study found that the nine different ML models developed the tools successfully estimated nutrients in foods. RABID algorithm was used to interpret skeletal properties from videos in order to observe and understand the eating behavior of 59 volunteers who were divided into forty-five meals. The authors stated that using the RAPID algorithm was similar to human reference (F1-score: 0.948; Cohen's kappa_ = 0.894) (Konstantinidis et al. 2020). In order to recommend appropriate foods in terms of serving and amount for 84 patients with chronic kidney disease, using two different techniques Semantic Web Rule Language and the Web Ontology Language based on their knowledge. The results of the study found that the Web Ontology Language can recommend appropriate food serving and amount as well as provide reasonable answers for questions and offer knowledge-based answers (Chi et al. 2015). Earlier research used AI in order to determine health issues, such as dehydration, for 17 volunteers. The authors applied an AI-based technique to automatically detect dehydration in response to cognitive tasks. The results were promising, and accuracy exceeded 91% using the Stroop test and pulse rate (Posada-Quintero et al. 2019). Similarly, a recent study used another radiometric sensitivity-based AI technique to predict dehydration caused by diabetes, vomiting, and diarrhea, and due to less sensation. The study concluded that using these techniques could detect dehydration in a few seconds, which could save time and the cost of health professionals (Owda 2024). Other techniques like Nutri-Educ (Buisson 2008), which balances diet based on energy, NutriNet (Mezgec and Koroušić Seljak 2017), an image-based tool for dietary evaluation for Parkinson's disease and food based data system and a k-means algorithm as a hybrid clustering for the knowledge base, and food preferences were extracted (Baek et al. 2019).

### 3.2.3 | *AI and Supplement*

Researchers have studied and evaluated Vit A traits as Anti-Covid supplement to mitigate the sign and symptoms. This is achieved through bioinformatics and computational analysis within a pharmacological protocol (R. Li et al. 2020). Similarly, a study was done to evaluate the potential combination of nutrients glycyrrhizic acid, curcumin and vitamin C. to treat Covid infection using an analysis of network (L. Chen et al. 2020). Moreover, AI-based network analysis was used to find the connection between Vit D and Alzheimer's onset through molecular identification (L. Chen et al. 2020). A recent study examined the potential of AI-based Guide (GenAISTM) prescription compared with traditional dietitian dietary prescriptions for treating LDL cholesterol. The authors concluded that the AI technique reduced cholesterol and TG more than the traditional prescription technique (Pokushalov et al. 2024).

### 3.2.4 | *AI in Trace Elements and Diseases*

AI has also been used by several researchers to identify elements and assess disease risk. The analysis of trace minerals was combined with AI to determine the effectiveness of ML (Adaboost) in relation to CVD diagnosis in hair samples of type 2 diabetic patients (Tan et al. 2009). The data revealed that the AI model can be used as an effective and promising tool to predict CVD. The same researchers later examined the effect of several elements, such as vanadium, nickel, manganese, iron, copper, chromium, zinc, and lithium in type 2 diabetic blood samples in comparison with analogous datasets in order to predict diabetes in the hair and urine of 105 people (H. Chen et al. 2014). To analyze data, a model was formed from a decision tree, a vendor machine support algorithm, and Fisher's linear discrimination. The results showed that the specificity and accuracy of both urine and hair were as high as 100%. However, the hair sample was superior to the urine. In order to another study, ML was used to reveal the relationship between serum trace elements and some biomarkers in Nasal Polyps patients. The study used various ML algorithms, including Naive Bayes, SVM, random forest, k-NN, and logistic regression. Furthermore, to interpret the key features affecting the efficacy of the top model, logistic regression and SHapley Additive exPlanations (SHAP) analysis were applied. The study concluded that these approaches can be used to achieve better predictability and interpretability (Aydin et al. 2026).

In addition to AI techniques applied to physiological issues, AI techniques have also been applied to psychological and neurological problems. A research study studied the relationship between trace elements and schizophrenia risk. The study used 228 samples from healthy and schizophrenic patients under the supervision of ML. The results showed that the ML can be a promising tool to diagnose schizophrenia (Lin et al. 2017).

A recent study used AI models (CatBoost, XGBoost, LGBM, and MLP) in combination with some biomarkers, including vitamins, trace elements, and cholesterol, in patients with critical situations to predict mortality. The study concluded that advanced AI models, particularly when combined in an ensemble, have shown increased predictive accuracy (Park et al. 2024).

### 3.2.5 | *AI and Nutrient Intake*

Several studies have used AI-based model to foster monitor, modulate and support nutrient intake, in particular patients (Table 6). A study developed novel AI-techniques to precisely assess nutrient intake through imaging coupled with meal

**TABLE 6** | The application of AI in food and nutrient intake.

| Intake types | AI model | Sample size | Population | Input data | Outcome | Reference |
|---|---|---|---|---|---|---|
| Food | SVMb, RBFkc | 18 | | Signal and sound | As high as 94% accuracy was achieved in food intake, and 84% in swallowing accuracy. | (Lopez-Meyer et al. (2010)) |
| Food | RF | 12 | | Jaw motion, hand gesture sensors, body acceleration, with the importance of time domain (TD), frequency domain | The data showed that the jaw motion sensor with TD was more accurate and relevant for food intake. | (Fontana et al. (2013)) |
| Nutrient intake (carbohydrate) | CVe, SVM using GoCARB-based smartphone | 144 | Type 1 diabetes | Image | The GoCARB was seen as applicable to evaluation carb intake | (Anthimopoulos et al. (2015)) |
| Food | SVM, DT | 10 | General healthy population | Jaw motion signal, body acceleration signal | Best results were obtained using both trained input data systems in detecting food intake. | (Farooq and Sazonov (2016)) |
| Energy | SRMh, NLPi, SMMj | 10 | General healthy population | Audio signaling (Speech-to-Nutrient-Information) (S2NI) | The data revealed that S2NI scored 80.6% accuracy in determining calorie intake | (Hezarjaribi et al. (2016)) |
| Nutrient intake | MTCNnet, DTM, RANSAC algorithm F | 644 | Hospitalized Patients | 322 images | The system facilitated the sequential semantic grouping of foods and the determine of consumed food size, allowing a fully automated evaluation of nutrient intake for each type of food with an estimated error margin of 15%. | (Y. Lu et al. (2019)) |
| Nutrient (lactose) | LASSOq, Ridge, FFNNr, XGBs models | 567 | General population | Text | The system was successful in determining nutrient intake with $R^2 = 0.76$ | (Chin et al. (2019)) |
| Nutrient intake | CNN, SMM in COCO Nutritionist app | 34 | Healthy individuals | Audio and text | The system proved to be sufficient and promising for automatically assessing nutrient intake. | (Taylor et al. (2021)) |
| Food | Time-CNN, ResN, FCN, IM, MLP | 17 | A general healthy individual | the Automatic Ingestion Monitor v2 and accelerometer sensor | The accuracies of Time-CNN, FCN, and ResNet were 88.8%, 90.1%, and 93.4%, respectively. | (Ghosh and Sazonov (2022)) |

(Continues)

**TABLE 6** | (Continued)

| Intake types | AI model | Sample size | Population | Input data | Outcome | Reference |
|---|---|---|---|---|---|---|
| Food items | deep neural networks | 22,544 Situation | Dishes | Image of 149 dishes | The results seemed to be excellent for 58 dishes (39%) and good for 20 dishes (19%) | (Van Wymelbeke-Delannoy et al. (2022)) |
| Food | Deep convolutional CNN | 689 | Dishes | Images | The model improves the accessibility of humans with greater precision and accuracy. | (Pfisterer et al. (2022)) |
| Food | SBFPT | 100 | Normal-weight individuals | Biometrics response to 8 foods | The biometric response did not help predict food intake items. | (Pedersen et al. (2022)) |
| Nutrient | RF, SVM, LDA, LR | 310 children and 308 urbanized children | Elementary school pupil | Text | RF performed best among other models to predict malnutrition | (Siy Van et al. (2022)) |
| Nutrient intake (potassium) | BN, BTANN | 375 | Healthy and kidney patient individuals | Text | The models aided an applicable approach to predict individuals' diet in clinical samples. | (Granal et al. (2022)) |
| Energy-nutrient intake | RGB-D fusion | 2960 | Pairs of images of food | Image | RBG-D based nutrient assessment scored a better performance. Mass and calorie mean error were 10.8% and 15%, respectively | (Shao et al. (2023)) |

Abbreviations: BN, Bayesian network; BTANN, Bayesian technique/algorithm with neural networks; CNN, conventional neural networks models; COCO, conversational calorie counter; CVe, carbohydrate volume evaluation/estimation; DT, decision tree; DTM, digital terrain model; FCN, fully convolutional network; FFNN, feed forward neural network; GoCARB, is a mobile phone-based system; IM, image-based ingestion monitoring; LASSO, least absolute shrinkage and selection operator; LDA, linear discriminant analysis; LR, logistic regression; MLP, multi-layer perceptron; MTCNet, multi-task convolutional network; RANSAC, random sample consensus; RBF, radial basis function kernel; ResNet, residual network; RF, random forest regression; RGB-D, combines color (red, green, blue); SBFPT, Steno biometric food preference task; SMM, self-monitoring methods; SVM, support vector machines; SVM, support-vector machines; XGB, gradient boosted.

consumption (Mohammed and Guda 2015). Another study compared nutrition therapy with an AI-supported mobile application (Oka et al. 2019). The results demonstrated that an AI-supported application can be developed based on scientific evidence. Another research used a GoCARB computerized based smartphone model in comparison of professional dietitian to control carb consumption in type 1 diabetic patients of 54 meal plates. The model demonstrated high accuracy in determining carbohydrate content, comparable to that of nutrition professionals (Vasiloglou et al. 2018). Self–administered 24 h dietary assessment tool (ASA24) taking lactose as an example in relation to the nutrition data system for research (NDSR) was studied. This system is a web-based model that allows automatic multiple 24hr food recalls. Another software application used is NDSR for analysis and recall meals. To compare with them, several novel models were developed based on the same nutrients as NDSR and ASA24 (Table 6). The findings revealed that the computerized techniques can be promisingly determine nutrient as standardized tools (Chin et al. 2019). A more recent study developed a rapid and automatic bite detector algorithm (RAPID) that illustrated the skeletal traits using videos compared to human annotation. Another research studied patients' eating behavior using three types of dishes of 45 meals. The results showed similar annotation (F1-score: 0.948; Cohen's kappa = 0.894) between the human and algorithm (Konstantinidis et al. 2020). To evaluate a system for recommending required food-group serving sizes, a group of researchers proposed a system-based knowledge approach for 84 patients with chronic kidney disease, using Semantic Web Rule Language (SWRL) and the Web Ontology Language (OWL). The results indicate that OWL can obtain logic questions and is precise in resolving knowledge issues whilst maintaining its ability to share knowledge-based information (Chi et al. 2015). A more recent study investigated the autoregressive nature of cognitive stress in relation to mild dehydration in 17 patients, using ML based on electrodermal activity fluctuations in pulse rate. The study reported that overall mild dehydration, all-system acceptability, and accuracy were 91.2% (Posada-Quintero et al. 2019).

In the era of AI, it may be possible to evaluate prototype and novel dietary-based solutions. For this reason, an early study proposed a menu using an incremental knowledge acquisition system (MIKAS). This was achieved by asking experts to expand their roles and actions so that they could be included, and MIKAS might automatically act accordingly in the future. (Khan and Hoffmann 2003). Nutri-Educ computer software was developed to recommend a balanced meal composition based on patients' calorie requirements. (Buisson 2008). For that reason, the model used Heuristic algorithms to generate a nutrition-based solution to transform it into a balanced meal. “NutriNet” was developed by Mezgec and Koroušiˊc Seljak to recognize images and assess nutrient intake and dietary intake. The system was trained on 520 foods and beverages, comprising 225,953 images. The results showed that the detection accuracy on the dataset was 94%. 47% on a collection containing 130,517 images (Mezgec and Koroušić Seljak 2017).

#### 3.2.6 | *Relationship of Diseases Risks and Nutrients*

The AI seems to be beneficial in the assessment of health risk issues depending on the dietary or food analysis. Some authors relied on the k-NN algorithm and statistical comparison to evaluate cardio-metabolic issues of ten years (2002-2012) of 3042 individuals in regard to food and nutrient patterns. The study stated that using AI is superior and more useful in the classification of health scores (B.; Wang et al. 2024). Furthermore, another study assessed the intern-personal variation of response of blood glucose and triglycerides and their possible risk of metabolic disease among 1002 healthy and twins groups. The study revealed that AI and more specifically ML model developed predicted food intake including both triglyceride and glycaemic responses in relation to cardio-metabolic risks by $r = 0.47$ and $r = 0.77$, respectively (Berry et al. 2020). An earlier study used an AI model of ANN to comprehend the relationship between nutrients (Folic acid, B12) and breast cancer. The model of ANN expressed variables by 94.2% the prediction of breast cancer (Naushad et al. 2016). Finally, a group of researchers assessed 106 volunteers with various ethnic backgrounds and colorectal cancer histories in connection with a healthy diet. AI and ML validated protocols were employed. Several nutrients were determined in relation to colon cancer using different ML methods(Shiao et al. 2018).

#### 3.2.7 | *AI and Medicinal Plants*

AI has been used in medical plants to foster its utilization for human nutrition and therapy (Figure 4). It assists scientists in precisely identifying plant species, finding novel bioactive nutritional compounds, forecasting herb-drug interactions, and guaranteeing the safety and quality of products (Azadnia et al. 2022).

Large biological and chemical datasets can be analyzed more quickly and accurately by AI systems, such as ML and DL, than by humans, which improves our understanding of how plant chemicals affect human health and nutrition (Sheth et al. 2025).

However, AI may also have unintended consequences if used incorrectly. Inaccurate predictions or misinterpretations of AI results can lead to wrong medical advice or unsafe herbal use. Over-reliance on AI without professional judgment may also reduce human decision-making in nutrition and diet (Spanakis et al. 2025).

Therefore, while AI supports scientific progress and safer medical practices, its application should always be guided by expert supervision and ethical standards. However, if AI is not employed effectively, it can have unintended consequences. Inaccurate predictions or misinterpretations of AI data can lead to incorrect nutritional advice. Overreliance on AI without professional judgment may limit human decision-making in due. As a result, while AI promotes scientific development and safer medical treatments, its implementation must always be subject to expert oversight and ethical standards (J. Zhang and Zhang 2023).

## 4 | The Challenges in the Future Perspectives of AI and Ethical Considerations

The adoption of AI in food science and nutrition represents a transformative milestone, reshaping the future of the field. The AI technologies improved the food production, food safety,

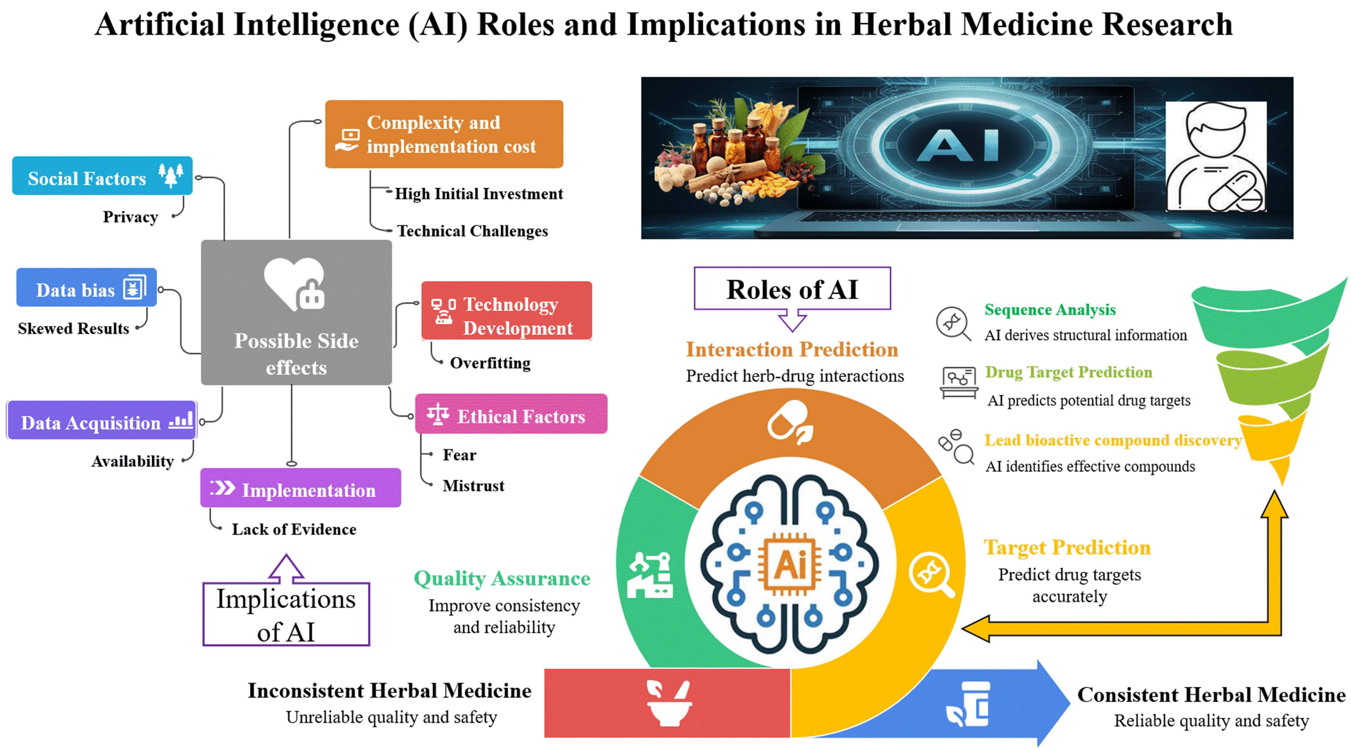


**FIGURE 4** | Application of AI in medical plants.

and quality, and shelf life determination (IM Almoselhy and Usmani 2024). Furthermore, these technologies have improved the food sector, enabling companies to anticipate current and future trends and engage with the market more efficiently. Furthermore, AI improved personalized meal recommendations, environmentally conscious consumption, and nutrient intake. Additionally, AI has improved personalized healthcare, accelerated product development, and enabled sustainable, eco-friendly products by collecting and analyzing consumer and patient data, yielding real-time insights to inform better choices. Last but not least, AI, ML, and other synergistic technologies in food and nutrition and made improvements, modernized the food and nutrition practice towards better production, engaging in efficient and suitable practices (Hassoun et al. 2024).

As discussed earlier regarding nutritional assessment, many AI applications in field of nutrition can be used to monitor nutrient intake, assess nutritional status and use in clinical aspects. However, there is always aspects of weakens to improvement. Many AI logarithms and application luck accuracy. Therefore, it is not without challenges. The primary challenge is possible bias in algorithmic AI, which might result in intended and potential biased results. For instance, when training data reflects dietary and socioeconomic biases, the resulting AI can generate and destroy those patterns (Hanna et al. 2025). Similarly, another study reported that using AI luck logical and ethical issue when used for personalized nutrition (Thomas et al. 2022). This occurs because underrepresented groups, biased results labels, and proxy features for socioeconomic status can skew model behavior, and deployment choices can amplify disparities. Another issue is the short-term outcome. AI is not trained for long-term data, particularly in relation to nutrient intake and disease, which need regular and long follow-up. Furthermore, the employment of AI and ML technology might pose serious questions regarding consumer privacy, data security, and, particularly, the nature of consumer preferences and the supply chain. Another challenge includes explainability (IM Almoselhy and Usmani 2024). The decision-making and outputs are difficult to interpret and require a more comprehensive understanding. Achieving this explain-ability make is it more powerful and comprehends. This poses a challenge for stakeholders to trust and/or comprehend the decision-making process and undermines ethical issues related to accountability and oversight (Talaei Khoei and Kaabouch 2023). Moreover, another Ethical Issue of AI the concerning is that it might cause the replacement of dictation and nutrition expert and community focus on AI for their food and diet that expert. However, this can be solved by the dietician and nutritionists by integrating the AI into their daily routine work (Detopoulou et al. 2023). Additionally, the ethical issue also concerns AI employment in food design that possibly displaces labor, particularly affecting small business producers who face challenges with AI adaptation without a thorough intervention of policy to guarantee these naive groups and pay special consideration and to ensure that all stakeholders advantage from AI employment all in the future (Harikrishnan et al. 2025).

## 5 | Conclusion

This work emphasizes the most recent application of AI and ML in both food science and nutrition. It was understood that the use of AI would enable the development of novel techniques across food science and nutrition and advance the state of the art. This is particularly evident in the production and processing of food, food quality and packaging, nutrient intake, and clinical nutrition plans. Advanced application techniques can be a milestone and a frontier in addressing various issues in food science and nutrition with high accuracy and precision. Despite advances in AI and ML in food science and nutrition, further improvements are needed to enable more efficient application of AI and/or ML in routine practice. Furthermore, another improvement that should be done is the intervention of humans and humanizing the results, since, without human intervention, results are still not completely reliable.

### Author Contributions

**Yaseen Galali:** data curation, writing – original draft. **Pary Hadi:** investigation, validation. **Arkan Mohammed Hassan:** funding acquisition, software. **Holem Hashm Balaky:** conceptualization, formal analysis. **Tavga Sulaiman Rashid:** resources, writing – review and editing. **Bashdar Abuzed Sadee:** methodology, project administration. **Tanya Salam Salih:** formal analysis, funding acquisition. **Hamed Hassanzadeh:** supervision, writing – review and editing.


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The authors declare no conflicts of interest.

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The authors state that no Gen AI used in the preparation of this manuscript.

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Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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