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Applications for Artificial Intelligence in Food and Dairy Science: Advancing Food Quality and Safety: A Review

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Abstract

Artificial intelligence (AI) has become a key tool in food science that significantly raises the safety and quality of food. AI methods like computer vision, machine learning, and artificial neural networks enable effective analysis of complex food data. These technologies are widely used in sensory evaluation, spoilage prediction, and quality assessment of food products. Because AI can detect chemical and microbiological contaminants early on, it is also crucial for human health. AI-powered solutions also enhance food manufacturing procedures and reduce waste. All things considered, applying AI to food science improves consumer protection and encourages more reliable decision-making.

Keywords: machine learning, contaminant detection, food safety monitoring, artificial intelligence.

1. Introduction

Numerous sectors and industries have profited from the quick developments in big data and artificial intelligence (AI). Systems for big data analytics have been designed to handle a wide variety of data types, variables, and sequences. AI-powered solutions have made decision-making faster by streamlining time-consuming tasks. This also applies to the food industry (1). Food production, processing, spoilage prediction, quality and safety assessment, supply chain monitoring, marketing, and consumer choice prediction have all improved thanks to artificial intelligence and big data (2).

The qualities of food that support both consumer approval and the anticipated product standards are collectively referred to as food quality. Depending on the particulars of the food item in question, assessing food quality entails looking at a variety of factors, including colors, mouthfeel, sizes, shapes, surface textures, aroma, and flavors (3). Every nation's economy and public health are significantly impacted by food, and governments, food producers, and consumers all need to ensure that food is of high quality. According to (4), food safety refers to the absence of dangerous pathogenic microorganisms and euphoric substances in the food. Safety factors include removing additional microbiological, chemical, and physical contaminants and conducting routine checks to ensure that food items, especially meat and fish, are not past their specified expiration dates (5).

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Subjective evaluations, internal and external disruptions, limitations pertaining to historical data, the vast array of possible risks, and sources of uncertainty are some of the difficulties that come with food quality and safety monitoring (6). Food monitoring problems have been addressed by AI systems that use data from multiple sources, which offer promising capabilities beyond human intelligence and data. According to (7), artificial intelligence (AI) systems enable machines to simulate and automate biological minds through the use of textual, acoustic, visual, and numerical data.

2. Overview of Artificial Intelligence in Food Science

A collection of technologies as modern artificial intelligence, improves machines' capacity to carry out tasks that are comparable to those of human cognition. Neural networks, natural language processing, and pattern recognition are some of the most widely used tools—often combined under the umbrella of "machine learning." Applications range from producing visual art to predicting changes in financial markets to scholarly publications. The emergence of big data is driving a resurgence of interest in well-established ideas like fuzzy logic and expert systems (8).

AI in food science can support sustainable practices, increase production efficiency, enhance sensory quality, and monitor human health. These applications spread the whole food chain, from agricultural production, transportation, and processing to consumption and disposal (9).

There are limitations on the application of AI in food systems as well. It is challenging to accurately mimic the sensory evaluation carried out by qualified professionals, which is the foundation of many quality-assurance procedures. The creation of predictive models is hampered by the unclear relationship between process parameters and food quality. Privacy issues arise when data is collected and shared on a wide scale. Furthermore, the food industry must overcome significant obstacles in areas like risk assessment and hazard identification due to strict safety regulations (10).

Data relevant to these uses can be categorized based on their scale, composition, origin, and other attributes. The information gathered may include production parameters, formulations, and the ultimate quality of the outputs, depending on the intricacy of the procedures and the variability of the products (11). Food quality and safety, processing and manufacturing, and the enforcement of data governance, ethics, and standard compliance are the three primary areas into which AI applications can be divided (12-13). Artificial intelligence can help with real-time food system monitoring and control by combining various data sources and historical records. Specifically, predictive models can be used to estimate footprints and find trends that support sustainability goals (2).

3. AI-Driven Quality Assessment and Assurance

A variety of sensors are used to collect information about the quality of the food. These include chemical sensors, such as electronic noses and tongues, spectrometers, computer vision technologies, and hyperspectral imaging systems. The integration of these sensors and the fusion of their data to monitor multiple quality indicators in real time is an active area of research, with online quality measurements of parameters such as fruit firmness, color, and soluble solids concentration being pursued. (2)

Food quality models can also be developed based on computer vision to analyze product attributes such as size, shape, color, and blemishes. Different models have been trained to assess olive grade, class fruit appearance, and the level of spoilage. Several types of measurement scenarios, such as automatic inspection during factory production lines or periodic assessment in storage rooms, have been implemented to evaluate the feasibility and effectiveness of the models. Metrics such as model performance (accuracy, F1 score) and operational stability (environmental influence and long-time reliability) have been used to assess model quality (14).

Process Analytical Technology (PAT) refers to a systematic approach for delineating and regulating food processing unit operations in relation to raw materials and the quality of the final product, with the objective of maintaining a consistent and optimal product quality during production (15). Within this framework, it is possible to develop quality predictive models derived from correlation analyses of quality data, which serve to elucidate the progression of final product quality. Subsequently, three distinct quality-control strategies may be employed: quality-feedback control, quality-feedforward control, and quality-specification control. Quality-predictive modeling is applicable to various foods, and a three-level modeling strategy (batch, continuous, and hybrid) can be utilized, while turbo-boosted regression tree and long short-term memory models are among the suitable choices for model establishment (16).

3.1. Sensor Data Integration and Quality Monitoring

Real-time monitoring of salvage food businesses takes immediate corrective actions and assures producers and consumers of product safety and quality (2). Food businesses increasingly embrace a diverse range of sensing technologies to monitor various indicators related to food quality and safety. Most sensing technologies have large sensor data volumes and processing burdens, which together hinder real-time monitoring, so, data fusion approaches need more development (17). Quality indicators relevant to different food processing stages include temperature information, chemical characteristics, and microbial sites. Sensor data obtained during these stages can be integrated to evaluate the overall quality (18).

3.2. Image-Based Quality Evaluation

The evaluation of food quality is one of the main tasks required along the food supply chain (19). Most of the quality evaluation methods are based on human vision. However, color perception is different among individuals. On the other hand, food quality is highly correlated with various quality attributes like color, shape, size, texture, and so on (20). These characteristics can be effectively and precisely recognized through methods grounded in computer vision. Techniques for image processing and analysis function on two-dimensional images, which capture a broader scope of a product when compared to one-dimensional sensors. (21).

Since food quality evaluation is highly dependent on quality-related feature extraction, various feature extraction algorithms have been widely applied, e.g., traditional thresholding, segmentation, edge detection, texture analysis, and so on. AI models, including statistical approaches and deep learning methods, can be applied for learning food attributes from an image (22). The choice of artificial intelligence models is influenced by the size of the dataset. In samples where the dataset pertains to food quality and is relatively huge, or in the case of high-dimensional image data, deep learning techniques tend to demonstrate superior performance compared to conventional statistical models. Within the foundational deep learning paradigm, a diverse array of deep network architectures, such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and capsule networks, can be developed in alignment with various quality advantages. At the evaluation phase, using the right metrics to determine acceptance or rejection is crucial (23). A range of metrics, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Squared Error (MSE), Root Mean Square Error (RMSE), along with additional metrics tailored for specific applications, may be employed to assess the level of satisfaction (24).

3.3. Process Analytical Technology and Predictive Quality Control

Process Analytical Technology (PAT) can be clarified as “a system for designing, analyzing, and controlling manufacturing through timely measurements of critical quality and performance attributes of raw and in-process materials and processes" (2). The application of PAT to the food industry is received with a lot of caution because food materials are subjected to a variety of biological, environmental, and processing fluctuations. Consequently, it is necessary to develop a novel intelligent quality control framework that integrates multi-source data using artificial intelligence techniques (25). Within this quality assurance framework, a novel quality-tracking method based on a multi-source predictive model is proposed that tracks the uncertainty of the quality indicator with propagation algorithms and enables transparent self-monitoring of the multi-source predictive methods through uncertainty estimation. Quality control strategies are designed and tested to generate alarms when the quality trajectory exceeds an acceptable region and to formulate recommended process adjustments (26). These quality assurance and control capabilities are finally obtained through the flexible integration of various soft sensors suitable for raw materials, process, and environment in the typical food-processing plants, as well as food safety-production systems. The full-scale process is simulated under different scenario settings, and the proposed architecture successfully mitigates the quality deviation caused by varying disturbances of time, quality, and capacity (27).

4. AI Applications in Food Safety

Human health encompasses the handling, storage, and preparation of food to prevent foodborne sickness and damage. Food safety hazards are classified into five categories: biological, chemical, allergenic, physical, and radiological. Particularly concerning are biological hazards, which cover fungi, microorganisms, viruses, and parasites. The main sources of contamination are cross-contamination, contaminated water, and hazardous raw materials (28). In order to prevent temperature abuse during food storage and transportation, it is imperative to maintain a cold chain. AI methods aid in detecting possible risks or hazards, rating risk levels, determining exposure, and assisting in decision-making in order to overcome these obstacles (2).

Among the instruments used to identify hazards to human health are smartphones, electric tongues, electric noses, and computer vision. Algorithms powered by artificial intelligence, including deep learning and support vector machines, analyze data from gas sensors, spectral sensors, cameras, and other detection devices (29). Information from these sensors is used to monitor food safety. Similar detection requirements based on sensing technologies, measurement techniques, and chemical or microbiological indicators are shared by consumer-oriented applications, such as food safety monitoring and quality identification. Thus, food safety monitoring is addressed by AI and computer vision techniques (30). Quick differentiation of detection results increases the value of consumer-oriented products and reduces participation in illegal activity. To accomplish rapid monitoring, instruments such as computer vision, spectral measurements, and gas analysis are used (31).

4.1. Hazard Identification and Risk Assessment

Consumption of contaminated foods may result in food-borne diseases with immediate or long-term effects. Risk assessment covers estimating the probability of disability to a healthy life, thereby determining the most appropriate actions to take. Jansen and Van der Wolf introduced the concept of chemical hazard identification and exposure assessment in 2010 (32). The classical approach of classifying hazard types is still very helpful in a wide range of risk assessment applications. Risk scoring is another widely employed approach that helps to prioritize risk management options (2).

An exposure assessment is needed to estimate the importance of hazardous substances. It consists of qualitative and quantitative assessments of food amounts consumed, and therefore of exposure on toxicological and economic grounds. Exposure assessment plays an important role in the implementation of a rising trend toward transparency and right-to-know of hazardous substance presence (33).

Intelligent decision support tools utilizing artificial intelligence are particularly well-suited for the aforementioned processes within the food supply chain. The well-known Hazard Analysis and Critical Control Points (HACCP) methodology includes a systematic hazard analysis component during the risk assessment phase that rates chemical hazards by giving scores to different categories of hazards (34). The HACCP score algorithm then uses these assigned scores to produce a thorough chemical hazard score. This score is then used to create a decision support tool based on An and Lichtenberg's theoretical framework (35). The compound hazard score that results creates a cutoff point that determines the need for conducting a comprehensive quantitative exposure assessment. The results of a quantitative exposure assessment can also be incorporated into An and Lichtenberg's model, providing more information about risk management and the assessment of risk-mitigation tactics (36).

4.2. Rapid Detection of Contaminants and Adulterants

Abundant food frauds afflict the food supply chain, posing serious health hazards, leading to substantial financial losses, and social unrest. The food supply's processing, production, distribution, and retail phases are all affected by fraudulent activities. According to (37), common food frauds include the substitution of high-value ingredients for low-value ones, the addition of hazardous substances, and the undeclared addition of other substances. Food fraud involving the adulteration of milk, honey, vinegar, and olive oil is frequently reported. In susceptible groups, milk adulteration can result in malnourishment and digestive issues. Effective monitoring and detection of food fraud is therefore desperately needed (38).

To determine the quality of food, several technologies have been developed. Food quality monitoring has made extensive use of technologies such as electronic tongue, electronic nose, and near-infrared spectroscopy. These technologies identify, categorize, and forecast food adulteration. They are able to correlate processing parameters with food's chemistry and sensory qualities. Food fraud can be tracked using this technology (39).

Self-sustaining food safety systems that can detect food adulteration without targeting have become essential due to the vast and varied food fraud operations and the ever-increasing complexity and sophistication involved. At the point of consumption in food supply chains, such a system is especially necessary (40). Reducing financial losses related to food fraud assessments and guaranteeing the successful detection of fraudulent activities in the food supply chain depend on the timely and reliable identification of food adulterants while avoiding time-consuming sample preparation (41).

4.3. Predictive Microbiology and Shelf-Life Modeling

In particular, predicting shelf-life based on raw material specifications and intended processing parameters is one of the many applications of predictive microbiology, which is concerned with the mathematical description of bacterial growth as a function of environmental factors (42).

5. AI in Food Processing and Manufacturing

Food manufacturing and processing have been deeply changed by artificial intelligence, which has improved efficiency, quality, and safety. By integrating intelligent systems into traditional industries, artificial intelligence approaches address issues by standardizing production procedures, reducing expenses and energy consumption, and improving the management of food waste (43). Applications in artificial food, energy efficiency, supply chain management, sales forecasting, assisted cooking, and customized nutrition are examples of recent developments. New synthetic foods, like plant-based meats and egg-free products, are made possible by technologies like biotechnology and machine learning. Marketing, Packaging, warehousing, distribution, and customer service are all becoming more automated (44). The accomplishment of Internet of Things (IoT) technology significantly enhances food safety by enabling the tracking and tracing of output during various stages of production and transformation. As ongoing research advances, it is anticipated that the proliferation of artificial intelligence (AI) applications will continue to rise, thereby catalyzing further transformations within the food industry (2). AI promoted food processing and manufacturing by enhancing efficiency, quality, and safety. It addresses the complexity and nonlinearity of processes, reduces food loss and waste, and enables value-added processing and resource utilization. In primary food processing, AI applications include using robotics and machine learning to reduce virus transmission in meat processing, predicting dust explosions in grain processing, and assessing meat quality and authenticity (45). AI also aids in fruit classification and defect detection. Overall, AI supports the movement toward intelligent and sustainable food manufacturing (46).

5.1. Optimization of Formulation and Process Parameters

Optimization of food formulations and process conditions is critical to ensure food quality, promote food safety, improve operational efficiency, and reduce environmental impact. Conventional approaches rely on a priori knowledge of the food products and producing the product according to a predetermined recipe. However, limited knowledge of how formulation and process conditions influence product quality, combined with the high dimensionality and non-linearity in product formulations, makes this optimization problem exceptionally challenging (47).

Artificial intelligence (AI) techniques have spurred new approaches and enabled greater flexibility. Food product formulations can be altered to target multiple objective functions and constrained by defined specifications. AI techniques, such as empirical modeling, reinforcement learning, evolutionary algorithms, and deep learning, help to explore combinations of raw ingredients, process parameters, and product quality attributes (48). Various approaches have emerged to tackle batch processes and high-dimensional data. These modeling approaches can help food scientists to understand the product and process, test formulations virtually, and lower the costs needed to produce physical prototypes (2).

5.2. Automation and Robotics in Production Lines

Automation in Food production has emerged as a highly competitive industry. In the modern food industry, food safety and quality assurance have turned into crucial components of food processing. In accordance with the "from farm to fork" principle advocated by the Food and Agriculture Organization of the United Nations (FAO), it is essential to implement quality assurance measures consistently across the entire food supply chain (3).

Food production automation is limited to the use of control systems for operating equipment in manufacturing facilities, boilers, machinery, processes in factories, boilers, and heat-treating ovens, switching on telephone networks, flight operations, and other applications with minimal or reduced human intervention (49). Within the food processing industry, diverse technologies, such as vision, robotics, and artificial intelligence, are being used to improve food safety and quality. Robotics and automation are the principal technologies currently employed. Automated continuous food production lines are widely used to produce large quantities of identical products in a very short span of time. Such production lines ensure consistent quality, minimize human interference, and comply with food safety regulations (50).

Automation is also used to control environmental factors such as temperature, humidity, gaseous composition of air, gas concentration, and the quality of water because these exterior factors affect food quality. Modeling the quality of fresh food has now become a hot area of research. It is of utmost significance to estimate, anticipate, track, and control the quality changes of food products throughout the supply chain, including during postharvest and storage periods (2,51).

5.3. Energy and Waste Reduction through Intelligent Control

AI enables energy and waste reduction in food manufacturing toward developing energy models, analyzing waste production, and implementing demand-response strategies. Reducing the energy wasted in food manufacturing and the food waste produced is critical to succeed in sustainable food production (52). Model-based or data-driven approaches can describe the relationship between food processing operations and energy consumption. Based on data analytics on waste production, the constituent or nature of food waste can be inferred. Machine-learning models help to generate optimum recipes or operating conditions that satisfy food quality constraints while reducing food waste (53).

Energy and waste production can be reduced by estimating the power consumption of food processing equipment, analyzing the waste production during food processing, and planning food processing recipes or conditions either to minimize power consumption or to minimize the food waste, respectively (2).

6. Data Management, Ethics, and Regulation

Artificial intelligence (AI) has deeply influenced the food industry, controlling, enhancing food production, quality, and safety. Knowledge-based expert systems capable of simulating expert decision-making are employed to assess food quality, detect safety issues, and optimize processes (54). AI applications deployed in the food industry typically combine machine learning with natural language modelling to continually improve performance. A typical knowledge-based expert system encompasses two core components, a knowledge base and a reasoning engine, which store facts and production rules to generate context-specific solutions. Such systems find widespread application in food safety, quality-testing, and risk-assessment scenarios (55).

6.1. Data Governance and Privacy

Data governance encompasses the management of the availability, usability, integrity, and security of data employed in an enterprise. An effective data governance strategy is essential for a successful AI system, particularly in establishing and securing data provenance, access control, data quality standards, and framework compliance (2). Data provenance denotes the process of data collection, source identification, utilization, and alterations made during storage or processing. It establishes ownership, allows monitoring of updates, and exhibits liability in data usage. Access control dictates the level of user access to confidentiality-protected data and the ability to manage and modify datasets. Data quality standards ascertain modulation accuracy, consistency, substance, and timeliness. Compliance frameworks validate that AI implementation, comprising data sourcing, model training, and deployment, adheres to rules, ethics, and confidentiality-maintaining principles (56).

6.2. Model Transparency, Validation, and Interpretability

A research investigation concentrating on food safety employs machine learning algorithms alongside interpretability methodologies, including SHAP, LRP, and LIME, to forecast indicators pertinent to powdered blackcurrant food items. Gaining insight into the model's internal mechanisms bears considerable consequences for the formulation of resilient and transparent monitoring frameworks. Confidence in datasets, particularly those sourced externally, is often diminished; thus, it is essential to assess the foundational rationales via post hoc interpretability methods to confirm that the model remains consistent with established expert knowledge (57).

6.3. Regulatory Compliance and Standards

Regulatory compliance and standards are major for ensuring food safety and quality, as well as for preventing food fraud. Artificial Intelligence (AI) has recently led to the development of innovative approaches for sensory analysis, such as electronic tongues, electronic noses, and computer vision. Compared with traditional methods, these technologies allow for objective, non-destructive analysis with minimal sample pre-treatment, require only one operator, and permit the permanent storage of data (2). Food industries is changing as a result of the widespread use of AI-assisted techniques by improving safety, traceability, quality control, and resource efficiency while cutting costs and waste through intelligent agriculture, automation, IoT systems, and associated solutions. Future food regulatory affairs and standards will be shaped by the new AI applications that keep emerging in supply-chain management, personalized nutrition, and synthetic food production as research advances (55).

7. Case Studies and Implementation Frameworks

AI-based solutions have a great deal of promise to enhance food safety and quality in a variety of intricate agri-food systems. Progress toward this goal is demonstrated by three representative case studies that combine data from multiple sources of sensors with various AI models and techniques. Online-grade prediction and coordinated multi-sensor checks are used to ensure the quality of fresh produce (58). Anomaly detection is the main goal of safety surveillance in dairy processing in order to spot deviations and lower safety risk. Using different modeling techniques, a framework for implementing AI solutions in food systems is explained, including governance and lifecycle management (59). By describing data options, component configurations, modeling techniques, and anticipated results, these resources expand on the general conversation about artificial intelligence in food science. It is anticipated that the insights will spur additional advancements in the agri-food industry (60).

The first case study demonstrates how artificial intelligence can be used to guarantee the quality of fresh produce and emphasizes how it could be applied to a range of other food products. The input data related to fruit farm operations includes video footage from on-site cameras and weather data from the Internet of Things (IoT), including local weather charts and temperature and moisture readings from multisensory industrial IoT devices (13). Pre-trained image-object detection models are tailored to each site to enable online-grade predictions from real-time batch image samples at packing facilities. Successful transfer of models has been achieved for strawberries, peaches, and tomatoes, and an AI-enhanced open-source industrial configuration for local computation is freely available (2).

The second case study presents AI-supported safety surveillance in a dairy-processing plant, using focused anomaly-detection to monitor raw milk quality and equipment faults. Data on raw volume, homogenizing pressure, pasteurization temperature, and souring time from manufacturing and lab systems are integrated into a monitoring database (61). Anomaly-detection algorithms identify process deviations, trigger alerts for production monitors, and enable broader plant-wide monitoring; automatic corrective actions are specified to address malfunctions (62).

The final case study outlines a framework for the structured, scalable deployment of AI within food systems, considering the interconnected transformation across agriculture, processing, marketing, and consumption. The framework supports food safety, sustainability, and nutritional security through technology-driven development incorporating multiple software, materials, and parameter strategies from diverse sectors with both domestic and international inputs. An AI deployment framework comprises governance, lifecycle management, stakeholder mapping, and scalability (63).

7.1. Case Study: Quality Assurance in Fresh Produce

Quality deterioration in fresh foods arises from biological, chemical, and physical processes during harvest, storage, and transport. Scale-appropriate intelligent systems monitor conditions and perform on-site analyses, reducing waste, limiting economic losses and safety concerns, and guiding consumers toward higher-quality products. The ability to choose high-quality items mitigates post-purchase deterioration, enhances visual appeal, and sustains consumer perception and value (64).

Temperature, humidity, ripening gases, and vibration are monitored by onboard equipment in intelligent systems designed for individual fruits, vegetables, or flower bundles. Deterioration indicators include shrinkage, greening, browning, and odor concentration. Non-destructive test methods—such as optical, electrical, electromagnetic, and ultrasonic techniques—assess deterioration, while a hierarchical state indicator scale (keeping fresh, mild deterioration, moderate deterioration, severe deterioration, and spoiled) evaluates the product's status (41). Key traceability attributes include harvest date, producing organization, location, certifications, and transport records (65).

7.2. Case Study: Safety Surveillances in Dairy Processing

Food safety is paramount in dairy processing due to the sensitivity of milk and related products to contamination, the severe consequences of spoilage, and the substantial economic impact of contaminated goods (66). Monitoring systems such as HACCP and various GMP frameworks have been implemented to safeguard products. Data from these systems is used to uncover and analyze hidden relationships among variables to improve safety management (67).

Although dairy plants employ monitoring systems including HACCP, GMP, and safety- and quality-identification mechanisms, raw data often fail to provide actionable guidance for timely adjustments. When products deviate from a predefined state, alarms are triggered, but the granularity of minute-level data may not yield actionable insights. Developing intelligent programs capable of performing subjective or corrective actions directly from dairy-safety information is therefore crucial (68).

7.3. Framework for AI Deployment in Food Systems

AI possesses transformative potential for enhancing food quality and safety through farm-to-table technologies. The deployment of AI-driven technologies generates voluminous data that influences local, global, and consumer decisions (69). Defects arising from contact with raw materials or improper processing can lead to rejection at later processing stages or by consumers, resulting in substantial losses for processors and retailers (70). While AI-enabled quality management can be applied to raw and semi-finished products, ready-to-eat meals, dietary supplements, and beverages can benefit from fresh and shelf-life monitoring, sensory analysis, product quality assessment, near-expiry detection, and related capabilities to enhance safety and quality assurance for fast-moving consumer goods (30). The widespread adoption of such technologies is expected to generate numerous new applications and business opportunities. Safety surveillance is therefore essential to prevent deviations and potential safety issues (71). High-cost, capital-intensive tools such as online contaminant detectors pose challenges for safety monitoring due to expensive procurement and limited ROI (72). While AI methods will not completely resolve safety concerns, they can assist stakeholders in preventing recurring out-of-control specifications and minimizing recalls, underscoring the importance of this initiative (2).

Data governance establishes principles, restrictions, and guidelines governing data access across data-sharing domains. It involves processes to define, develop, coordinate, and oversee policies, standards, and practices in compliance with legal, regulatory, and internal guidelines. Data provenance enables scrutiny of critical datasets and demonstrates compliance with regulatory and quality-assurance controls (73). Secure and controlled retention of dataset ownership history and usage is necessary for data exploration, data-preparation tracking, model-building, model-revision, and protection of data-based intellectual property. Data access control governs access to data resources, including input data collections, model configuration parameters, and model outputs. It entails creating a tiered hierarchy, organizing repository information, managing logins, defining roles, IP address geofencing, and data-sharing procedures (74). Data quality standards define policies for retention datasets, training datasets, delivered datasets, and partitions. Data protection requires an audit trail documenting who modified specific parameters and when, with pathways to revert to the most recently operational model (75).

8. Challenges, Limitations, and Future Directions

AI is expanding rapidly within the food sector and has the potential to influence various aspects—including quality, flavors, and nutritional values; human health and hygiene's; productivity (energy efficiency and waste reduction); cost reduction; and the rejection of counterfeit products (2).

Over the past decade, advances in AI and related technologies, such as large-scale data analytics, IoT, and robotics, have yielded substantial benefits across manufacturing and agriculture in both developed and developing regions (76). The integration of AI into the food industry—from procurement to processing to consumption—has enabled productivity gains and improved food quality, health, and convenience (77). AI can address critical challenges toward extracting real-time insights from data, combining historical production and condition data with current meteorological information (78).

9. Conclusion

Ensuring food safety and human health, the agro-food sector is vital for public health and economic resilience. The pandemic has underscored the importance of early-stage safety detection through multiple delivery channels. AI is employed across all stages of food processing, enabling automated and continuous monitoring, assessment, forecasting, and routing. This paper synthesizes the applications of AI in agro-food safety and quality from recent literature, outlining state-of-the-art AI methods and pertinent data types. The applications are categorized into five core goals, with detailed discussions on monitoring and assessment; safety hazards and contaminant countermeasures, and food processing and manufacturing. The framework provides a concise visualization of AI capabilities, data types, methods, and application areas.

Governments, companies, and consumers are increasingly prepared to adopt AI in food systems, driven by compelling economic and sustainability incentives. However, continued AI research, investment, and infrastructure development, as well as enhanced supply chain coordination, are required before new applications can be realized. Concerns remain regarding the availability, transparency, and security of proprietary data. Given the diversity of AI models, methods, goals, and applications—many of which remain experimental—there is a substantial potential for further advancement.

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