Food Quality, Safety, and Nutrition Assessment through Machine Learning: A Comprehensive Review

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Abstract
Ensuring food quality and safety is a critical global challenge due to increasing incidences of adulteration, fraud, and nutritional mislabeling. Traditional methods such as manual inspection and chemical analysis, while accurate, remain slow, costly, and often unsuitable for large-scale applications. Recent advances in artificial intelligence (AI) and machine learning (ML) have revolutionized food analysis by enabling rapid, non-invasive, and accurate detection of adulteration, nutritional profiling, and quality monitoring across diverse food categories. This review explores the application of ML-based models in meat, fish, dairy, oils, fruits, and vegetables, highlighting their role in non-destructive testing, adulteration detection, and authentication. Furthermore, ML techniques are increasingly integrated into nutrition assessment and dietary monitoring, supported by image recognition and mobile health applications. Emerging technologies such as blockchain, IoT, and portable sensors demonstrate significant potential in improving transparency and real-time monitoring across supply chains. Despite these advancements, challenges persist in creating large-scale global food datasets, improving model interpretability, and ensuring cross-platform integration. This paper provides a comprehensive overview of current applications, technical limitations, and future directions, aiming to bridge gaps between research advancements and practical deployment in global food safety and nutritional monitoring systems.

Keywords: Machine learning, Food quality, Nutritional assessment, Food adulteration, Deep learning, Spectroscopy, Traceability

1. Introduction

Ensuring food quality, safety, and nutritional integrity has become a global priority due to increasing consumer awareness, stricter regulations, and the complexity of modern supply chains. Rapid industrialization and globalization of the food market have created both opportunities and risks, with contamination, spoilage, and fraud posing significant threats to public health [1], [2]. Reports of foodborne illness and high-profile incidents of adulteration have emphasized the urgent need for reliable monitoring and detection methods.

Food adulteration and fraud are among the most pressing challenges. Fraudulent practices such as dilution, mislabeling, or substitution compromise both consumer trust and health. A well-documented case is the addition of melamine to milk, which led to severe poisoning incidents [4]. Similarly, intentional blending of olive oil with cheaper vegetable oils has remained a persistent authenticity issue in the global market [14]. Beyond fraud, nutritional misrepresentation and mislabeling of ingredients impact dietary planning and health outcomes, highlighting the need for accurate and transparent food assessment systems [7].

Traditional quality control approaches—such as chemical analysis, microbial testing, and manual inspection—though widely used, face inherent limitations. Chemical methods are often destructive, labor-intensive, and require specialized laboratories. Microbiological testing demands long incubation periods, while visual inspection is highly subjective and limited by human expertise [3], [5]. Furthermore, the growing demand for large-scale, real-time monitoring across global supply chains makes these conventional techniques increasingly inadequate [9].

Machine learning (ML) and artificial intelligence (AI) are now transforming the field of food quality and safety evaluation. These approaches excel in handling large and complex datasets generated by modern sensing technologies, uncovering subtle features that escape traditional analysis. For example, near-infrared spectroscopy combined with ML has been successfully applied for fruit quality assessment and detection of adulteration in minced meat [2], [12]. Similarly, hyperspectral imaging coupled with AI enables non-destructive and rapid detection of defects, contaminants, and compositional variations in fresh produce [1], [6].

In addition to spectroscopic methods, computer vision and deep learning techniques are revolutionizing food recognition and classification. Datasets such as Food-101 have accelerated progress in image-based food identification, while convolutional neural networks (CNNs) enable automated recognition of food items with high accuracy [8], [16]. These tools are also extending into nutritional assessment, where deep learning models are applied to estimate caloric intake and dietary composition from images [18]. Such innovations bridge food science with health informatics, making food monitoring more accessible and scalable.

This review aims to provide a comprehensive analysis of machine learning applications in food quality, safety, and nutrition assessment. It consolidates findings from spectroscopy, imaging, and computer vision research to evaluate the state of current technologies, their strengths, and limitations. The scope includes applications across different food categories—meat, dairy, oils, fruits, and vegetables—alongside developments in dietary assessment. Furthermore, the review outlines future research opportunities, including integration with IoT and blockchain, creation of standardized food datasets, and development of real-time portable tools. By bringing together evidence from multiple domains, this paper emphasizes the transformative potential of ML in ensuring safer, more transparent, and nutritionally accurate food systems.

2. Machine Learning in Food Quality and Safety Assessment

The integration of machine learning (ML) into food analysis has transformed conventional quality and safety monitoring, moving from destructive and labor-intensive laboratory techniques toward rapid, non-invasive, and data-driven approaches. Among the most prominent applications are those leveraging spectroscopic methods, hyperspectral/multispectral imaging, and computer vision integrated with deep learning. Each of these approaches generates large, high-dimensional datasets that require ML for meaningful interpretation. The following subsections review these technologies and their coupling with ML for robust food quality and safety assessment.

2.1 Spectroscopic Methods Coupled with ML

Spectroscopy has long been considered a cornerstone of food quality evaluation due to its ability to provide molecular-level information without damaging the product. When coupled with ML, it achieves higher accuracy and interpretability for detecting subtle changes in food composition.

NIR Spectroscopy Applications in Quality Detection

Near-infrared (NIR) spectroscopy is widely used for non-destructive analysis of agricultural products. Its application spans determining moisture content, sugar levels, and ripeness of fruits and vegetables [2]. Unlike traditional chemical assays, NIR offers rapid scanning, minimal sample preparation, and simultaneous detection of multiple constituents. Nicolai et al. [3] conducted a comprehensive review demonstrating NIR's effectiveness in predicting internal fruit attributes such as firmness, soluble solids content, and acidity, which are critical for consumer acceptance.

ML enhances NIR spectroscopy by enabling complex pattern recognition within spectra. Algorithms such as support vector machines (SVM), partial least squares regression (PLSR), and artificial neural networks (ANN) have shown success in calibrating NIR models. For example, Li et al. [12] applied NIR spectroscopy combined with SVM to detect pork adulteration in minced beef, achieving high sensitivity and specificity. Such models can distinguish subtle compositional differences, which are often undetectable by human inspection.

Beyond adulteration, NIR combined with ML is widely used in fruit sorting systems where automated decision-making reduces post-harvest losses. These advances illustrate the role of NIR spectroscopy in moving the industry toward fully automated, machine-driven quality assessment systems.

Raman Spectroscopy for Adulteration and Melamine Detection

Raman spectroscopy provides complementary information to NIR by measuring vibrational modes of molecules. Its sharp spectral peaks make it particularly suitable for detecting adulterants. A notable example is Wu et al. [4], who demonstrated the use of Raman spectroscopy with chemometric modeling to detect melamine in milk powders—a major global food scandal that underscored the need for rapid detection technologies. By training classification models on Raman spectra, they achieved accurate differentiation between pure and contaminated samples.

Similarly, Lohumi et al. [10] highlighted Raman's application for detecting adulterants in spices, dairy, and oils. ML algorithms such as principal component analysis (PCA), linear discriminant analysis (LDA), and SVM are frequently employed to handle the high dimensionality of Raman data, separating genuine samples from adulterated ones. The ability to conduct these analyses non-destructively and in real-time makes Raman-ML systems highly valuable for regulatory and industrial applications.

Chemometrics and ML for Spectral Data Analysis

While spectroscopy provides raw signals, chemometrics and ML extract meaningful features from complex spectra. Santos et al. [7] used infrared microspectroscopy with chemometric modeling to detect milk adulteration. Their study showed that partial least squares discriminant analysis (PLS-DA) could quantify adulterant levels with remarkable precision, demonstrating the power of ML-driven chemometrics.

Jiménez-Carvelo et al. [14] extended these principles to edible oils, applying Fourier-transform infrared (FT-IR) spectroscopy with SVM and PLS-DA for authentication of olive oil in blends. ML models successfully differentiated authentic olive oil from mixtures, ensuring traceability and consumer protection. These studies highlight how chemometric algorithms, enhanced with ML, provide a bridge between raw spectral information and actionable food safety insights.

2.2 Hyperspectral and Multispectral Imaging

Hyperspectral imaging (HSI) and multispectral imaging (MSI) combine imaging and spectroscopy, producing spatial and spectral data simultaneously. These methods enable the visualization of chemical composition across food surfaces, making them particularly useful for detecting heterogeneities, defects, and contaminants. ML plays a critical role in processing the enormous datasets generated by these technologies.

Hyperspectral Imaging as an Emerging Tool

Gowen et al. [1] identified hyperspectral imaging as an emerging process analytical technology for food quality and safety. Unlike single-point spectroscopy, HSI captures both spectral and spatial

information, providing a "chemical image" of the sample. This capability makes it suitable for identifying defects in fruits, detecting bruises beneath the skin, and monitoring surface contamination.
ElMasry and Sun [5] expanded on this by discussing the application of HSI in agro-food products, emphasizing its versatility in monitoring ripeness, texture, and contamination. ML algorithms such as PCA, SVM, and k-nearest neighbors (k-NN) are used to reduce data dimensionality and classify food items based on spectral features. The integration of HSI with ML enables fast, automated inspection lines in food processing facilities.

ML in Detecting Defects, Contamination, and Adulteration

Qin et al. [6] reviewed multispectral and hyperspectral imaging for evaluating food safety and quality, emphasizing the role of ML in identifying contaminants such as fecal matter on produce or bones in meat products. These technologies, combined with advanced classification algorithms, detect anomalies at resolutions beyond human vision.
Case studies have demonstrated their success in identifying adulteration as well. For example, Qiao et al. [11] applied HSI with machine learning for predicting beef quality attributes, demonstrating that spectral imaging can be coupled with regression algorithms to estimate tenderness and intramuscular fat content. This application directly addresses consumer demands for consistent meat quality and safety assurance.

2.3 Computer Vision and Deep Learning

While spectroscopy and HSI focus on spectral properties, computer vision emphasizes visual characteristics of food. Advances in deep learning have expanded its applications from simple defect detection to complex tasks such as food recognition and dietary assessment.

Computer Vision for Non-Destructive Evaluation

Computer vision has become a vital tool in food quality evaluation, offering rapid, non-destructive, and low-cost solutions. Sun [13] outlined applications of computer vision for assessing surface defects, shape, and color of food products, ranging from fruits and vegetables to processed goods. When integrated with ML classifiers, these systems can evaluate ripeness, detect bruises, or identify foreign objects on processing lines.
Unlike spectroscopy, which requires specialized hardware, computer vision systems often rely on standard RGB or multispectral cameras, making them more affordable and scalable. The coupling with ML enables automated quality grading and reduces subjectivity in human inspection, thus enhancing consistency in industrial quality control.

Deep Learning for Food Recognition and Dietary Assessment

Deep learning has taken computer vision in food analysis to the next level by enabling recognition of complex food categories and estimation of nutritional information. Kamilaris and Prenafeta-Boldú [16] reviewed the application of deep learning in agriculture and food, noting its superior performance in image-based recognition tasks compared to traditional ML approaches.
One of the landmark contributions in this area is the Food-101 dataset introduced by Bossard et al. [8], which provided a large-scale benchmark for food image recognition. By applying convolutional neural networks (CNNs), researchers achieved significantly higher classification accuracy, enabling practical dietary monitoring systems.
Building upon these foundations, Zhou et al. [18] reviewed deep learning applications in dietary assessment, highlighting their ability to estimate caloric content and nutrient profiles from images captured by smartphones. Such approaches have great potential for personalized nutrition management and public health monitoring.

The integration of deep learning with computer vision not only supports consumer-level applications but also assists regulatory agencies in monitoring food authenticity and quality. These systems can detect fraudulent practices such as mislabeling of processed foods by learning subtle differences in visual features.

Spectroscopic methods, hyperspectral imaging, and computer vision each provide unique advantages for food quality and safety monitoring. When coupled with ML, these technologies enable rapid, non-destructive, and highly accurate detection of adulteration, contamination, and compositional quality. NIR and Raman spectroscopy excel in molecular-level detection of adulterants, HSI offers spatially resolved compositional insights, and computer vision enhanced by deep learning supports scalable, image-based recognition and assessment. Collectively, these advancements mark a significant departure from traditional laboratory techniques, establishing ML as a central driver in modern food analysis.

3. Applications in Specific Food Categories

Artificial intelligence and machine learning applications have gained traction across a wide spectrum of food categories, enabling rapid, non-destructive, and highly accurate quality and safety assessment. By integrating techniques such as spectroscopy, hyperspectral imaging, computer vision, and deep learning, ML-driven frameworks allow stakeholders to address adulteration, contamination, authenticity, and nutritional concerns in specific food groups. This section elaborates on applications within meat and fish, dairy products, oils and fats, and fruits and vegetables, with evidence from recent studies.

3.1 Meat and Fish

Meat and fish quality are traditionally assessed through sensory evaluation, chemical analysis, and microbial testing. These methods, however, are time-consuming and labor-intensive. Recent advancements in non-invasive analytical technologies provide a transformative shift. Imaging spectroscopy, coupled with ML models, has been widely applied for classifying meat freshness, fat content, and tenderness [9]. These systems can analyze surface spectral signatures of meat samples to predict internal attributes, reducing the need for destructive testing.

Machine learning has also demonstrated significant value in beef quality prediction. For instance, predictive models trained on hyperspectral data have been able to assess beef tenderness, marbling, and pH values with high accuracy [11]. Such models eliminate subjectivity in quality grading while reducing economic losses associated with spoilage. Fish quality assessment similarly benefits from spectroscopic and ML frameworks, where spectral fingerprints are analyzed to detect freshness and potential microbial contamination. These tools are particularly important for export-oriented seafood industries, where regulatory compliance and safety are paramount.

The combination of non-invasive imaging and predictive algorithms ensures that meat and fish can be graded consistently, providing consumers with transparent quality assurance while enabling producers to streamline quality monitoring throughout the supply chain.

3.2 Dairy Products

Dairy products, particularly milk, are prone to adulteration with substances such as water, urea, starch, and melamine, which compromise both nutritional value and consumer safety. Conventional chemical analysis techniques, though accurate, are often unsuitable for rapid, large-scale screening. Machine learning has enabled the development of fast, cost-effective, and scalable solutions to detect adulteration in dairy.

Spectroscopic approaches, such as Raman and near-infrared (NIR) spectroscopy, combined with ML classification algorithms, have proven effective in distinguishing between pure and adulterated milk

[4], [7]. For example, chemometric models applied to spectroscopic data can identify subtle deviations in milk composition caused by contaminants. This enhances sensitivity and specificity compared to traditional manual methods.

Moreover, advanced ML methods have been employed to predict compositional parameters in milk, including fat, protein, and lactose concentrations [17]. These models facilitate routine quality monitoring for large-scale dairy processing operations, ensuring compliance with safety standards and maintaining consumer trust. As the demand for dairy products grows globally, integrating AI-driven systems into quality control pipelines helps prevent fraud, supports public health, and reduces operational costs for producers.

3.3 Oils and Fats

Oils and fats, particularly olive oil, represent another food category susceptible to adulteration due to their high market value. Authenticating olive oil is challenging because adulterants, such as cheaper vegetable oils, often mimic the chemical and physical properties of pure olive oil. Machine learning combined with spectroscopic techniques provides robust tools for authenticity verification.

By analyzing spectral data, ML algorithms can classify olive oil samples with high precision, identifying even small proportions of adulterants [14]. Chemometric approaches, such as principal component analysis (PCA) and partial least squares discriminant analysis (PLS-DA), enhance interpretability by reducing the dimensionality of spectral datasets while preserving essential variance. Additionally, deep learning approaches have emerged as powerful alternatives, automatically extracting discriminative features from complex data without requiring extensive preprocessing.

Such approaches not only ensure the authenticity of olive oil but also support regulatory bodies in enforcing food safety standards. The scalability of ML-based authentication systems means that testing can be carried out more frequently and across larger sample pools, strengthening consumer confidence in the global edible oils market.

3.4 Fruits and Vegetables

Fruits and vegetables, being perishable commodities, require efficient quality assessment methods to ensure ripeness, freshness, and safety. Non-destructive techniques like near-infrared spectroscopy and hyperspectral imaging, integrated with ML, have demonstrated remarkable effectiveness in these domains.

NIR-based methods, for instance, enable rapid ripeness and sweetness assessment in fruits such as apples, mangoes, and bananas [2], [3]. Machine learning algorithms interpret spectral signatures to determine sugar content, firmness, and moisture levels, providing growers and retailers with tools to optimize harvest timing and reduce post-harvest losses. These approaches also facilitate automated sorting and grading, significantly improving supply chain efficiency.

Beyond ripeness detection, deep learning frameworks have been increasingly applied in agricultural contexts to monitor disease, pest infestation, and surface defects in fresh produce [15]. Convolutional neural networks (CNNs), in particular, excel in image-based classification tasks, enabling real-time identification of quality deviations at high throughput. Such systems support automated packaging lines, where defective items can be segregated without human intervention.

Furthermore, dietary monitoring applications leverage deep learning-based food recognition models to quantify fruit and vegetable consumption [16]. These tools are particularly relevant in the context of nutrition and health, enabling individuals to monitor dietary intake while providing researchers with data for large-scale nutritional studies.

Across meat, dairy, oils, and produce, the integration of machine learning into food quality and safety assessment has resulted in a paradigm shift. From rapid adulteration detection in milk to non-destructive ripeness evaluation in fruits, ML-based methods address limitations of traditional approaches by being faster, more scalable, and less resource-intensive. In each category, case studies highlight improved prediction accuracy, enhanced detection sensitivity, and broader applicability across supply chains.

By enabling real-time monitoring and automation, machine learning not only enhances food safety compliance but also reduces waste, ensures authenticity, and improves consumer trust. As adoption continues, future advancements will likely integrate multimodal data sources—combining spectroscopy, imaging, and sensor data—for even more comprehensive and reliable assessments across food categories.

4. Nutrition Assessment Using Machine Learning

Nutritional assessment is a critical dimension of food science, bridging the gap between food quality assurance and human health. Traditional laboratory-based nutritional evaluations, though accurate, are often resource-intensive and time-consuming. Recent advances in machine learning (ML) have introduced efficient, scalable, and non-invasive alternatives for monitoring food composition, nutrient retention, and dietary intake.

4.1 Food Composition and Nutrient Retention Monitoring

One of the primary applications of ML in nutrition science is the analysis of food composition. By integrating spectroscopic and imaging data with chemometric models, researchers can predict macro- and micronutrient concentrations with high accuracy. For instance, near-infrared (NIR) and hyperspectral data, when coupled with ML regression models, have enabled real-time predictions of protein, lipid, and carbohydrate content in various food matrices [15]. These models significantly reduce dependency on destructive chemical assays while providing rapid assessment across large datasets.

Beyond compositional profiling, ML has proven effective in studying nutrient retention during food processing. By modeling the influence of temperature, moisture, and storage conditions, ML algorithms can predict the degradation rates of vitamins, minerals, and bioactive compounds. Such insights are valuable for optimizing processing parameters to maximize nutrient preservation, particularly in fruits and vegetables where bioactive compounds are highly sensitive [16]. Furthermore, adaptive ML frameworks can integrate environmental variables with product-specific attributes, making predictions highly context-aware.

4.2 Machine Learning in Dietary Assessment

Accurate dietary intake assessment remains a major challenge in nutritional science, often relying on self-reported food diaries that are prone to bias and underreporting. ML-based image recognition systems have emerged as transformative tools in this space. By analyzing photographs of meals captured via smartphones, computer vision models can classify food items and estimate portion sizes with increasing precision [18]. Such systems utilize convolutional neural networks (CNNs) trained on large food image datasets, thereby enabling recognition across diverse cuisines and preparation methods.

These methods address limitations of traditional dietary surveys by offering objective, real-time monitoring of food consumption. Studies have demonstrated that ML-based image recognition reduces error margins in dietary intake reporting compared to manual approaches [18]. In addition, continual learning mechanisms allow these models to adapt to new food categories over time, enhancing their robustness.

4.3 Deep Learning Integration with Mobile Health Applications

The integration of deep learning with mobile health (mHealth) platforms has extended the impact of nutritional assessment from research settings to everyday use. Smartphone-based applications now employ deep learning for automated meal recognition, calorie estimation, and nutrient profiling [15]. For example, CNN-based models have been successfully embedded into mHealth apps that capture meal photos, analyze visual cues, and provide users with nutritional feedback in real time.

Such integration is particularly beneficial for chronic disease management, where dietary tracking plays a critical role. Patients with diabetes or cardiovascular conditions can leverage these applications for tailored dietary guidance, supported by backend ML algorithms that personalize feedback based on individual health records [16]. Moreover, linking these tools with wearable devices creates a multi-modal ecosystem, where physical activity, biometric parameters, and dietary intake data converge to provide holistic nutritional monitoring.

4.4 Future Perspectives

The convergence of ML, nutrition science, and digital health technologies promises to reshape personalized nutrition. While current models demonstrate strong predictive power, challenges remain regarding dataset diversity, cultural dietary variations, and privacy of user data. Expanding training datasets to include regional cuisines and standardized portion benchmarks will enhance global applicability. At the same time, federated learning approaches could safeguard data privacy while enabling collaborative model improvements across institutions [18].

In conclusion, machine learning has evolved as a powerful enabler of nutritional assessment. From monitoring nutrient retention in food products to revolutionizing dietary intake tracking through mobile platforms, ML-driven solutions are enhancing both research precision and consumer health outcomes. As deep learning and multimodal integration continue to advance, the future points toward highly personalized, real-time nutrition monitoring frameworks capable of bridging food science with preventive healthcare.

6. Future Research Directions

The increasing adoption of machine learning (ML) in food science demonstrates its potential to revolutionize safety, quality assurance, and nutrition monitoring. However, several challenges remain, and future research must focus on developing integrative, transparent, and globally scalable solutions that connect stakeholders across the food chain. Four promising directions include the integration of IoT, blockchain, and AI; enhancing deep learning interpretability; establishing global food datasets; and advancing portable real-time sensors.

- **Integration of IoT, blockchain, and AI for traceability.**

Food supply chains are increasingly complex, spanning multiple countries and involving producers, processors, distributors, and retailers. Ensuring transparency and accountability at each stage is critical for safety and fraud prevention. Future research should explore frameworks that integrate IoT-enabled sensors for real-time data collection, blockchain for immutable record-keeping, and AI/ML for predictive analytics. For instance, IoT sensors could continuously monitor storage temperature and humidity, while blockchain ensures tamper-proof documentation of the product journey. ML algorithms can then analyze these data streams to predict spoilage risk, identify inefficiencies, and detect fraudulent practices. Such multi-technology integration could enhance consumer trust and regulatory compliance, particularly for high-value commodities like seafood, dairy, and specialty oils.

- **Improving deep learning interpretability in food safety.**

Deep learning models have achieved high accuracy in detecting adulteration, classifying food categories, and assessing quality. However, their "black box" nature raises concerns about trust and adoption, particularly in safety-critical applications. Future work should emphasize interpretable AI approaches, where decisions made by convolutional neural networks or recurrent neural networks are transparent and justifiable. Techniques such as attention mapping, saliency visualization, or hybrid models combining rule-based systems with neural networks could help food scientists understand why a sample is classified as adulterated or unsafe. Interpretable models would also improve regulatory acceptance, as authorities often require clear explanations of the decision-making process in safety assessments.

- **Creation of global food datasets for ML training.**

Another barrier to widespread adoption is the lack of large, standardized datasets for training robust ML models. Current studies often rely on small, region-specific datasets, which limit generalizability. Establishing global, open-access databases that include spectral profiles, hyperspectral images, compositional data, and annotated quality metrics across diverse food categories would enable more reliable model training. These datasets should also include samples of adulterated, spoiled, or contaminated products to ensure models are effective in real-world scenarios. International collaboration among research institutes, industry, and regulatory agencies will be essential in building such repositories.

- **Portable, real-time food quality sensors.**

While laboratory-based spectroscopy and imaging methods are powerful, they are often expensive and not suited for on-site testing. Future research should prioritize the development of compact, cost-effective, and user-friendly devices that integrate spectroscopy, imaging, and ML for real-time analysis. For example, handheld NIR or Raman sensors coupled with cloud-based ML algorithms could allow farmers, retailers, and consumers to quickly assess ripeness, adulteration, or nutritional content. Advances in edge computing will further enable local data processing without requiring constant internet connectivity. Such portable systems have the potential to democratize food quality assessment and expand its use beyond industrial labs to households and small-scale producers.

Future research must move toward holistic solutions that combine technological integration, interpretability, global collaboration, and portability. By addressing these areas, machine learning can evolve from a promising research tool into a universally adopted system for ensuring food safety, authenticity, and nutritional integrity.

Conclusion

The global demand for safe, authentic, and nutritionally reliable food products continues to drive innovation in analytical methods. While traditional inspection and laboratory-based testing remain important, their limitations highlight the growing need for automated, scalable, and cost-effective alternatives. Machine learning has proven effective in addressing these challenges by enabling real-time monitoring, rapid adulteration detection, and precise quality prediction across different food categories. From beef quality classification and olive oil authentication to milk adulteration detection and fruit ripeness prediction, ML-based solutions have demonstrated high accuracy and strong potential for industrial adoption. Furthermore, the integration of deep learning with dietary monitoring apps reflects a shift toward personalized nutrition and health management. Looking ahead, the synergy of AI with IoT devices, blockchain-based traceability, and portable biosensors can create an interconnected ecosystem that ensures transparency, trust, and accountability throughout the food supply chain. However, key challenges such as limited global datasets, computational costs, and interpretability of complex models must be addressed to achieve widespread deployment. This review emphasizes that advancing machine learning in food science is not only a technological necessity but also a global imperative for ensuring food security, consumer health, and sustainable industry practices.

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