AI-Driven Predictive Modeling for Food Shelf-Life Estimation and Spoilage Detection: Progress, Challenges, and Future Directions

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Abstract

Food spoilage is a persistent challenge that affects food quality, consumer safety, and the sustainability of food systems worldwide. Traditional methods for determining shelf life and detecting spoilage are often time-consuming, labor-intensive, and unable to provide real-time information. In recent years, artificial intelligence (AI) has emerged as a promising solution, offering faster and more accurate approaches to predicting food shelf life and identifying early signs of spoilage. By combining data from sensors, imaging systems, laboratory analyses, and environmental monitoring tools, AI models can recognize complex patterns that conventional methods often miss. This review examines recent advances in AI-driven predictive modeling for food shelf-life estimation and spoilage detection across a wide range of food products, including dairy, meat, seafood, fruits, vegetables, and processed foods. The review focuses on machine learning and deep learning techniques such as artificial neural networks, support vector machines, random forests, and convolutional neural networks, which have shown strong predictive performance in food quality assessment. The review also discusses how AI technologies can support real-time monitoring, improve supply chain management, reduce food waste, and enhance consumer confidence in food safety. Despite these advantages, several challenges continue to limit large-scale implementation, including limited availability of high-quality datasets, concerns regarding model transparency, sensor-related constraints, and regulatory considerations. Emerging developments such as explainable AI, digital twins, edge computing, and multimodal data integration are highlighted as potential pathways for overcoming these barriers. Overall, AI-driven predictive modeling represents a transformative approach to food shelf-life assessment and spoilage detection, with significant potential to improve food safety, quality management, and sustainability in the years ahead.

Keywords: Artificial intelligence; Machine learning; Shelf life; Spoilage; Food quality

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Introduction

Food spoilage remains a leading cause of food waste globally, resulting in substantial economic losses and environmental burdens. According to the United Nations Food and Agriculture Organization (FAO), approximately one-third of all food produced for human consumption is lost or wasted each year. Such losses (Table 1) not only reduce food availability but also contribute significantly to greenhouse gas emissions, resource depletion, and sustainability challenges throughout the food supply chain. More recent global accounting reinforces the scale of this problem: the United Nations Environment Program's Food Waste Index Report 2024 estimated that 1.05 billion tonnes of food were wasted at the household, food-service, and retail levels in 2022 alone, and that food loss and waste together cost the global economy approximately USD 1 trillion annually while contributing 8–10% of global greenhouse gas emissions (2024).

This review adopted a narrative literature review methodology to synthesize and critically evaluate recent evidence regarding AI-driven approaches for food shelf-life prediction and spoilage detection. Relevant studies published between 2023 and 2026 were identified through searches in major scientific databases, including Google Scholar, Scopus, Web of Science, ScienceDirect, and Wiley Online Library. Search terms included "Artificial Intelligence," "Machine Learning," "Deep Learning," "Shelf-Life Prediction," "Food Quality Monitoring," "Smart Packaging," "Internet of Things (IoT)," "Food Spoilage Detection," "CNN," "LSTM," and "Support Vector Machine."

Studies were included if they focused on AI-based approaches for predicting food shelf life, monitoring food quality, detecting spoilage, or integrating smart packaging and sensor technologies. Peer-reviewed review articles, original research papers, and authoritative reports published in English were considered. Studies unrelated to food systems, duplicate

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publications, and papers lacking sufficient methodological details were excluded. Data extracted from the selected studies included publication year, food category, AI technique used, sensor technologies, prediction performance, applications, challenges, and future prospects. The collected information was then categorized into key themes, including traditional versus AI-based prediction methods, machine learning and deep learning techniques, applications across food categories, smart packaging and IoT integration, challenges, and future research directions.

Accurate shelf-life prediction is essential to ensure food safety, maintain product quality, and reduce waste throughout the supply chain. Traditional shelf-life determination methods rely heavily on laboratory testing, microbial analyses, sensory evaluation, and accelerated storage experiments. Although these methods are scientifically reliable, they are often expensive, time-consuming, and difficult to implement continuously across large-scale food systems.

Recent advances in Artificial Intelligence (AI) have transformed the way shelf life is estimated and managed. According to (Rashvand et al., 2025), AI technologies integrate complex datasets from environmental sensors, packaging systems, imaging technologies, and food composition analyses to predict product deterioration more accurately than conventional methods. Machine learning algorithms can identify hidden relationships between storage conditions and quality attributes, providing dynamic predictions that adapt to changing environments.

Table 1. Key global food loss and waste statistics (2024)**.**

Metric	**Value**	**Source**
Total food wasted (2022)	1.05 billion tonnes	UNEP (2024)
Share of consumer-available food wasted	~19%	UNEP (2024)

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Estimated economic cost	~USD 1 trillion/year	UNEP (2024)
Share of global GHG emissions	8–10%	UNEP (2024)
People facing hunger	783 million	UNEP (2024)

Similarly, Liang et al. (2026) reported that deep learning approaches have become increasingly popular for shelf-life prediction because they can process large, multidimensional datasets. These models can continuously learn from new information, making them suitable for real-time monitoring systems and smart food supply chains. The growing availability of sensor technologies, cloud computing, and Internet of Things (IoT) devices has further accelerated the adoption of AI-driven shelf-life management systems.

Traditional versus AI-Based Shelf-Life Prediction Approaches

Traditional shelf-life prediction methods are primarily based on kinetic models, microbial growth equations, Arrhenius models, and statistical regression techniques. These approaches generally require predefined assumptions regarding spoilage mechanisms and often focus on a limited number of quality indicators. While useful, they may struggle to capture the complex interactions among biological, chemical, and environmental factors that influence food deterioration.

Cui et al. (2023) noted that conventional models perform adequately under controlled conditions but often lose accuracy when applied to real-world food supply chains with fluctuating temperatures, humidity, and handling practices. Their review showed that machine learning models outperform traditional approaches on nonlinear, multidimensional datasets.

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AI-based models eliminate many limitations of conventional prediction methods. Instead of relying on fixed mathematical assumptions, machine learning algorithms learn directly from historical data and continuously improve prediction accuracy. Li et al. (2024) emphasized that AI techniques can analyze multiple variables simultaneously, including storage conditions (Table 2), packaging characteristics, microbial activity, and sensor outputs, resulting in more robust shelf-life predictions for fruits and vegetables. Consequently, AI-based systems are increasingly viewed as complementary or superior alternatives to traditional shelf-life assessment methods.

Table 2. Comparison of Conventional and AI-Based Shelf-Life Prediction Systems

Feature	**Conventional Methods**	**AI-Based Methods**
Approach	Laboratory testing and statistical models	Machine learning and deep learning models
Accuracy	Moderate; depends on controlled conditions	High; captures complex data patterns
Monitoring	Periodic and offline	Continuous, real-time monitoring
Time	Time-consuming	Rapid and automated
Scalability	Limited	High
Adaptability	Fixed models	Continuously improves with new data
Limitations	Labor-intensive and costly	Requires quality data and computational resources

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Artificial Intelligence Techniques Used for Shelf-Life Prediction

A variety of AI techniques (Table 3) have been applied to food shelf-life prediction, each offering unique advantages depending on the data and prediction objectives.

Support Vector Machines (SVM)

Support Vector Machines are among the most widely used machine learning algorithms for food quality assessment. SVM models perform particularly well with limited datasets and can effectively classify products as fresh, acceptable, or spoiled. Madhu (2025) reported successful SVM applications in dairy, meat, and packaged food quality monitoring systems.

Artificial Neural Networks (ANN)

Artificial Neural Networks imitate the structure of the human brain and can model highly complex relationships between input variables and shelf-life outcomes. ANN models have demonstrated superior performance compared to traditional regression models in many food applications.

Convolutional Neural Networks (CNN)

CNNs are specifically designed for image analysis and have become valuable tools for evaluating food freshness through visual characteristics such as color changes, texture degradation, and surface defects. Kang et al. (2025) observed extensive use of CNNs in agricultural product freshness assessment, where imaging systems can detect spoilage before it becomes visible to consumers. For example, Kang et al. (2025) reported that a CNN-based visual labeling system achieved approximately 95.3% accuracy in classifying meat freshness, while a CNN-LSTM model applied to hyperspectral images of spinach and Chinese cabbage achieved a classification accuracy exceeding 80% for leafy-vegetable freshness.

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The superior performance of CNNs largely stems from their ability to identify complex visual features associated with food deterioration automatically. During spoilage, biochemical and microbial processes alter surface color, texture, moisture distribution, and structural integrity. Unlike traditional feature-engineering approaches, CNNs learn these discriminative characteristics directly from raw images, enabling more accurate identification of subtle quality changes that may not be visible to the human eye. This capability explains their growing adoption for automated freshness assessment across multiple food categories.

Long Short-Term Memory Networks (LSTM)

LSTM networks are specialized deep learning models that can analyze time-series data. Madhu (2025) demonstrated that LSTM models effectively predict shelf life by processing sequential changes in temperature, humidity, gas concentrations, and quality indicators over time.

Data Fusion and Hybrid Models

Recent studies increasingly combine multiple sensor technologies with machine learning algorithms. Kodogiannis & Alshejari (2025) integrated electronic nose data with multispectral imaging for meat spoilage detection, improving prediction accuracy over single-sensor approaches. Similarly, Cui et al. (2024) developed machine learning models that predict shelf life across multiple marine fish species using integrated quality indicators. Elfattah et al. (2025) further demonstrated the value of hybrid feature-optimization pipelines, combining a VGG19 convolutional network with an Improved Artificial Protozoa Optimizer for feature selection to classify meat as fresh, half-fresh, or spoiled, reporting an accuracy of 98.51%, a sensitivity of 98.54%, and a specificity of 99.24%.

Performance Evaluation of AI Models

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Researchers commonly evaluate the effectiveness of AI-based shelf-life prediction systems using metrics such as accuracy, precision, recall, F1-score, root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). These indicators provide valuable information regarding the reliability and practical applicability of predictive models across different food categories.

Although CNN and LSTM models generally achieve higher predictive performance, they often require large datasets and substantial computational resources. In contrast, SVM models remain attractive for industrial applications involving limited datasets because of their lower computational requirements and easier implementation. Therefore, the choice of AI model should depend not only on predictive accuracy but also on practical considerations such as cost, interpretability, and data availability.

Recent studies show that deep learning and machine learning approaches often outperform conventional statistical models when handling complex, multidimensional datasets. AI and deep learning systems used for food freshness classification have reported accuracies ranging from 95% to 100%, while predictive models for quality indicators have achieved R^2 values between 0.86 and 0.99.

Reported figures from individual studies illustrate this range concretely. For fruits and vegetables, Li et al. (2024) summarized several regression-based shelf-life models, including a partial least squares regression (PLSR) model for strawberry appearance scoring that achieved an R^2 of 0.97 and an RMSE of 0.17, a random forest model for fresh-pizza shelf-life prediction that reached an R^2 of 0.99, and a k-nearest-neighbour model for rice shelf life that achieved a comparatively modest R^2 of 0.72, illustrating how performance varies considerably with product type, sensor combination, and algorithm choice. For meat products, reported CNN-based freshness classification accuracies have ranged from around 86% for hyperspectral

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beef classification to 93.70% for gas-chromatography-based species and freshness classification, and above 98% for colorimetric- and optimized-feature-based CNN systems (Elfattah et al., 2025). For dates, Haque et al. (2025) reported that a lightweight TinyML model deployed on a low-power multichannel gas-sensor device achieved 91.9% classification accuracy and an area under the curve (AUC) of 0.98 for real-time shelf-life estimation.

Convolutional Neural Networks (CNNs) and hybrid CNN-LSTM architectures have shown particularly strong performance because they can capture both spatial and temporal changes associated with food deterioration. Researchers increasingly combine these models with hyperspectral imaging, electronic noses, and IoT-enabled sensing systems to improve prediction accuracy and real-time monitoring (Melikoğlu, 2026; Rashvand et al., 2025).

Beyond classification accuracy, recent studies have emphasized model robustness and external validation. Models trained on laboratory-generated datasets often perform worse in industrial environments because of variations in raw materials, storage conditions, and processing practices. Consequently, researchers increasingly advocate for cross-validation, transfer learning, and external dataset testing to improve model generalizability and real-world applicability. Furthermore, uncertainty quantification techniques are emerging as valuable tools for estimating confidence levels associated with AI predictions, thereby supporting risk-based decision-making in food quality management.

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Table 3. Comparison of AI techniques applied to food shelf-life prediction and spoilage detection.

AI Technique	Key Strength	Typical Data Need	Reported Performance	Representative Study
SVM	Effective with small/limited datasets	Low	Classification-based (fresh/acceptable/spoiled)	(Madhu, 2025)
ANN	Models complex nonlinear relationships	Moderate	R^2 0.86–0.99	(Rashvand et al., 2025)
CNN	Image-based freshness/defect detection	High (large image datasets)	86.1%–100% accuracy	(Kang et al., 2025); (Elfattah et al., 2025)
LSTM	Sequential/time-series prediction	High	Used for dynamic multi-day forecasting	(Madhu, 2025)
Hybrid/Fusion (sensor + ML)	Combines multiple data streams for robustness	High	Up to 98.5% accuracy	Kodogiannis & Alshejari (2025); (Elfattah et al., 2025)

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Although AI models generally demonstrate superior predictive performance, direct comparisons between studies remain difficult because of differences in datasets, food products, validation methods, and evaluation metrics. Therefore, future research should focus on establishing standardized benchmarking frameworks to facilitate objective model assessment.

While reported predictive performances are generally encouraging, comparisons across studies should be interpreted cautiously. Differences in food matrices, storage conditions, sensing technologies, dataset sizes, and validation strategies substantially influence reported accuracy. For example, CNN-based models frequently outperform conventional machine learning algorithms when image or hyperspectral data are available because they automatically extract hierarchical spatial features. In contrast, algorithms such as support vector machines often perform competitively with smaller datasets and structured physicochemical measurements while requiring considerably fewer computational resources. Consequently, no single AI algorithm is universally superior. Instead, model selection should be guided by the specific food product, available sensing technologies, computational constraints, and the intended industrial application.

Applications Across Different Food Categories

Meat and Poultry Products

Meat products are highly susceptible to microbial spoilage and quality deterioration. Machine learning systems integrated with electronic noses, hyperspectral imaging, and gas sensors have shown remarkable success in detecting spoilage compounds before visible signs appear. Kodogiannis & Alshejari (2025) demonstrated that combining multispectral imaging with machine learning significantly improves meat freshness assessment and shelf-life prediction.

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Recent comparative studies illustrate the range of performance achievable with different sensing and modeling combinations. Elfattah et al. (2025) reviewed several approaches, noting that a colorimetric sensor array combined with deep learning reached 98% accuracy in detecting trimethylamine vapor associated with spoilage, while a hyperspectral VGG16–SVM hybrid model achieved 98.1% accuracy in classifying beef adulterated with soybean protein, and near-infrared hyperspectral imaging of beef as fresh, abused, or frozen exceeded 90% accuracy, though it struggled to separate the three categories. Their own optimized VGG19-based feature-selection model achieved 98.51% classification accuracy across fresh, half-fresh, and spoiled meat categories.

Dairy Products

The dairy industry has increasingly adopted AI technologies (Table 4) for quality monitoring and shelf-life management. Golzarijalal et al. (2024) reported that machine learning models can accurately predict spoilage in milk and dairy products by analyzing physicochemical properties, microbial counts, and storage conditions. Sunithamani et al. (2024) further showed that AI-assisted monitoring systems enable continuous quality assessment throughout distribution and retail stages.

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Table 4. Representative AI/sensor approaches and reported performance by food category.

Food Category	AI/Sensor Approach	Reported Performance	Reference
Meat and Poultry	VGG19 + IAPO feature selection	98.51% accuracy	(Elfattah et al., 2025)
Meat and Poultry	Hyperspectral CNN (beef)	86.1%–88.9% accuracy	(Elfattah et al., 2025)
Dairy	ML on physicochemical/microbial data	Qualitative improvement reported	(Golzarijalal et al., 2024)
Fruits and Vegetables	PLSR (strawberry appearance)	$R^2 = 0.97$	(Li et al., 2024)
Fruits and Vegetables	Random Forest (fresh pizza)	$R^2 = 0.99$	(Li et al., 2024)
Dates	TinyML + multichannel gas sensor	91.9% accuracy, AUC 0.98	(Haque et al., 2025)
Seafood	Multi-objective ML (5 fish species)	Model comparison, no single figure reported	(Cui et al., 2024)
Seafood	Portable e-nose + ML classifier	Field-deployable, qualitative	(Setyagraha et al., 2025)

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Fruits and Vegetables

Fresh produce presents unique challenges because of rapid physiological and biochemical changes after harvest. Li et al. (2024) highlighted the growing role of machine learning in predicting freshness, controlling storage conditions, and extending shelf life in fruits and vegetables. As noted above, reported performance for fruit and vegetable quality prediction spans a wide range — from an R^2 of 0.97 for strawberry appearance scoring using PLSR to an R^2 of 0.99 for random-forest-based shelf-life prediction of fresh pizza, and 0.85–0.86 for titratable acidity and pH prediction using electronic-nose data (Li et al., 2024) — underscoring that model choice and sensor type must be matched to the specific quality attribute being predicted. Advanced imaging systems and sensor technologies allow real-time monitoring of ripening and spoilage processes. The effectiveness of AI-based prediction in fresh produce is closely linked to postharvest physiological changes. Respiration, ethylene production, enzymatic browning, moisture loss, chlorophyll degradation, and microbial colonization progressively modify spectral signatures, volatile organic compound profiles, and visual appearance. AI algorithms detect these multidimensional changes simultaneously, enabling earlier and more reliable prediction of quality deterioration than conventional single-parameter assessment methods. Haque et al. (2025) developed a machine learning-based shelf-life estimator for dates using multichannel gas sensors. Their study showed AI's effectiveness in detecting volatile compounds associated with spoilage, enabling accurate and cost-effective shelf-life prediction.

Seafood and Aquatic Products

Seafood is among the most perishable food categories, and its freshness is conventionally assessed through indicators such as total viable count, total volatile basic nitrogen, and sensory evaluation of color, eye clarity, and gill appearance. AI-based systems increasingly automate

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this assessment. Cui et al. (2024) developed multi-objective machine learning models, including backpropagation neural networks, genetic-algorithm-optimized backpropagation networks, radial basis function networks, and extreme learning machines, to predict shelf life across five marine fish species under varying storage temperatures. Setyagraha et al. (2025) designed a portable, real-time electronic-nose system paired with machine learning classifiers for seafood freshness evaluation, supporting on-site, non-destructive assessment outside laboratory settings. Complementary image-based approaches have also been reported: Rodrigues et al. (2023) applied vision transformer architectures to classify seabream freshness from images, reflecting a broader shift toward transformer-based models alongside conventional CNNs for aquatic product quality assessment.

Smart Packaging and Internet of Things (IoT)

Integrating AI with smart packaging and IoT technologies represents a major advancement in food preservation and shelf-life management. Smart packaging systems incorporate sensors that monitor environmental conditions such as temperature, humidity, gas composition, and microbial activity throughout storage and transportation.

Djafar et al. (2026) noted a rapid increase in research on Smart Packaging 4.0, driven by the convergence of AI, IoT, blockchain, and advanced sensing technologies. These systems facilitate real-time data collection and automated decision-making across food supply chains.

The Nanomaterials review (2026) described how IoT-enabled packaging can wirelessly transmit sensor data to cloud-based platforms, where AI algorithms analyze patterns and estimate remaining shelf life. Such systems enable proactive interventions before spoilage occurs. Beyond spoilage prediction, smart packaging systems are increasingly being integrated with complementary Industry 4.0 technologies such as blockchain, cloud computing, and advanced analytics. Combining AI and blockchain can improve traceability by creating

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transparent, tamper-resistant records of storage conditions, transportation history, and product quality throughout the supply chain. Such integrated systems can support regulatory compliance, strengthen consumer confidence, and facilitate more efficient food distribution networks. Furthermore, the convergence of AI, IoT, and smart packaging technologies is expected to play a key role in reducing food waste and improving sustainability across modern food systems (Gbashi & Njobeh, 2024).

Huang et al. (2026) further emphasized the importance of AI throughout the packaging life cycle, from material design and manufacturing to distribution, monitoring, and waste management. These innovations support both food safety and sustainability objectives.

Challenges and Limitations

Despite significant progress, several challenges continue to limit the widespread adoption of AI-based shelf-life prediction systems. One major obstacle is data availability and quality. Floor et al. (2025) noted that many food industries and regulatory agencies struggle to collect sufficiently large, standardized, high-quality datasets needed for effective AI model development.

Data heterogeneity also remains problematic. Food products differ significantly in composition, processing methods, packaging systems, and storage environments, making model generalization difficult. Dimitrakopoulou & Garre (2025) emphasized that AI performance depends fundamentally on training data quality and that poor datasets can lead to unreliable predictions.

Another challenge is limited explainability. Many deep learning models operate as "black boxes," making it difficult for food manufacturers and regulators to understand how they generate predictions. The Food Safety (2025) review highlighted the growing demand for

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Explainable Artificial Intelligence (XAI), transparent algorithms, and publicly accessible reference databases to increase trust and regulatory acceptance.

Economic considerations, implementation costs, cybersecurity concerns, and limited technical expertise further restrict adoption, particularly among small and medium-sized food enterprises.

Another important limitation is model robustness under real-world operating conditions. AI models trained on controlled laboratory datasets may see substantial drops in predictive accuracy when exposed to seasonal variability, supplier differences, packaging changes, or unexpected environmental fluctuations. Dataset imbalance, overfitting, concept drift, and limited external validation further reduce confidence in long-term deployment. Addressing these issues will require continuous model updating, standardized benchmarking datasets, and extensive validation across geographically diverse production systems.

Beyond technical considerations, successful industrial implementation requires seamless integration with existing manufacturing and quality management systems. Many food companies still rely on conventional hazard analysis, laboratory testing, and regulatory compliance protocols not designed for AI-assisted decision-making. The costs associated with sensor installation, cloud infrastructure, workforce training, and continuous model updating remain significant barriers, particularly for small and medium-sized enterprises. Demonstrating clear economic benefits through reduced waste, improved inventory management, and enhanced product consistency will therefore be essential for widespread commercial adoption.

Research Gaps

Despite substantial progress in AI-driven shelf-life prediction, several important research gaps remain. Many currently available studies rely on datasets generated under controlled laboratory

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conditions, which may not adequately represent the dynamic and variable environments encountered in real-world food supply chains. As a result, model performance often decreases when systems are deployed at industrial scale.

Another major limitation is the lack of standardized datasets and benchmarking protocols. Variations in sensor technologies, food matrices, storage conditions, and evaluation criteria make it difficult to compare results across studies and establish universally accepted performance standards. In addition, many AI models remain black-box systems, limiting interpretability and reducing stakeholder confidence in model outputs.

Another underexplored area is integrating omics technologies, including metabolomics, proteomics, and microbiome profiling, with AI-based prediction systems. Such multidimensional datasets may provide deeper insights into spoilage mechanisms and improve the biological interpretability of predictive models. However, limited availability of integrated datasets currently restricts widespread implementation.

Research efforts have also been concentrated primarily on high-value commodities, while staple foods and products commonly consumed in developing countries remain relatively underrepresented. Addressing these challenges will require interdisciplinary collaboration, improved data-sharing frameworks, and transparent AI systems that support regulatory and industrial decision-making.

Another emerging research priority is developing foundation AI models that can transfer knowledge across multiple food products. Most current predictive systems remain commodity-specific and require extensive retraining for each new application. Transfer learning, multimodal learning, and large-scale foundation models may substantially reduce this limitation by enabling generalized prediction across diverse food matrices while minimizing data requirements.

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Future Directions

Future research is expected to focus on developing more transparent, scalable, and cost-effective AI systems for shelf-life management. Madhu (2025) suggested that Explainable Artificial Intelligence (XAI) will become increasingly important for improving stakeholder trust and facilitating regulatory approval. Concrete evidence supports this trust-building effect: Balakrishnan et al. (2025) reported that adding SHAP-based interpretability to machine learning pipelines in recent food-adulteration studies improved user trust in model outputs by approximately 28%, illustrating that explainability is not merely a theoretical requirement but a measurable driver of stakeholder confidence and regulatory acceptance. The authors also emphasized the need for standardized data-sharing frameworks and interoperability standards to support global implementation. Digital twin technology is expected to become an important component of next-generation food quality management systems. Digital twins create virtual representations of food products, storage facilities, and supply-chain operations, enabling continuous simulation of quality changes under varying environmental conditions. When integrated with AI algorithms, these systems can provide dynamic shelf-life predictions and support proactive interventions before spoilage occurs. Real-world deployments are beginning to demonstrate this potential. Fleck et al. (2025) reported that the ZL2030 project successfully developed digital twins for minced pork that were transferable to beef and chicken products under laboratory conditions, with the models subsequently piloted in daily operations at a large German producer and across a retailer's supply chain — one of the first documented industrial-scale applications of digital twin technology to shelf-life management.

Another emerging area is federated learning, which addresses one of the most significant barriers in food AI research: limited access to large, high-quality datasets. Rather than transferring sensitive industrial data to centralized servers, federated learning lets AI models

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train across multiple decentralized datasets while preserving privacy and data ownership. This approach may encourage greater collaboration among food industries, researchers, and regulatory agencies while improving model robustness and generalizability. Fendor et al. (2024) reviewed 86 published applications of federated learning in food research between 2019 and 2024 and found that current use cases concentrate on crop disease monitoring, yield prediction, quality assessment, and pesticide residue risk analysis. The review also identified centralized horizontal federated learning as the dominant architecture, noting the near-complete absence of vertical federated learning, federated transfer learning, and fully decentralized architectures as a significant research gap.

Edge AI and TinyML technologies represent another promising direction. Haque et al. (2025) demonstrated the potential of lightweight machine learning models that can operate directly on low-power sensor devices. Such systems can provide real-time shelf-life predictions without relying heavily on cloud infrastructure.

Future food supply chains may increasingly integrate AI, IoT, blockchain, digital twins, and smart packaging into unified decision-support platforms. These technologies could reduce food waste, improve food safety, enhance supply-chain efficiency, and support sustainability goals worldwide.

Future progress will increasingly depend on the convergence of artificial intelligence with advanced sensing technologies, digital manufacturing, and sustainable food systems. Rather than functioning solely as predictive tools, next-generation AI platforms are expected to become intelligent decision-support systems that continuously optimize storage conditions, logistics, packaging strategies, and inventory management. Such integrated ecosystems could transform reactive quality control into proactive food quality management across the entire

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supply chain. Overall, AI is rapidly evolving from a supplementary analytical tool into a central component of modern food shelf-life prediction and management systems**.**

Conclusion

Artificial intelligence is rapidly transforming food shelf-life estimation and spoilage detection by enabling faster, more accurate, data-driven decision-making than conventional approaches. Machine learning and deep learning models have demonstrated strong predictive capabilities across diverse food categories, particularly when integrated with advanced sensing technologies, smart packaging systems, and Internet of Things platforms. Despite significant progress, challenges related to data quality, model transparency, standardization, and regulatory acceptance continue to limit widespread adoption. Emerging technologies such as explainable AI, digital twins, federated learning, and edge computing offer promising ways to address these limitations. Despite existing challenges related to data quality, model transparency, regulatory acceptance, and industrial implementation, the rapid evolution of explainable AI, digital twins, multimodal sensing, and federated learning indicates that intelligent predictive systems will become an integral component of future food quality management. Continued collaboration among food scientists, computer scientists, engineers, regulatory agencies, and industry stakeholders will be essential to translate these advances into safe, reliable, and commercially viable solutions that reduce global food waste while ensuring sustainable food production.

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