



From Spoilage to Sustainability: A Prescriptive Framework for AI-Enabled Remaining Shelf-Life Prediction

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Abstract

Food spoilage is a major barrier to developing a sustainable food system, as it leads to the loss of valuable resources, economic losses, and avoidable greenhouse gas emissions. Traditional methods of detecting food spoilage are predominantly retrospective, confirming deterioration only after it has already occurred. This perspective presents a prescriptive framework for AI-enabled monitoring of food spoilage through the integration of microbiology and machine learning. The framework is aimed at identifying deterioration trends, estimating remaining shelf life (RSL), and enhancing local accountability and accessibility to support food loss reduction and climate-mitigation efforts. Rather than replacing traditional microbiological methods, this framework is intended to function as an intelligent decision-support tool for producers, supporting higher-quality food production with reduced waste.

Keywords:

food spoilage; predictive shelf life; Remaining Shelf Life (RSL); artificial intelligence; sustainability; hyperspectral imaging; electronic nose; Explainable Artificial Intelligence (XAI)

1. Introduction: The Cost and Complexity of Food Spoilage

Food spoilage refers to the deterioration of food quality caused by biological, chemical, or other degradation processes, which can make food unsuitable for consumption. Approximately 1.3 billion tons of food are lost or wasted annually within the global food system [1]. The FAO, Food Loss Index and the UNEP Food Waste Index are used to measure progress towards achieving SDG 12.3 [2,3]. A substantial proportion of food loss and waste is attributable to microbial spoilage of perishable foods, with environmental implications extending beyond nutrient loss, particularly through methane emissions. Even in advanced supply chains, spoilage can occur when the early stages of deterioration are not detected in time.

This article focuses on food spoilage and decision-support systems for estimating remaining shelf life. Al-

though food safety and pathogen risk assessment are closely related to spoilage monitoring, they are not the primary focus of the proposed framework.

2. Spoilage Dynamics: A Microbial and Chemical Orchestra

Food spoilage is driven by complex, nonlinear interactions among microorganisms, food substrates, processing conditions, storage conditions, and time. Chemical reactions such as lipid oxidation, pigment degradation, and Maillard-type reactions alter texture, color, and sensory quality, while microbial activity, such as *Pseudomonas* species in refrigerated meat and milk, can lead to slime formation and off-flavors through proteolytic and lipolytic processes [4,5]. Physical and chemical signals, including gas emissions, spectral changes, and pH shifts, can serve

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as measurable indicators of spoilage that AI systems may use to monitor and predict quality changes [5].

3. Traditional Detection Methods: Strengths and Weaknesses

Traditional methods for detecting food spoilage typically rely on microbiological, chemical, or organoleptic evaluations. Common spoilage evaluation methods include plate counts, peroxide value measurement, and titratable acidity analysis. These methods are considered retrospective because they assess the current or already-developed condition of the product rather than predicting its future quality status. These tests generally require laboratory settings and trained personnel, which limits their applicability for continuous real-time monitoring [6].

4. From Reactive to Predictive: The Importance of AI

Predictive modeling provides the link between microbiology and computational intelligence. Machine learning approaches can integrate temperature history, product handling conditions, gas emission profiles, conductivity signals, and product-level quality proxies to identify patterns of spoilage prior to the appearance of visible signs of deterioration [7,8]. Conventional expiration-date systems have generally relied on fixed calendar-based estimates. In contrast, AI-enabled remaining shelf life (RSL) prediction enables continuous updates of estimated shelf life

based on actual storage and transportation conditions [7,9]. For example, a carton of milk that has undergone multiple temperature fluctuations should not be treated the same as one stored consistently at a constant refrigeration temperature. Predictive modeling enables a shift in quality control from fixed date coding to a continuously adaptive system that evolves as new data are acquired [8,10].

The fundamental contribution of artificial intelligence is to generate data-driven signals that can precede human judgment by time scales ranging from a few seconds to several months. While microbiologists may confirm deterioration through culture-based or laboratory analyses, an algorithm can detect temperature anomalies, volatile organic compound (VOC) signatures, or spectral drift before laboratory results are available. Four key components underpin systems for modeling spoilage dynamics and estimating remaining shelf life (RSL): (1) Data inputs, comprising cold-chain monitoring data, product-level quality proxies, and batch-level contextual variables; (2) Modeling, including approaches such as regression-based methods and risk classification techniques; (3) Outputs, consisting of RSL estimates or categorical spoilage-risk classifications linked to operational decision pathways, such as release, hold-and-verify, rerouting, discounting, or disposal; and (4) Governance, encompassing model drift monitoring, retraining triggers, accountability mechanisms for decision-making, and systematic decision logging to ensure transparency, auditability, and traceability [8,11,12]. Figure 1 summarizes this prescriptive workflow.

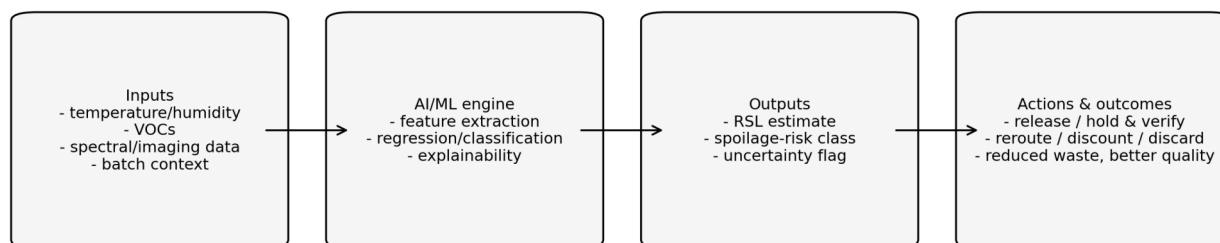


Figure 1: Prescriptive framework for AI-enabled spoilage monitoring and remaining shelf-life prediction.

5. Streams of Data That Support Spoilage Prediction

Predictive systems rely on the continuous acquisition of relevant data that are validated against reliable ground-truth measurements. The four primary data streams currently used for spoilage prediction are as follows:

1. Cold-chain dynamics can be captured in real time through sensor networks that measure temperature and rel-

ative humidity. These data can then be used to develop kinetic models linking storage history to microbial growth and quality deterioration [11].

2. Electronic noses can detect microbial activity in meat, fish, and dairy products through volatile organic compound (VOC) profiles [13,14].

3. Spectroscopic and imaging techniques, such as near-infrared (NIR) spectroscopy, Raman spectroscopy, and hyperspectral imaging, can detect spoilage as well as

subtle physical and chemical changes associated with food deterioration [15].

4. The hybrid reconstruction model enables the use of low-cost RGB images in combination with deep learning to reconstruct information that would otherwise require hyperspectral imaging systems [16].

Individually, each modality captures only part of the spoilage process; however, when integrated, these data sources can generate a digital representation of product freshness at the batch, pallet, or individual-package level. Examples include early detection of bacterial contamination in mozzarella using hyperspectral imaging, predictive spectral analysis of fungal contamination in baked goods, and electronic nose systems combined with random forest models to distinguish among fresh, borderline-acceptable, and spoiled meat products [9].

6. How AI Learns, Explains, and Improves

Most AI models are trained using supervised learning. Regression methods are used to predict remaining shelf life (RSL) as a numerical value based on variables associated with spoilage risk, whereas classification approaches provide categorical outputs, such as spoiled versus non-spoiled products. Explainable AI (XAI) tools improve transparency in machine learning models and are particularly useful for interpreting predictions through methods such as SHAP and LIME. These approaches help identify the independent variables (IVs) that most strongly influence model predictions [7,17,18], enabling quality managers to determine whether spoilage classifications for a cheese batch are driven by factors such as temperature spikes, volatile organic compound (VOC) concentrations, or specific spectral bands. This allows the factors underlying spoilage-related decisions to be examined and validated using evidence rather than relying on opaque model outputs. For example, if SHAP analysis indicates that an ammonia (NH₃) signal strongly influences the spoilage

classification of a cheese batch, the quality manager can make risk-based decisions to improve processing conditions or optimize packaging to reduce ammonia accumulation [12,13].

To ensure that model outputs remain reliable throughout operational use, appropriate governance mechanisms should support periodic retraining, drift detection, and performance validation across variations in seasonality, product type, and geographic location [11,12].

7. Validation, Trust, and Integration in Regulatory Compliance

Predictive spoilage models should demonstrate performance that is at least equivalent to, or complementary to, established microbiological methods. The EFSA BIOHAZ Panel has outlined relevant principles for predictive microbiology, while ISO 7218 and the Codex Alimentarius (CXG 21-1997) emphasize the importance of robust microbiological foundations within quality management systems [19–21]. Validation should include both technical and operational components. Technical validation involves comparing AI-predicted freshness classifications or RSL estimates with laboratory results using performance metrics such as accuracy, ROC-AUC, and root mean square error (RMSE). Operational validation links AI outputs to predefined decision thresholds and facility actions, such as release, hold-and-verify, or do-not-release decisions [20–22].

At present, these models are best positioned as decision-support tools. They can enhance microbiological verification and documentation, but should not be considered stand-alone substitutes for established microbiological methods until broader regulatory acceptance is achieved. Documentation, audit trails, and explainability are therefore central to traceability and trust [20–22]. **Figure 2** outlines the validation and governance pathway.

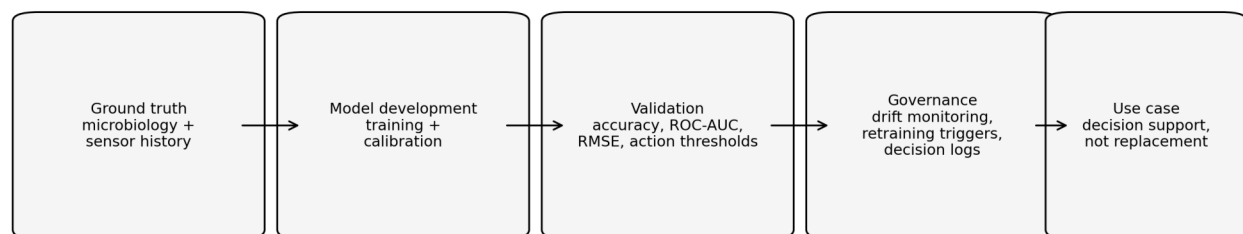


Figure 2: Validation and governance pathway for interpretable AI-based spoilage decision support.

8. Sustainability, Circular Economy, and Future Directions

Food spoilage is both a technical challenge and a sustainability issue. Improved spoilage prediction can support Sustainable Development Goal (SDG) 12.3 by reducing avoidable food loss, greenhouse gas emissions, water waste, and upstream agricultural resource use [8,11,23,24]. AI-generated freshness data could also support circular-economy pathways by enabling near-expiry products to be dynamically rerouted to processing, donation, or secondary markets. When integrated with carbon-accounting tools, such models may also help quantify avoided emissions per kilogram of food saved [24,25].

The broader value of AI in this domain lies not in novelty itself but in enabling a more responsible approach to quality management that intervenes before food waste becomes inevitable. Future work should further integrate spoilage prediction with sustainability metrics, food system dashboards, and transparent decision-making frameworks grounded in microbiological evidence.

9. Conclusions

Food systems are inherently vulnerable to spoilage; however, spoilage resulting from inappropriate or avoidable storage and handling conditions can be mitigated or prevented. By incorporating microbiological, chemical, and environmental signals into interpretable AI workflows, food quality management systems can shift from confirming spoilage after it occurs to anticipating and preventing spoilage before it develops. Using AI as a decision-support tool for release, hold, rerouting, or disposal decisions, rather than as a replacement for microbiological methods, can improve the accuracy and consistency of early spoilage detection, reduce product discard rates, and enable measurable sustainability gains across the food supply chain.

List of Abbreviations

AI	Artificial Intelligence
FAO	Food and Agriculture Organization of the United Nations
HACCP	Hazard Analysis and Critical Control Points
HSI	Hyperspectral Imaging
IoT	Internet of Things
LIME	Local Interpretable Model-Agnostic Explanations
NIR	Near Infrared
RGB	Red, Green, Blue
RMSE	Root Mean Square Error

ROC-AUC	Receiver Operating Characteristic—Area Under the Curve
RSL	Remaining Shelf Life
SDG	Sustainable Development Goal
SHAP	Shapley Additive Explanations
UNEP	United Nations Environment Programme
VOC	Volatile Organic Compound
XAI	Explainable Artificial Intelligence

Author Contributions

Conceptualization and literature curation: F.A.-A.; Writing—original draft preparation: F.A.-A.; Validation, visualization: F.A.-A.; Critical review and editing, and supervision of manuscript structure: B.K. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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AI Declaration

The authors used Grammarly solely as an automated tool for language-related corrections in this manuscript. No AI tools were used in the development of the scientific content presented in this manuscript, including hypothesis formulation, literature interpretation, argument construction, conclusion development, figure preparation, and reference compilation. The authors accept full responsibility for the scientific content and the final version of the manuscript.

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