Perspective

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

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Abstract

A major barrier for developing a sustainable food system is food spoilage as it leads to the loss of valuable resources, economic loss, and contributes to avoidable emissions. Traditional methods of detecting food spoilage are predominantly retrospective which confirming the food deterioration after it has already occurred. However, the purpose of this editorial is to explain a prescriptive framework to use AI-enabled monitoring of food spoilage through the application of microbiology and machine learning in order to identify trends of deterioration, establish remaining shelf life (RSL), and enable local accountability and accessibility to influence food loss and climate-mitigation efforts. Therefore, rather than replacing traditional microbiological methods, this prescriptive framework is meant to serve as an intelligent decision-support tool for producers, enabling them to produce food with a higher quality and less waste.

Keywords: Food Spoilage; Predictive Shelf Life; Remaining Shelf Life (RSL); Artificial Intelligence; Sustainability; Hyperspectral Imaging; Electronic Nose; Explainable Artificial Intelligence (XAI).

Introduction: The Cost and Complexity of Food Spoilage:

Food waste is the amounts of food that no longer can be consumed because of spoilage due to biological, chemical, or related quality deterioration processes. About 1.3 billion tons of food are wasted or lost in the global food system annually [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 significant portion of both food waste and food loss can be attributed to microbial spoilage of perishable foods, which has environmental consequences beyond just loss of nutrients because of methane emissions. In even the most modern supply chains, spoilage occurs when the early onset of spoilage is not recognized in time.

Scope note: this editorial will discuss spoilage and decision support for remaining shelf life; food safety pathogen risk assessment is closely related but will not be the focus of the proposed framework.

1. Spoilage Dynamics: A Microbial and Chemical Orchestra:

Food spoilage is driven by complex and nonlinear interactions among microorganisms, substrates, processing conditions, and time. Chemical reactions—such as lipid oxidation, pigment degradation, and Maillard-type reactions—affect texture, color, and sensory quality, while microbial activity, for example by *Pseudomonas* species on refrigerated meat and milk, produces slime and off-flavors through proteolytic and lipolytic processes [4,5]. Physical and chemical signals, including gas emissions, spectral changes, and pH shifts, serve as measurable indicators of spoilage that AI systems can use to monitor and predict quality changes [5].

2. Traditional Detection Methods: Strengths and Weaknesses:

Traditional methods of detecting food spoilage typically rely on microbiological or organoleptic evaluations. Common methods of evaluating spoilage include using plate counts, peroxide values, and titratable acidity. These methods are considered to be retrospective; they provide identification of a condition of food that has already occurred rather than an estimation of the condition of a product in the future. Laboratory settings and trained individuals are necessary to accurately carry out these tests, thus restricting their ability to be continuously monitored in real time [6].

3. From Reactive to Predictive: The Importance of AI:

The connection between microbiology and computational intelligence is made through predictive modelling. Machine-learning strategies are able to take into account the temperature history, product handling conditions, gas emission patterns, conductivity signals and product-level quality proxies in order to identify observable patterns of spoilage before visual signs of deterioration are present [7]. Conventional methods of determining expiration dates have relied on fixed calendars. Some methods use AI-enabled RSL prediction, allowing for ongoing updates of estimated reachability given the actual conditions of storage and transportation [8,9]. For example, a carton of milk that has experienced several temperature variations should not be given the same treatment as a carton that has been stored at a constant temperature in a refrigerator. Predictive modelling facilitates a quality control transition from a fixed date coding to a continuously evolving learning system through continued collection of new data [10, 11].

Artificial Intelligence's fundamental contribution is to offer signals based on data that will precede humane judgement by a timescale that usually ranges from a few seconds to potentially a few months. In the case of microbiologists confirming the deterioration via culture or laboratory results, an algorithm will be capable of identifying temperature anomalies, VOC signatures, or spectral drift well before the laboratory report arrives (most likely several hours or even several days prior). Furthermore, based on these four activity specifications associated with facilitating spoilage and measuring and predicting RSL's (1) Data Inputs, including cold-chain data, product level quality proxies, batch context (2) Modelling, for example using regression or risk classification; (3) Output, for example, as RSL estimates or spoilage risk category tied to action (e.g. release, hold and verify, reroute/discount or discard), and (4) Governance, including drift monitoring, retraining triggers for decision making accountability, and decision logging to enable transparency and accountability [11-13]. **Figure 1** summarizes this prescriptive workflow:

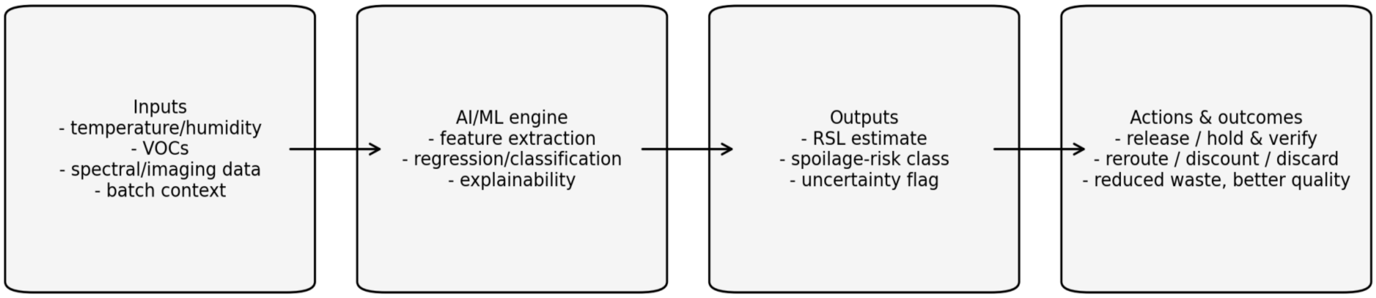

Figure 1. Prescriptive framework for AI-enabled spoilage monitoring and remaining shelf-life prediction.

4. Streams of Data That Support Spoilage Prediction:

Predictive systems rely on continuously capturing relevant data that is directly connected to reliable ground truth. The four primary data streams used for spoilage prediction today are as follows:

1. Cold chain dynamics are captured in real time through sensor networks, which measure temperature and relative humidity, and are used to create kinetic models that relate the storage history of food products to microbial growth and reduced quality [14].

2. Through the use of electronic noses, volatile production through the action of microbes found on meat, fish and dairy can be accurately detected via the production of volatile organic compounds (VOCs) [15].

3. Using spectroscopic & imaging techniques (NIR, Raman, and hyperspectral imaging), it is possible to detect not only the presence of spoilage but also subtle physical and chemical changes indicative of spoilage in food products [16].

4. The hybrid reconstruction model made it possible to use lower cost RGB images together with deep learning to reconstruct information that would otherwise have to be gathered from hyperspectral systems [17].

In totality, each modality captures part of the overall picture of how spoilage occurs; however, once combined, these data sources create a digital representation of the freshness of a specific product either at the batch, pallet or packaged level. Examples include early notification through use of hyperspectral imaging for bacterial contamination in mozzarella, high accuracy in predictive spectral analysis of fungal contamination in baked goods, and use of "e-nose" systems in combination with random forest predictive model to distinguish between a fresh, borderline acceptable and/or spoiled meat product [8].

5. How AI Learns, Explains, and Improves:

The majority of AI models are trained with the use of supervised learning. The methods employed for regression includes predicting an RSL (e.g. numerical) based on other variables associated with potential spoilage (e.g., spoilage risk) and for classification it provides a predictive categorization (e.g. spoiled vs not spoiled). Explainable AI (XAI) tools, which provide transparency and explainability into the decision-making processes of machine learning, prove particularly useful in providing justification for decision-making via transparency (e.g. (SHAP & LIME, respectively) and to help identify the independent variables (IVs) which are most significantly impacting a model "prediction", i.e., by assisting a quality manager to determine if the spoilage classification of a cheese batch is being driven due to the IVs associated with temperature spikes (or VOC concentrations/ spectral bands, etc.)[9,16,18-20] and thus investigate these IVs to validate reasons for spoilage decision with evidence vs. through non-transparent (opaque) models. If SHAP shows, for example, that the presence of an NH3 "signal" is an IV that is driving the spoilage classification of a cheese batch, then the quality manager can make risk-based decisions about how to improve processes or improve the packaging of cheese to minimize NH3 levels during production [13,15].

To ensure that model outputs remain reliable during the useful life of the model, so too should they govern the predictive output during the period to allow for retraining, as well as drift detection and validation of performance based on seasonality, product type and geographic location. [12,17].

6. Validation, Trust, and Integration in Regulatory Compliance:

Predictive spoilage models should demonstrate performance at least equivalent to, or complementary with, established microbiological methods. The EFSA BIOHAZ Panel has outlined relevant concepts for predictive microbiology, while ISO 7218 and Codex Alimentarius CXG 21-1997 reinforce the need for sound microbiological principles within quality systems [10,21,22]. Validation is both technical and operational. Technical validation compares AI-predicted freshness classes with laboratory results using measures such as accuracy, ROC-AUC, and RMSE. Operational validation links AI outputs to predefined decision thresholds and facility actions, for example release, hold and verify, or do not release [21-23].

At present, the most appropriate role for these models is decision support. They can strengthen microbiological verification and documentation, but they should not be treated as stand-alone substitutes until wider regulatory acceptance is established. Documentation, audit trails, and explainability are therefore central to traceability and trust [21-23]. **Figure 2** outlines the validation and governance pathway.

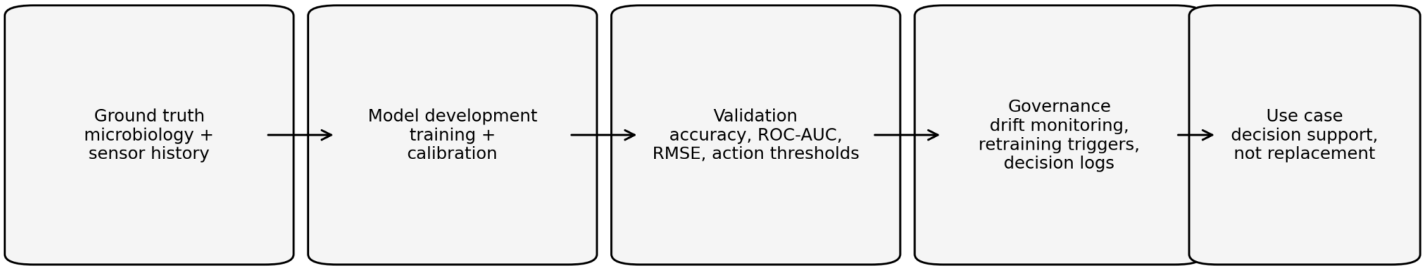

Figure 2. Validation and governance pathway for interpretable AI-based spoilage decision support.

7. Sustainability, Circular Economy, and Future Directions:

Food spoilage is not only a technical problem; it is also a sustainability problem. Better spoilage prediction can support SDG 12.3 by reducing unnecessary food loss, greenhouse-gas emissions, water waste, and upstream agricultural inputs [11,12,24,25]. AI-generated freshness data could also support circular-economy pathways by helping near-terminal products be rerouted in real time to processing, donation, or secondary markets. When connected to carbon-accounting tools, such models may also help quantify avoided emissions per kilogram of food saved [25,26].

The broader promise of AI in this area is not novelty for its own sake, but a more responsible form of quality management - one that acts before waste becomes inevitable. Future work should continue linking spoilage prediction with sustainability metrics, food-system dashboards, and transparent decision-making practices grounded in microbiological evidence.

Conclusion:

Biological systems naturally experience spoilage, although spoilage caused by inappropriate or avoidable actions can be avoided. By incorporating microbiological, chemical, and environmental signals into interpretable AI workflows, food quality management systems can shift away from confirming spoilage too late, towards preventing spoilage before it occurs. Using AI as an aid to help in making sound release decisions early on (rather than as a replacement for microbiology) will allow for greater accuracy and consistency in making early indications of spoilage, resulting in lower rates of product discards, and measurable gains in sustainability across the entire food supply chain.

Abbreviations:

AI: Artificial Intelligence

HSI: Hyperspectral Imaging

NIR: Near-Infrared Spectroscopy

VOC: Volatile Organic Compound

RSL: Remaining Shelf Life

XAI: Explainable Artificial Intelligence

SHAP: Shapley Additive Explanations

LIME: Local Interpretable Model-Agnostic Explanations

IoT: Internet of Things

VOCs: Volatile Organic Compounds

HACCP: Hazard Analysis and Critical Control Points

Figure Originality:

We confirm that all figures included in the manuscript are original and were created specifically for this work. No reproduced figures from previously published sources were used.

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F.A-A. : Responsible for conceptualization, literature curation, and preparation of the original draft.

B.K. : Conducted critical review and editing, validation, and supervised the manuscript structure.

The authors have reviewed and approved the final draft of this manuscript to ensure the authenticity, credibility, integrity, and creation of scientific knowledge is upheld in every facet of the submitted document.

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AI Declaration:

The authors used Grammarly to edit this manuscript using an automated tool solely for language-related corrections. No AI tool was used to scientific aspects contained within this manuscript and independently developed hypotheses, interpreted literature, formed arguments, came to conclusions, created figures and created references. The authors have a total responsibility for the scientific content of the manuscript, the interpretation of the results, and the final version of the manuscript.

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Conflict of Interest:

The author(s) declare no conflicts of interest regarding this manuscript.

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