Applications of Artificial Intelligence in Spoilage Detection and Shelf-Life Estimation of Perishable Food: A Systematic Review

Atheeya Azha Jakeer, and M.F.F. Nuha

Abstract Food spoilage and limited shelf life significantly contribute to food waste across supply chains and households. Recent advances in Artificial Intelligence (AI), particularly Deep Learning (DL), have enabled vision-based, nondestructive approaches for food quality assessment. This study presents a systematic literature review (SLR of AI-driven techniques for spoilage detection and shelf-life estimation in selected perishable foods, including bananas, tomatoes, strawberries, and red meat. Following PRISMA 2020 guidelines, studies published between 2020 and 2025 were identified from IEEE Xplore, Scopus, PubMed, and Google Scholar. The review examines applied AI techniques and image acquisition strategies, highlighting that convolutional neural networks (CNNs) and temporal models such as CNN–LSTM outperform conventional methods under controlled conditions. However, limitations including dataset scarcity, laboratory-bound imaging, and lack of standardized acquisition protocols restrict real-world generalizability. The review highlights the need for scalable and standardized AI frameworks to support practical deployment.

Index Terms— **Food spoilage detection, shelf-life estimation, deep learning, computer vision, perishable foods, spoilage prediction**

I. Introduction

PERISHABLE foods such as fruits and meats are highly susceptible to spoilage due to biochemical and microbial processes, leading to substantial economic losses and potential health risks. Traditional methods for assessing food quality rely on human inspection or sensor-based measurements, which are often time-consuming, inconsistent, and prone to subjective error [1][2]. Subtle early signs of spoilage, such as minor color changes or textural degradation, are frequently overlooked, reducing the reliability of manual assessment [3][4].

Recent advances in DL and computer vision offer promising solutions for automated food quality assessment. Convolutional neural networks (CNNs) and related DL architectures can analyze visual cues, detect spoilage patterns, and classify foods with higher accuracy than traditional inspection methods [5][6]. However, most existing studies focus on static classification of food items as fresh or spoiled under controlled conditions, often restricted to single food categories, and rarely model the progression of spoilage over time [7][8]. Another critical challenge is the practical applicability of these models. While DL approaches can identify spoiled items, they rarely provide actionable guidance, such as estimating remaining shelf-life or suggesting safe utilization for slightly spoiled foods.

This systematic review addresses these gaps by examining vision-based deep learning methods for spoilage detection and shelf-life estimation across perishable foods. By synthesizing current knowledge and identifying research gaps, this review aims to guide the development of more accurate, interpretable, and practical deep learning frameworks for perishable food management.

II. Literature Review

Recent literature shows a growing interest in applying AI and DL for spoilage detection and shelf-life estimation of perishable foods. CNNs, LSTMs, and hybrid architectures are the most widely used methods, particularly in image-based classification, temporal modeling, and predictive estimation of remaining shelf-life [1][2]. Despite promising lab results, most studies remain proof-of concept, with limited deployment in real-world supply chains due to small datasets, inconsistent preprocessing, and lack of standardized evaluation metrics [3][4].

A. AI Methods in Fruit Spoilage Detection

Several studies have investigated AI applications for fruit spoilage detection. Bhat et al. [5] applied CNNs to classify bananas into fresh, mid, and spoiled stages. The model achieved high accuracy under controlled lighting conditions but showed reduced performance in natural or variable

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lighting, highlighting challenges in generalizability.

Similarly, Sharma et al. [6] used DenseNet for tomato quality grading, achieving over 95% accuracy on laboratory datasets. While DL models excel at detecting subtle visual cues like discoloration or bruising, real-world variations such as handling damage, occlusion, and lighting remain challenging.

B. Temporal Models for Shelf-Life Prediction

Beyond static classification, temporal modeling has been applied for dynamic shelf-life estimation. Li et al. [7] proposed a CNN-LSTM framework for strawberries, achieving a mean absolute error of 0.8 days in predicting remaining shelf-life. This approach captures both spatial and temporal features, allowing continuous monitoring during storage. Similarly, hyperspectral imaging combined with CNNs has been applied to red meat spoilage detection, enabling early identification of microbial growth before visible signs appear [8]. These methods provide actionable insights for inventory management, consumption planning, and reducing food waste.

C. Data Preprocessing and Augmentation Strategies

Data preprocessing is critical for model robustness, especially when datasets are small. Common techniques include:

- Image normalization, rotation, scaling, and color jittering to reduce overfitting [9].
- Attention mechanisms and saliency maps to highlight regions of spoilage, improving interpretability and trust in automated predictions [10].

Despite these advances, most studies focus on single food categories, limiting cross-category applicability.

D. Explainability in AI-Based Spoilage Detection

Explainability remains a major challenge in deploying AI for spoilage detection. DL models often act as black boxes, making it difficult for supply chain managers or consumers to trust predictions. Common explainability techniques include:

- Grad-CAM overlays: Highlight affected regions in bananas or red meat, providing actionable insights [11].
- Attention mechanisms: Identify features most relevant to spoilage prediction, e.g., color changes, texture, or bruises [8][9][10].

While these techniques improve interpretability, most studies stop at visualization and do not provide practical recommendations, such as prioritizing consumption, adjusting storage, or reordering stock [12].

E. Limitations Across Studies

Despite high predictive performance in laboratory settings, several limitations persist:

1. Small, uni-centric datasets limit generalizability across food varieties and storage conditions [5][6][7].
2. Variations in imaging conditions (lighting, occlusion, camera angle) challenge robustness [5][6].
3. Inconsistent evaluation metrics complicate comparisons across studies [3][4].
4. Limited real-world deployment: Few studies integrate AI predictions into supply chain decision-making.
5. Explainability not fully actionable: Visual explanations rarely guide interventions or operational decisions.

F. Research Gaps

Based on the reviewed literature, key research gaps include: In summary, AI and DL models show strong predictive capabilities for spoilage detection and shelf-life estimation in perishable foods. CNNs, LSTMs, and hybrid architectures achieve high accuracy under controlled conditions, while explainability techniques like Grad-CAM improve interpretability [12]. However, challenges remain in dataset diversity, standardization, real-world application, and actionable explainability. The present review aims to systematically evaluate both accuracy and explainability of AI-based spoilage detection systems, which are critical for practical adoption in supply chains and consumer guidance.

III. METHODOLOGY

This systematic literature review (SLR) was conducted following the PRISMA 2020 guidelines to ensure transparency, reproducibility, and rigor in reporting [13], [14]. To address the interdisciplinary nature of this study which bridges computer science (AI/Deep Learning) and food science (spoilage detection and shelf-life estimation. While the protocol was not formally registered in PROSPERO due to its technical focus, a prospectively designed internal protocol was implemented to minimize bias and maintain consistency throughout the review process.

A. Research Questions

Based on the objectives of this study, the following primary research questions (RQs) were formulated to guide the data extraction and synthesis:

RQ1 – Techniques and effectiveness: What techniques have been reported in the literature for spoilage detection and shelf-life estimation in perishable foods, and how effective are these approaches? This question investigates the range of applied methods, including AI-based (ML/DL) and conventional approaches (manual inspection, biochemical testing, and sensor-based evaluation). Effectiveness is assessed through performance metrics (Accuracy, F1-score, RMSE) and a comparative analysis of

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cost, scalability, and ease of adoption between AI and traditional methods [13], [14], [15].

RQ2 – Image acquisition and preprocessing strategies: What image acquisition strategies and preprocessing techniques are reported to improve the accuracy and robustness of vision-based spoilage detection models for fruits and red meat? This focuses on the technical pipeline, examining how acquisition conditions (lighting, background, camera type) and preprocessing steps (segmentation, augmentation, feature enhancement) influence model performance in non-controlled environments.

RQ3 – Explainability and trust: How are interpretability techniques integrated into AI-driven spoilage detection to support model transparency and actionable decision-making? This question examines how methods like Grad-CAM and saliency maps bridge the gap between "black-box" predictions and the practical needs of supply chain stakeholders [16], [17], [18].

B. Search Strategy

Searches were conducted across IEEE Xplore, PubMed, and Scopus to capture an interdisciplinary scope. To ensure a comprehensive search, these database queries were supplemented by manual snowballing techniques (forward and backward citation tracking) via Google Scholar [13], 23], [24], [25]. [Search queries were strictly tailored to map to each Research Question:

- Query 1 (RQ1): ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("food spoilage" OR "perishable foods" OR "fruit" OR "meat") AND ("accuracy" OR "performance" OR "conventional methods")
- Query 2 (RQ2): ("image acquisition" OR "preprocessing" OR "augmentation") AND ("vision-based" OR "robustness") AND ("food spoilage" OR "perishable foods")
- Query 3 (RQ3): ("explainable AI" OR "XAI" OR "interpretability" OR "GradCAM" OR "LIME" OR "SHAP") AND ("food spoilage" OR "quality assessment")

C. Inclusion and Exclusion Criteria

To maintain relevance and quality, clear inclusion and exclusion criteria were applied.

TABLE I
INCLUSIVES AND EXCLUSIVES

Category	Inclusion	Exclusion
Publication Type	Peer-reviewed journals and conference proceedings	Theses,preprints, book chapters, editorials, grey literature
Timeframe	2018–2025	Before 2018
Language	English	Non-English
Focus	AI/ML/DL applicationsfor spoilage detection or shelf-life estimation of perishable foods	Theoretical AI studies without practical application; insufficient results or unclear methodology

D. Study Selection Process

The PRISMA flow diagram (Figure 1) illustrates the flow of studies through identification, screening, eligibility, and inclusion phases:

1. Identification: All studies retrieved from database queries were imported into a reference manager, and duplicates were removed.
2. Screening: Titles and abstracts were reviewed for relevance to the research questions.
3. Eligibility: Full-text articles of potentially relevant studies were assessed against the inclusion/exclusion criteria.
4. Inclusion: Studies meeting all criteria were included in the final analysis for detailed review*]*, [18],[19], [20].

This structured approach ensures objectivity, reproducibility, and transparency in selecting studies for the SLR, while also capturing recent interdisciplinary contributions across AI and food science [26], [28].

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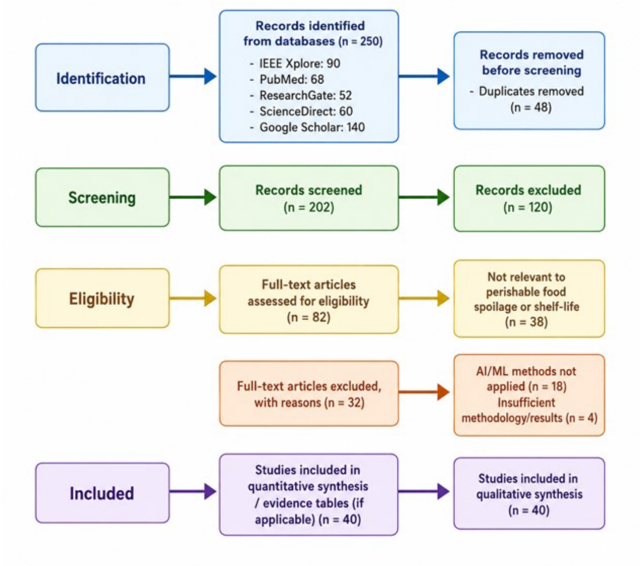

Fig 1. PRISMA flow diagram

E. Data Extraction and Synthesis

A narrative synthesis was conducted due to the heterogeneity in datasets, models, and food types. Techniques and Effectiveness (RQ1): Collection of evaluation metrics (Accuracy, Precision, RMSE) and a detailed comparison with conventional methods to assess improvements in detection vs. cost and scalability [23], [24], [25], [26].

1. Acquisition and Robustness (RQ2): Analysis of imaging conditions and preprocessing pipelines used to enhance model reliability in diverse environments [5], [6].

2. Explainability and Actionability (RQ3): Examination of interpretability methods (Grad-CAM, SHAP, LIME) and their role in supporting user trust and actionable decision-making [14], [16], [17], [18], [27], [29], [30].

IV. Results And Discussion

A. RQ1: What techniques have been used for detection of spoilage and shelf-life estimation in perishable foods, and how effective are these approaches?

The reviewed literature indicates a strong shift from traditional spoilage assessment methods toward AI driven and vision-based techniques, particularly deep learning (DL) models. Across fruits, vegetables, and red meat, these techniques demonstrate superior effectiveness in detecting early spoilage cues and estimating remaining shelf life when compared to conventional approaches.

1) Spoilage Detection Techniques and Effectiveness Across fruits such as bananas, tomatoes, and strawberries, CNNs are the most frequently adopted technique for spoilage stage classification. CNN based approaches consistently report high classification accuracies (90–97%) under controlled experimental settings.

For instance, tomato spoilage detection studies using CNN architectures successfully captured color degradation, mold growth, and surface texture irregularities, enabling early-stage spoilage detection. Similar outcomes were reported for bananas and strawberries, where CNNs distinguished fresh, mid-spoilage, and spoiled stages based on bruising patterns and surface discoloration.

In contrast, conventional techniques including manual visual inspection, rule-based image processing, and handcrafted feature extraction (e.g., color histograms, thresholding, edge detection) demonstrated lower robustness and reduced accuracy. These methods were particularly sensitive to lighting variations and food orientation, limiting their effectiveness outside laboratory conditions.

2) Shelf-life estimation techniques

Beyond static spoilage classification, several studies employed temporal deep learning architectures, such as CNN–LSTM models, to estimate RSL. These models analyze visual changes over time, enabling progressive spoilage modeling rather than discrete classification.

Reported results show low prediction errors (e.g., MAE < 1 day) for fruit-based shelf-life estimation tasks. Compared to conventional regression models often reliant on temperature measurements or microbial counts vision-based DL models provide non-destructive, sensor-free shelf-life prediction, reducing system complexity.

However, most shelf-life estimation studies focus on single food types and fixed storage conditions, limiting cross-category applicability and real-world reliability.

3) Red Meat Spoilage Detection Techniques

For red meat, studies predominantly employed CNNs combined with RGB or hyperspectral imaging. These approaches demonstrated strong effectiveness in detecting microbial spoilage indicators before visible degradation occurs, offering a faster and non-destructive alternative to traditional microbiological testing.

Despite promising results, meat-related studies remain less mature than fruit-based research. Challenges include smaller datasets, sensitivity to surface moisture, and lighting variability, which affect model robustness.

4) Reliability and Generalizability of Techniques

While AI-based techniques outperform conventional methods in controlled environments, their generalizability remains limited. Performance degradation is commonly observed under:

- Variable lighting conditions
- Different camera devices

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- Diverse food varieties and physical forms (e.g., sliced vs. whole produce, different meat cuts)
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This indicates that current techniques are best suited as decision-support tools rather than fully autonomous spoilage assessment systems.

AI-driven and vision-based techniques, particularly CNNs and temporal DL models, are significantly more effective than conventional methods for spoilage detection and shelf-life estimation. However, broader applicability requires standardized datasets, multi-food training strategies, and real-world validation.

Summary of Techniques and Effectiveness by Food Category

B. RQ2: What image acquisition strategies and preprocessing techniques are reported to improve the accuracy and robustness of vision-based spoilage detection models for fruits and red meat?

Image acquisition and preprocessing play a critical role in determining the effectiveness of vision-based spoilage detection systems.

1) Image Acquisition Strategies

Most studies rely on RGB imaging under controlled lighting environments, typically using fixed camera setups and uniform backgrounds. Controlled illumination significantly improves model accuracy by reducing shadows, reflections, and color distortion. For red meat applications, hyperspectral imaging is frequently employed to capture chemical and microbial changes not visible in RGB images. While highly informative, hyperspectral systems are expensive and less practical for consumer-level deployment. However, few studies evaluate robustness across different cameras, lighting setups, or real-world environments, limiting the applicability of proposed systems beyond laboratory conditions.

2) Preprocessing Techniques

Common preprocessing steps include:

- Background removal and segmentation
- Color normalization
- Noise reduction
- Data augmentation (rotation, flipping, brightness variation)

These techniques improve model robustness and reduce overfitting, especially in small datasets. Data augmentation, in particular, was shown to enhance generalization under moderate environmental variation.

Despite this, preprocessing pipelines vary widely across studies, and no standardized preprocessing framework exists for food spoilage detection tasks. 3) Limitations in Current Imaging Pipelines.

Although preprocessing improves performance, many studies:

- Do not report detailed acquisition settings
- Rely on ideal imaging conditions
- Fail to evaluate performance under real-world variability

This limits reproducibility and cross-study comparison. Carefully designed image acquisition strategies and preprocessing pipelines substantially improve model accuracy and robustness. However, the lack of standardized imaging protocols and real-world testing remains a major barrier to practical deployment.

C. Cross-Cutting Discussion and Identified Research Gaps. Synthesizing findings across both research questions reveals the following gaps:

TABLE II :LIMITATIONS

FOOD CATEGORY	AI TECHNIQUES USED	PRIMARY TASK	KEY PERFORMANCE OUTCOMES	IDENTIFIED LIMITATIONS
Bananas	CNN, CNN + Grad-CAM	Spoilage stage classification (fresh / mid / under spoiled)	High classification accuracy (>90%) under controlled lighting; effective detection of bruising and discoloration	Reduced robustness under variable lighting and real-world handling conditions
Tomatoes	CNN (DenseNet, ResNet variants)	Quality grading and spoilage detection	Accuracy reported above 95% in laboratory datasets; strong sensitivity to color and texture changes	Limited generalization to different tomato varieties and occlusion scenarios
Strawberries	CNN-LSTM	Shelf-life estimation and	Mean absolute error < 1 day for remaining	Small dataset sizes; performance

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		spoilage progression modeling	shelf-life prediction; effective temporal modeling	dependent on consistent storage conditions
Red Meat	CNN, Hyperspectral CNN, Attention-based models	Early spoilage detection and microbial activity inference	Early detection of spoilage before visible degradation; non-destructive assessment	High sensitivity to lighting, surface moisture, and dataset scarcity
Multi-food datasets	CNN, Attention mechanisms	Cross-category spoilage classification	Demonstrated potential for generalization when trained on diverse samples	Lack of standardized datasets and evaluation metrics

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B. Cross-Cutting Discussion and Identified Research Gaps. Synthesizing findings across both research questions reveals the following gaps:

1. Static vs. Progressive Modeling: Most studies focus on static classification rather than continuous spoilage progression.

2. Single-Food: Focus Techniques are typically optimized for one food category, limiting generalization.

3. Imaging Standardization Gap: There is no unified standard for image acquisition or preprocessing.

4. Limited Real-World Validation: Most systems remain laboratory-bound.

5. Technique-Centric: Evaluation Performance metrics dominate evaluation, while deployment feasibility is underexploited

4) Preprocessing for Model Robustness:

To overcome the pervasive issue of small, unicentric datasets, preprocessing strategies have become critical for enhancing model generalization.

Common steps include background subtraction (segmentation) to focus the model on the food item and extensive data augmentation such as color jittering, rotation, and brightness variation to simulate the noise of real-world environments [9][10].

These strategies have been shown to reduce overfitting significantly. However, a cross-cutting limitation identified in the literature is the lack of standardized acquisition protocols; without a unified framework for how food images are captured and pre-processed, comparing the "effectiveness" of one model against another across different studies remains methodologically challenging [29][30].

D. RQ3: Explainability and Actionable Insights in Spoilage Management

Explainability has emerged as a critical requirement for the practical adoption of AI in the food supply chain. Stakeholders, from warehouse managers to consumers, are unlikely to trust "black-box" predictions without visual or logical justification.

1) Interpretability Techniques:

Post-hoc visualization techniques, primarily GradCAM and saliency maps, have been integrated into DL frameworks to provide transparency [11][14]. These methods generate heatmaps that highlight specific regions of interest influencing the model's prediction. such as fungal growth on strawberries or fat oxidation zones in red meat [11]. Attention mechanisms further improve this by identifying the most relevant features, such as texture granularity or moisture loss, during the training phase itself [10].

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2) The "Actionability" Gap:

Despite the progress in visualization, a major research gap persists: explainability is currently descriptive rather than prescriptive. While a model can "explain" where the spoilage is, it rarely suggests a practical intervention.

For example, current literature stops at identifying a "mid spoilage" stage but fails to provide actionable guidance such as recommending immediate price reduction, adjusting storage humidity, or suggesting the item be repurposed for processing rather than discarded. Bridging this gap by linking explainable AI outputs to decision- support systems is the final frontier for making AI truly practical for food waste reduction [17][18][27].

The reviewed literature confirms that vision-based AI techniques provide a powerful and nondestructive alternative to conventional spoilage assessment methods, offering superior accuracy and early detection capabilities.

TABLE III
SUMMARY OF TECHNOLOGY STACK

CATEGORY	TECHNIQUE	APPLICATION	STRENGTHS	LIMITATIONS
Post-hoc Visualization	Grad-CAM / Grad-CAM++	Highlights spoilage regions (e.g., discoloration, mold)	Easy to interpret; widely used	Low spatial resolution
	Saliency Maps	Identifies important visual features	Fast and simple	Sensitive to noise
	LRP	Explains pixel-level relevance	Fine-grained explanations	Model-dependent
Attention Based	Attention Maps	Localizes spoiled regions during training	Built-in explainability	Requires large datasets
Feature-Based	Color & Texture Analysis	Detects color and texture changes due to spoilage	Food-specific and intuitive	Limited feature coverage
Temporal	Time-Series Visualization	Explains spoilage progression over time	Useful for shelf-life prediction	Rarely used; data intensive
Model-Agnostic	SHAP / LIME	Explains individual predictions	Model independent	Computationally expensive
Hybrid	DL + Rule-Based Models	Combines AI with safety thresholds	Improves trust	Less flexible

V. CONCLUSION

This systematic literature review highlights the growing potential of artificial intelligence and deep learning in spoilage detection and shelf-life estimation of perishable foods, including bananas, tomatoes, strawberries, and red meat. The reviewed studies demonstrate that AI-driven approaches, particularly convolutional neural networks and hybrid CNN–LSTM architectures, can significantly enhance food quality assessment by automating visual inspection, detecting subtle early-stage spoilage indicators, and estimating remaining shelf life with higher consistency than conventional manual or rule-based methods.

Across food categories, AI models showed strong performance in controlled environments, achieving high classification accuracy and low prediction error for shelf-life estimation. Vision-based deep learning approaches were especially effective in identifying color changes, texture degradation, and surface anomalies associated with spoilage progression. Temporal modeling further improved prediction capability by capturing dynamic deterioration patterns over time. However, performance was not uniform across all studies, with reduced robustness observed under variable lighting, diverse food varieties, and real-world handling conditions.

Explainability emerged as a critical requirement for practical adoption. Techniques such as Grad-CAM, saliency maps, attention mechanisms, and feature attribution methods help visualize regions associated with spoilage, improving transparency and user trust. These methods bridge the gap between black-box predictions and human interpretability, supporting decision-making for supply chain operators, retailers, and consumers. Nevertheless, explainability is often applied post hoc and remains insufficiently linked to actionable recommendations, such as prioritizing consumption, adjusting storage conditions, or repurposing food nearing spoilage. practical adoption is constrained by limited generalizability, non-standardized imaging pipelines, and insufficient real-world validation. These findings highlight the need for integrated, standardized, and scalable frameworks capable of operating across multiple perishable food categories.

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Despite promising results, several challenges persist. Most studies rely on small, single-source datasets, limiting generalizability. The absence of standardized datasets, benchmarking protocols, and evaluation metrics complicates cross-study comparison and real-world deployment.

Furthermore, few studies validate AI systems under operational conditions such as retail environments or household settings, restricting their translational impact.

Overall, the evidence suggests that AI should be viewed as an assistive technology rather than a replacement for human judgment in food quality management. A hybrid approach, combining A-I driven efficiency with human oversight, appears to be the most reliable pathway for deployment. Future research should focus on developing multi-food, large-scale datasets, standardized evaluation frameworks, explainable and user-centered models, and real-world validation studies. Achieving these goals will require close collaboration between AI researchers, food scientists, and industry stakeholders to ensure that AI-based spoilage detection systems are accurate, interpretable, and practically relevant for sustainable food management.

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