Journal of Robotics and Control (JRC)
Volume 6, Issue 3, 2025
ISSN: 2715-5072, DOI: 10.18196/jrc.v6i3.25792

Smart Innovations in Food Spoilage Detection: A Focus on Electronic Nose, Machine Learning and IoT for Perishable Foods

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***Abstract*—This review article provides a comprehensive analysis of advanced technologies for detecting, analyzing, and controlling food spoilage, with a focus on perishable foods such as fruits, vegetables, and meats. Although traditional methods such as microbiological testing and sensory evaluation remain fundamental, emerging technologies such as machine learning (ML), computer vision, and electronic noses (enoses) offer transformative potential for real-time monitoring and predictive analytics. However, practical implementation of these technologies faces significant challenges, including heterogeneity in data, computational constraints, and environmental variability. For example, ML models, particularly deep learning architectures, require extensive labeled datasets and high-performance computing resources, which are often inaccessible in resource-constrained settings. Similarly, electronic noses, while effective in detecting volatile organic compounds (VOCs) associated with spoilage, suffer from sensor drift and cross-sensitivity issues, necessitating frequent recalibration. Blockchain technology, though promising for improving traceability and transparency in the food supply chain, struggles with scalability and energy efficiency. This review critically evaluates these limitations, highlighting gaps in current methodologies, such as the overreliance on external spoilage indicators in computer vision systems and the lack of standardized protocols for data collection and model evaluation. By addressing these challenges, future research can advance the development of robust, scalable and cost-effective solutions for food spoilage detection, ultimately contributing to improved food safety, reduced waste, and enhanced supply chain efficiency.**

Keywords*—Perishable Foods; Spoilage Management; Spoilage Biomarkers; Machine Learning; Electronic Nose; Computer Vision; IoT

I. Introduction

Food spoilage remains a critical global challenge, with approximately one-third of all food produced for human consumption equivalent to 1.3 billion tons annually lost or wasted due to inefficiencies in detection and management [1]. This not only exacerbates food insecurity, but also contributes significantly to greenhouse gas emissions, accounting for nearly 8% of global emissions related to food waste [2]. Traditional methods for detecting spoilage, such as microbiological culture and sensory evaluation, have long served as foundational approaches. However, these methods are increasingly inadequate to address the complex modern supply chain due to their time-consuming nature, subjectivity, and inability to detect spoilage in the early stages [3]. For example, conventional microbiological tests require 5-7 days for results, in which time perishable goods such as leafy greens or poultry may already be unusable [4], while sensory evaluation suffers from human bias and inconsistent thresholds for "spoiled" classification [5].

The advent of advanced technologies including machine learning (ML), electronic noses (enoses), and the transformative potential of computer vision to overcome these limitations. ML algorithms, for example, can analyze real-time sensor data to predict the probability of spoilage with more than 95% precision, enabling proactive interventions [6]. Similarly, as shown in Fig. 1. e-noses equipped with metal-oxide semiconductor (MOS) sensors detect volatile organic compounds (VOCs) such as ethanol and geosmin, providing rapid, non-destructive spoilage assessments [7]. Computer vision further improves traceability by creating immutable records of storage conditions and handling practices in supply chains [8]. However, these innovations are not without challenges. ML models often require large annotated datasets that are scarce for niche food products, while e-noses face sensor drift and cross-sensitivity to environmental variables such as humidity [9,10]. Blockchain energy-intensive consensus mechanisms (e.g. proof-of-work) and lack of standardization also hinder scalability in decentralized food networks [11].

This review critically examines as shown in Fig. 1 the efficacy of these emerging technologies in addressing the shortcomings of traditional spoilage detection methods. Specifically, we (1) evaluate the origin of spoilage and analytical tool for detection; (2) presents non-conventional approaches such as ML; (3) describes machine models for food food spilages; (5) and (6) evaluate the technical capabilities and limitations of ML, e-noses, and computer vision in perishable food monitoring; (7) analyze gaps in current methodologies, such as the overreliance on superficial spoilage indicators in computer vision systems; and (8) present interdisciplinary strategies to enhance robustness, scalability, and cost-effectiveness. Through the synthesis of advances in artificial intelligence, sensor technology, and decentralized systems, this study seeks to guide researchers and industry stakeholders toward integrated solutions designed to reduce food waste, improve safety, and optimize the resilience of the supply chain.

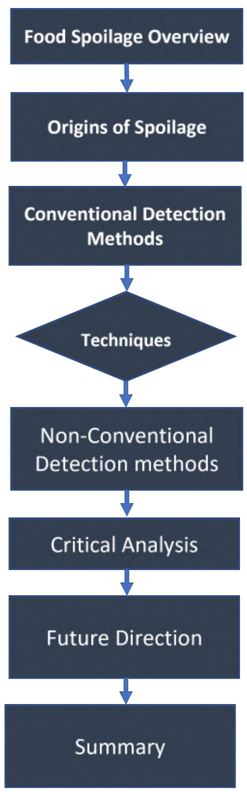

Fig. 1. Flowchart to visually represent the research framework

II. Origins of spoilage and analytical tools for detection

Microbiological spoilage of fruits and vegetables can be caused by various microorganisms that contaminate the food at any stage from producer to consumer [8, 9]: Gram-positive and Gram-negative bacteria, as well as fungi, yeasts, and molds, represent common culprits [10]. Physiological changes during ripening and spoilage make fresh vegetables more susceptible to microbial contamination [11]. The probability of contamination at any stage depends on factors such as morphology, stage of development, and post-harvest handling [12]. Once fruits and vegetables lose their natural supply of nutrients, quality begins to deteriorate, with ripening and aging being the most vulnerable periods to spoilage [13]. Food spoilage is of crucial importance due to the different consequences influencing people's quality of life, for example, socioeconomic losses, threats to public health, allergic reactions, gastrointestinal infections, and other health issues [14, 15]. Certain spoilage-causing fungal pathogens, such as Aspergillus, Fusarium, Penicillium, Alternaria, etc., produce mycotoxins, which are recognized as dangerous to human health [16]. More than 250 recognized pathological conditions can result from eating foods contaminated with bacteria, viruses, heavy metals, and other substances [17]. Foods may also contain pesticides [18], antibiotics [19], and various chemical agents [20] in harmful amounts, which might lead to health risks such as food poisoning, allergies, and even cancer.

Contamination can occur under various agronomic and ecological conditions [21]. Vegetables and fruits are vulnerable because they are grown in unprotected natural environments [22 - 24], such as soil, which serves as a habitat for many different microorganisms, bacteria and fungi [21]. Natural protective mechanisms and barriers can be compromised by insect bites or agricultural machinery during harvesting. The internal tissues of vegetables and fruits, rich in nutrients and carbohydrates, provide a nourishing environment for the growth and proliferation of foreign microflora [25]. Sources of biological contamination during the growing season include soil, fertilizers, seeds, irrigation water, solid biological waste, biological additives, domestic animals, wildlife, insects, and humans [26 - 32]. Often, the disinfecting agents used for crop processing are ineffective against the mechanisms of contamination of crops under field conditions [25]. For example, natural epiphytic microflora (epiphytes), such as *Aureobasidium pullulans*, can co-exist with pathogenic microorganisms responsible for spoilage. Strains like *Arthrobacter sp., Bacillus sp., B. Polymyxa, B. pumilis, B. cereus, B. megaterium, Agrobacterium sp.*, and the *Cytophagus Flavobacterium complex*, identified using fatty acid profiles, have been reported in sterilized potato tubers with a healthy surface [33]. These bacterial species are natural endobionts (endophytes) of tubers [34]. However, latent infections can become active after harvest and cause spoilage [35].

Harvesting methods significantly influence the quality and contamination levels of fruits and vegetables throughout the food supply chain. [36 - 38]. Coarse or mechanical harvesting practices often damage the integrity of the cellular and tissue, creating pathways for microbial infiltration and growth within the cellular sap [9, 35, 38, 39, 40]. Microorganisms responsible for decay secrete hydrolytic enzymes, such as pectinases, cellulases, proteases, and xylanases, which degrade plant cell walls and accelerate spoilage [41]. A prominent example is soft rot caused by the Erwinia carotovora bacterium, a common and devastating disease in potatoes that leads to significant yield losses [42 - 44]. This pathogen, widely present in soil, poses a continuous threat during storage, highlighting the importance of safeguarding healthy tubers against mechanical and biological damage [45]. In the case of Ready to Eat (RTE) vegetables and fruits post-harvest handling introduces additional risks for fresh-cut products subjected to processes such as cleaning, trimming, washing, and slicing [47]. Tissue damage during these processes triggers the oxidation of phenolic compounds via polyphenol oxidase, resulting in undesirable discoloration (e.g., browning or reddening) that reduces marketability [48]. Unlike typical enzymatic browning, fluorescent Pseudomonads, which are primarily responsible for plant tissue breakdown, cause rapid browning and severe decay, particularly on cut surfaces such as lettuce leaves [49]. Specific pathogens, including Pseudomonas marginalis, are closely associated with vegetable deterioration, while Pseudomonas cichorii induces necrotic spots in iceberg lettuce, significantly compromising its visual and structural quality [50][51]. Furthermore, spoilage by P. viridiflava and P. chromraphis involves the production of pectolytic enzymes, such as aspartate lyase, which degrade the tissue integrity of fresh cut products, particularly during cold storage [52, 53]. Another significant concern is the spoilage caused by Bacillus subtilis, a microorganism that is often implicated in the decay of vegetables and food products. Although most of the spoilage associated with B. subtilis involves nonpathogenic strains and does not cause direct illness, its activity contributes to methane emissions, a greenhouse gas with 21 times the global warming potential of carbon dioxide [54]. Such environmental implications underline the dual importance of managing spoilage both for food security and sustainability.

Comprehensive measures to mitigate these risks include improving harvesting techniques to minimize tissue damage, optimizing post-harvest processing to reduce oxidative reactions, and implementing advanced storage protocols to limit microbial growth and enzymatic activity. These practices are essential to maintain the quality, safety and environmental sustainability of fresh produce. Currently, spoilage is detected through temperature control in the store, expert visual inspection (sensory analysis), and the presence of characteristic odors. However, these methods do not detect the critical early stages of spoilage. Thus, store and warehouse managers, as well as food processors, require an early detection system that applies conventional microbiological testing or analytical evaluation for spoilage-causing microorganisms and instances of spoilage to take corrective measures before changes begin. Microbiological testing includes conventional microbiological and biochemical testing, and analytical methods:

- Conventional microbiological and biochemical methods, which rely on bacterial culture, are user-friendly, cost-effective, and highly reliable. However, these methods require cell culture for at least five to six days in a specialized laboratory with trained personnel [55]. Other detection techniques, such as ELISA, single radial immunodiffusion, and immunofluorescence analysis, are fast but complex to use, and they often struggle to provide high detection performance. Polymerase chain reaction (PCR)-based analysis is a more modern approach that offers significant potential as shown in Fig. 2. Multiplex PCR enables the simultaneous detection of multiple targets, in addition to the advantages of conventional PCR methods; it also improves identification accuracy [56, 57, 58]. However, this method requires expensive reagents and specialized laboratory equipment.

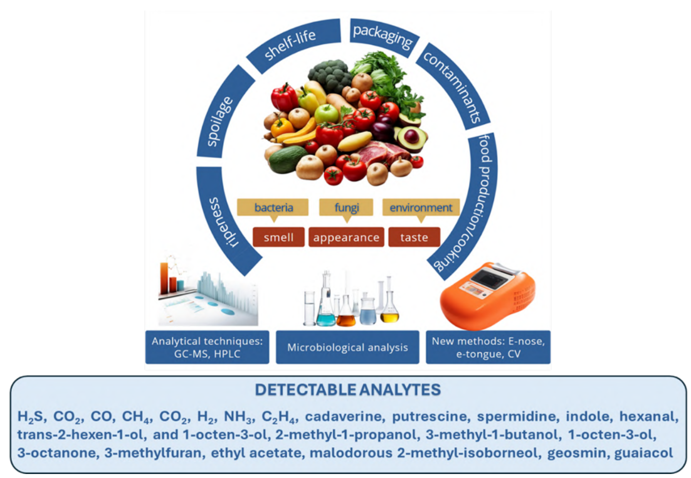

Fig. 2. An overview of processes and issues concerning food quality, test methods, and analytes as a result of fungal and microbial activities

- Moreover, analytical evaluation is a mandatory procedure for certifying the food quality before it is declared suitable for individual consumers and large retail chains. This process verifies that the food characteristics listed on the label and/or accompanying documents are compliant with the requirements of regulatory standards [59]. Analytical evaluation criteria fall into two categories: sensory and physicochemical instrumental methods [60]:
  1) Sensory analysis is a method used to determine quality indicators based on the organoleptic characteristics of the food under study. According to the international analytical standards [60], [61], the organoleptic properties of food products are determined by indicators of sensory characteristics [62, 63]. These characteristics should remain unchanged during transportation, packing, and storage. They provide a preliminary evaluation of the freshness and quality of the food [64]. Organoleptic evaluation of food products is carried out by an accredited commission of experts [65], who assess the condition of vegetables and fruits based on visual, tactile, olfactory, and taste characteristics. The advantages of organoleptic methods include availability,

speed, and lack of need for expensive analytical equipment for identifying standard inconsistency. However, these methods are subjective due to individual sensory perception differences, and they cannot estimate the nutritional properties or contaminant content. Therefore, organoleptic evaluation is often supplemented by quantitative instrumental analytical methods [66, 67].

2) Current physicochemical instrumental methods include Infrared spectroscopy, electrochemical biosensors, surface plasmon resonance, gas or liquid chromatography, high-performance liquid chromatography (HPLC), and tandem analytical units with mass spectrometry (MS) and ion mobility spectrometry. These methods, however, require complex sample preparation for separation and concentration of target molecules using different extraction techniques [69]-[71]. These methods are applied to the release of mycotoxins or other harmful microbial metabolic compounds. Most of these toxins, such as patulin, ochratoxin A, trichothecenes, and Alternaria toxins, are organic compounds with carcinogenic and mutagenic effects on humans [68]. Due to the presence of a multicomponent matrix in fruits and vegetables, accurate detection of small amounts of such toxins is a difficult task. The chosen analytical method should be able to selectively detect the target analytes or their mixture, or separate and determine several required compounds.

Thus, the use of traditional and accredited methodologies for testing fruit and vegetable quality should take into consideration such drawbacks: (1) the subjectivity of an expert panel using organoleptic evaluation; (2) complex procedures of sample preparation for microbiological screening by immunofluorescence analysis or PCR, and (3) cost of analytical equipment for instrumental analysis.

III. Non-Conventional Approaches

A. 1. Machine Learning (ML)

Machine learning is a subset of artificial intelligence (AI) that focuses on creating algorithms and statistical models that allow computers to perform tasks related to food spoilage without explicit instructions. Instead, these systems learn from data, identifying patterns, and making decisions based on that information. For example, an ML model could analyze historical data on food storage conditions and spoilage rates to predict the likelihood of spoilage for different food items under various conditions. Artificial intelligence (AI) encompasses a broader range of technologies, including ML, which is specifically concerned with the ability of machines to learn and adapt. In the context of food spoilage, AI could involve the use of sensors, image recognition, and other technologies to monitor food quality and detect spoilage. For example, an AI system could use computer vision to analyze food images and identify signs of spoilage, such as mold or discoloration. Within ML, there are several key classes, as defined below and shown in Fig. 3.

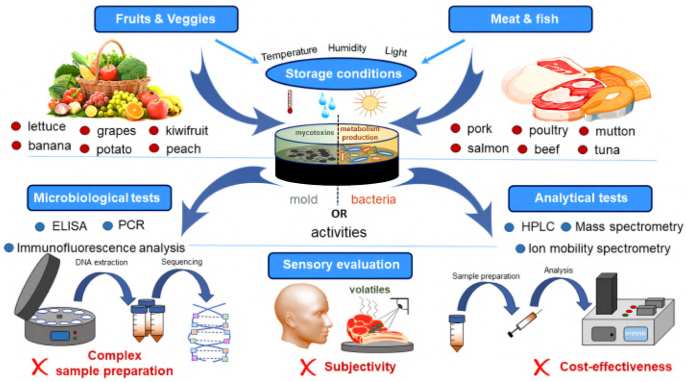

Fig. 3. Food spoilage assessment approaches

1) Supervised Learning (SL) In supervised learning, you could train a model to predict whether a food item is spoiled or not based on labeled data. For example, you might have a dataset where each entry includes features like temperature, humidity, storage time, and a label indicating whether the food is spoiled. The model learns from these data and can then predict spoilage for new, unseen data. Common applications could include classifying food as fresh or spoiled (classification) or predicting the number of days until spoilage (regression).
2) Unsupervised Learning (UL) Unsupervised learning could be used to identify patterns or groupings in data without predefined labels. For example, you might use clustering algorithms to group different types of food based on their spoilage characteristics. This could help identify which foods spoil under similar conditions or discover new patterns in spoilage data that were not previously known. Association tasks could help in finding relationships between different spoilage factors, such as certain temperature and humidity combinations that lead to faster spoilage.
3) Reinforcement Learning (RL) Reinforcement learning could be applied to optimize storage conditions to minimize food spoilage. An agent (e.g., a smart refrigerator system) could be trained to adjust the temperature and humidity settings to extend the shelf life of food items. The agent would receive rewards for actions that successfully preserve food and penalties for actions that lead to spoilage. Over time, the agent learns the best strategies for maintaining optimal storage conditions.
4) Deep Learning (DL) Deep learning could be used to analyze complex patterns in large datasets related to food spoilage. For example, deep neural networks could be employed to analyze images of food to detect signs of spoilage, such as discoloration or mold. Additionally, deep

learning models could process sensor data from storage environments to predict spoilage more accurately by considering multiple factors simultaneously. This approach is particularly useful when dealing with large and complex datasets where traditional machine learning methods might fall short.

ML is increasingly recognized as a powerful tool for combating food spoilage, offering advanced detection and prediction capabilities across a wide range of food products. Using ML in conjunction with complementary technologies such as the Internet of Things (IoT) and spectroscopy, researchers are creating innovative systems capable of real-time monitoring and accurate prediction of spoilage. These systems not only improve food safety, but also significantly reduce waste, contributing to more sustainable food management practices. ML algorithms are particularly effective in optimizing food storage conditions and minimizing spoilage. They achieve this by analyzing vast amounts of data collected from various sensors, which monitor environmental factors such as temperature, humidity, and gas composition, as well as shelf life and consumption patterns. This data-driven approach allows ML models to detect subtle changes that may indicate the onset of spoilage, enabling timely interventions. For instance, predictive models can suggest optimal storage arrangements, ensuring that food products are stored under conditions that maximize their freshness and longevity. This not only reduces waste, but also improves the efficiency and sustainability of food storage systems. Furthermore, ML techniques are being integrated with computer vision to analyze visual cues, such as changes in color, texture, or the presence of mold, which are critical indicators of food quality. Additionally, ML models can assess gas composition data to detect the release of spoilage-related gases, such as ethylene or ammonia. By combining these diverse data sources, ML provides a comprehensive assessment of the factors influencing food quality over time. This multimodal approach enables more accurate and reliable spoilage detection, ensuring that food safety standards are maintained throughout the supply chain. The integration of ML with IoT, spectroscopy, and computer vision is revolutionizing the way food spoilage is detected and managed. These technologies work together to create intelligent systems that not only predict and prevent spoilage but also optimize storage conditions, reduce waste, and improve food safety. As these systems continue to evolve, they have the potential to transform the global food supply chain into a more sustainable and efficient ecosystem, as shown in Fig. 4.

An extreme gradient boosting model was developed to predict Leuconostoc spp. growth in cooked deli foods, achieving 98% precision and outperforming the conventional Baranyi model [71]. Known for its robustness and efficiency in handling large datasets, the extreme gradient boosting model was trained on various environmental and microbial growth parameters. The model's high accuracy indicates its potential for practical applications in the food industry, where precise predictions of microbial growth are crucial for ensuring food safety and quality. Research using IoT sensors to monitor environmental factors and ML to identify spoilage patterns improves food safety and reduces waste [72].

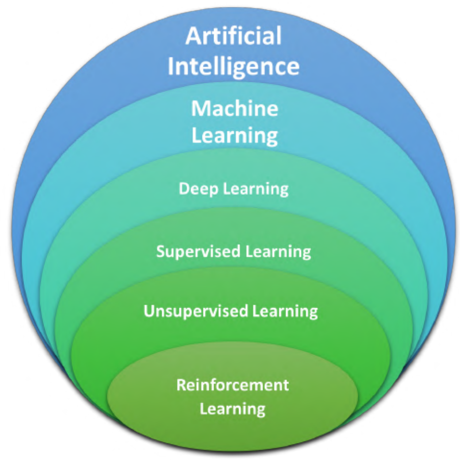

Fig. 4. AI and its sub classes

IoT sensors were deployed to continuously collect data on temperature, humidity, and other relevant environmental conditions. The machine learning algorithms were then applied to this data to detect patterns indicative of spoilage. This approach not only improves the accuracy of spoilage detection, but also allows real-time monitoring, enabling timely interventions to prevent food waste. Another study combines electrical impedance spectroscopy and data augmentation-based ML to detect spoiled apple juice with precision 98% [73]. Electrical impedance spectroscopy, a technique that measures the resistance of a material to an electrical current, was used to gather data on the apple juice samples. Data augmentation techniques were used to enhance the dataset, allowing the machine learning model to achieve high accuracy in distinguishing between fresh and spoiled juice.

K.B. Anusha, K. Uma, Jayasri Kotti, et al. [74] employ ML algorithms within an IoT system to monitor and predict spoilage, achieving 92% accuracy. The integration of machine learning algorithms with IoT systems enables continuous monitoring of food products. The algorithms analyze data from various sensors to predict spoilage, providing early warnings and reducing the risk of consuming spoiled food. Research utilizing Back Propagation Neural Networks and Linear-Support Vector Machines to classify spoilage stages in chicken breast fillets with high accuracy demonstrates the models' ability to accurately classify the spoilage stages, helping in better managing the shelf life of poultry products [75]. Using resistance values from gas sensors and a neural network to classify food as fresh or spoiled, gas sensors were used to detect volatile compounds emitted by food products [76]. The resistance values from these sensors were fed into a neural network, which classified the food as fresh or spoiled based on the detected gas patterns. Another study employs ML to classify contamination in leftover cooked foods based on smell, achieving 90-100% accuracy [77]. Electronic noses, devices that mimic the human sense of smell, were used to detect odors from leftover cooked foods. Machine learning algorithms were then used to classify the level of contamination based on the detected odors. A prediction algorithm combining ML and data mining to forecast grocery spoilage provides notifications about potential spoilage [78]. The algorithm analyzes historical data on grocery spoilage and environmental conditions to predict future spoilage events. Notifications are sent to grocery store managers, allowing them to take preventive measures to reduce waste. A smartphone application with an ML classifier for real-time food spoilage monitoring, achieving 98.8% accuracy , uses the smartphone's camera and sensors to collect data on food products [79]. Machine learning algorithms analyze this data to determine the freshness of the food, providing users with real-time information on spoilage.

Another research article discussing the use of ML algorithms to process real-time data from IoT sensors for detecting food quality and spoilage highlights the importance of real-time data processing in ensuring food safety [80]. Machine learning algorithms analyze data from IoT sensors to detect changes in food quality, allowing for immediate action to prevent spoilage. ML analyzes sensor data to detect meat spoilage, enabling timely alerts to prevent consumption of spoiled meat [81]. Sensors placed in meat storage areas collect data on temperature, humidity, and gas emissions. Machine learning algorithms analyze this data to detect spoilage, sending alerts to prevent the consumption of spoiled meat. A CNN model designed to predict and prevent food spoilage by monitoring gas emissions, humidity, and temperature uses convolutional neural networks to analyze complex patterns in the data collected from sensors [82]. The model predicts spoilage based on gas emissions, humidity, and temperature, providing a comprehensive solution for food spoilage detection. ML algorithms analyze data from IoT sensors to detect deviations in food freshness, predicting spoilage likelihood and alerting suppliers and retailers [83]. By predicting spoilage likelihood, suppliers and retailers can take proactive measures to ensure food quality. ML analyzes data on temperature, humidity, and storage time to predict food spoilage, enabling timely interventions to prevent waste [84]. Machine learning algorithms analyze environmental data and storage conditions, helping in making informed decisions to prevent food waste. An ML algorithm to predict food spoilage and the number of days until spoilage, integrated into an app for consumers, provides users with information on the freshness of their food and the estimated number of days until spoilage, helping them manage their food consumption more effectively [85].

Deep learning algorithms are used to analyze real-time data from IoT sensors for food quality monitoring [86]. These algorithms process large volumes of data from IoT sensors, providing accurate and timely information on food quality. A CNN model that monitors food spoilage by assessing gas emissions, humidity, and temperature uses convolutional neural networks to analyze sensor data, providing a reliable method for detecting food spoilage [87]. An IoT-based framework utilizing Adaptive Random Forest prediction to monitor environmental parameters affecting food spoilage (Nov, 2022) [88] combines IoT technology with adaptive random forest algorithms to monitor and predict food spoilage, providing a scalable solution for the food industry. A CNN for gas identification related to food spoilage, achieving a 96.67% accuracy rate [89], demonstrates the effectiveness of convolutional neural networks in identifying gases associated with food spoilage, providing a non-invasive method for spoilage detection. A CNN for gas identification related to food spoilage, achieving a 96.67% accuracy rate, highlights the potential of CNNs in gas identification for food spoilage detection. Using CNNs for efficient and nondestructive detection of fruit freshness, addressing food spoilage [90], convolutional neural networks analyze images of fruits, providing a non-destructive method for assessing freshness and detecting spoilage. A Deep Learning model designed to detect food spoilage, specifically distinguishing between fresh and rotten fruits, uses deep learning techniques to analyze visual and sensor data, accurately distinguishing between fresh and rotten fruits [91]. ML, particularly using Random Forest and XGBoost regressors, effectively predicts food spoilage by analyzing sensor data [92]. The study highlights the effectiveness of random forest and XGBoost algorithms in predicting food spoilage, providing a robust solution for the food industry.

ML methods, particularly CNNs, for detecting fruit spoilage, highlight their effectiveness in classifying defective fruits [93]. Convolutional neural networks analyze images of fruits, accurately classifying them based on their freshness and detecting spoilage. A mobile application using deep learning techniques for rapid detection of meat freshness uses deep learning algorithms to analyze data from sensors and images, providing users with real-time information on meat freshness [94]. A real-time detection and sorting system for spoiled fruits using deep learning uses deep learning algorithms to analyze images of fruits, automatically sorting them based on their freshness and detecting spoilage [95]. ML, specifically using CNNs, is employed to detect food spoilage by monitoring gas emissions, humidity, and temperature [96]. Convolutional neural networks analyze complex patterns in sensor data, providing a reliable method for detecting food spoilage in Table I. ML models, including Logistic Regression and Random Forest, classify fruits and vegetables into fresh, semi-fresh, and spoiled categories [97]. Logistic regression and random forest algorithms analyze data on fruits and vegetables, accurately classifying them based on their freshness. Predicting food wastage using ML, specifically highlighting XGBoost's effectiveness , demonstrates the effectiveness of XGBoost algorithms in predicting food wastage, providing a valuable tool for reducing waste in the food industry [98]. Implementing ML to estimate the likelihood and duration of food spoilage based on vendor-specific data uses machine learning algorithms to analyze data from vendors, providing accurate estimates of the likelihood and duration of food spoilage, helping vendors manage their inventory more effectively[99].

IV. Machine Learning Models for Food Spoilage Detection: A Technical Taxonomy

The integration of machine learning (ML) into food spoilage detection has enabled rapid, non-destructive, and scalable solutions. This section categorizes key ML algorithms, their architectures, and applications in food quality monitoring, emphasizing performance metrics, limitations, and domain-specific implementations.

A. Supervised Learning Approaches

1) Convolutional Neural Networks (CNNs) : CNNs excel in processing spatially structured data, such as hyperspectral or RGB images, by leveraging convolutional layers to extract hierarchical features (e.g., texture, color gradients). Applications include:

1) Fruit Freshness Analysis: Detection of spoilage indicators (discoloration, mold) in apples and strawberries through image classification, achieving 95% precision [93].
2) Environmental Monitoring: Multimodal CNN architectures correlate gas emissions (e.g., ethylene, ammonia) with temperature/humidity data to predict microbial activity in perishables [96].
3) Non-Destructive Testing: Real-time sorting systems for fruits using CNN reduce physical damage, as demonstrated in mango quality grading (F1-score: 0.94) [100].

B. Support Vector Machines (SVMs)

SVMs identify optimal hyperplanes for classification in high-dimensional spaces. Variants include:

1) Linear-SVM: Binary classification of spoilage stages in chicken breast fillets using spectral data (accuracy: 89%) [101].
2) Kernel-SVM: Non-linear separation of VOC profiles from electronic noses (e-noses) to detect contamination in cooked foods [102].

C. Gradient Boosting Algorithms

1) XGBoost: A gradient-boosted decision tree framework achieves 98% accuracy in predicting microbial growth (e.g., Leuconostoc spp.) in deli meats, outperforming kinetic models like Baranyi [71]. It also analyzes vendor-specific sales data to forecast spoilage risks (RMSE: 1.2 days) [92, 98].
2) Adaptive Random Forest (ARF): Combines IoT sensor streams with incremental learning for real-time spoilage prediction in supply chains, maintaining 92% precision under concept drift [107].

D. Deep Learning Architectures

1) Hybrid Neural Networks:

1) Backpropagation Neural Networks (BPNNs): Utilize gradient descent to classify spoilage stages in chicken fillets (accuracy: 91%) by training on spectral reflectance data [101].
2) Recurrent Neural Networks (RNNs): Process temporal sensor data (e.g., temperature fluctuations) to model time-dependent spoilage kinetics in dairy products [105].

E. Data-Augmented Models

Synthetic dataset expansion via rotation, scaling, and noise injection improves generalization in CNN-based freshness classifiers, reducing overfitting in small datasets (e.g., 15% accuracy gain in leafy greens).

1) Gas Sensor-Driven Networks: MLPs (Multilayer Perceptrons) and 1D-CNNs analyze resistance patterns from metal-oxide semiconductor (MOS) sensors to detect VOCs (e.g., ethanol, acetone) emitted during spoilage, achieving 97% specificity in meat quality assessment [103].

F. Ensemble and Traditional Methods

1) Random Forest (RF): An ensemble of decision trees classifies fruits/vegetables into freshness tiers (fresh, semi-fresh, spoiled) using multispectral features (κ-score: 0.88) [109]. RF's feature importance metrics also identify critical spoilage predictors (e.g., pH, CO_2 levels).

2) Logistic Regression: A baseline for binary classification, logistic regression achieves 85% accuracy in fruit freshness categorization, though it underperforms non-linear models in complex VOC datasets [109].

G. Integrated Systems and Deployment Platforms

1) Electronic Nose (E-Nose) Systems: E-noses paired with ML (e.g., PCA-SVM, LDA classifiers) detect spoilage-induced VOCs in cooked leftovers, achieving 94% accuracy via sensor array fusion [103].

2) IoT-Edge Frameworks:

- Smartphone-Based Solutions: Mobile CNNs analyze produce images captured by built-in cameras, providing consumer-facing freshness scores (AUC: 0.91) [104].

TABLE I. ML AND IOT IN FOOD SPOILAGE DETECTION

Study	Objective	Method	Outcome	Reference
Extreme Gradient Boosting for Microbial Growth Prediction	Predict Leuconostoc spp. growth in cooked deli foods.	Developed an extreme gradient boosting model trained on environmental and microbial parameters.	Achieved 98% accuracy, outperforming the Baranyi model.	Mayumi Kataoka et al. [71]
IoT and ML for Spoilage Detection	Monitor environmental factors and identify spoilage patterns.	IoT sensors collected real-time data (temperature, humidity), and ML algorithms detected spoilage indicators.	Enhanced detection accuracy and enabled real-time interventions.	Keerthana Mogilipalem et al. [72]
Data Augmentation with Electrical Impedance Spectroscopy	Detect spoiled apple juice.	Combined spectroscopy data and augmented datasets with ML algorithms.	Achieved 98% classification accuracy.	Zhenchang Gao et al. [73]
IoT Systems with ML Integration	Predict spoilage of various food products.	IoT data analyzed via ML algorithms for real-time monitoring.	Achieved 92% accuracy, reducing spoilage risks.	K.B. Anusha et al. [74]
Neural Networks for Gas-Based Food Classification	Classify food as fresh or spoiled.	Neural networks analyzed resistance values from gas sensors.	Provided accurate spoilage detection.	Andrei Tămâian et al. [76]
Deep Learning for Meat Freshness Detection	Detect spoilage stages in chicken breast fillets.	Back Propagation Neural Networks and Linear-Support Vector Machines analyzed spoilage data.	High classification accuracy achieved.	Aftab Siddique et al. [75]
Mobile Applications for Real-Time Spoilage Monitoring	Develop consumer-friendly tools for spoilage detection.	Smartphone-based ML classifiers analyzed sensor data.	Achieved 98.8% accuracy.	Vakkas Doğan et al. [79]
IoT Frameworks with Adaptive Algorithms	Monitor environmental parameters affecting spoilage.	Adaptive Random Forest algorithms within IoT frameworks.	Scalability and predictive efficiency demonstrated.	Ahmed et al. 2022 [88]
CNN Models for Non-Invasive Quality Assessment	Monitor food freshness and quality.	Convolutional Neural Networks analyzed sensor and image data.	High reliability in spoilage prediction.	Sai Prasad Baswoju et al. [82]
Data-Driven Supply Chain Management	Reduce waste through predictive analytics.	Random Forest and XGBoost algorithms predicted spoilage likelihood and timelines.	Enhanced inventory management.	Paul Wunderlich et al. [92]

- Cloud-Edge Pipelines: Federated learning frameworks train global models on distributed IoT data (temperature, humidity) while preserving data privacy [105].

3) Blockchain-ML Integration: Decentralized ledgers timestamp sensor data validated by ML anomaly detectors (e.g., autoencoders), ensuring tamper-proof traceability in seafood supply chains [78].

V. COMPARATIVE ANALYSIS AND CHALLENGES

A critical evaluation of ML algorithms for food spoilage detection reveals trade-offs between computational efficiency, accuracy, and deployability. The Table II synthesizes these aspects, while subsequent sections detail domain-specific challenges.

Domain-Specific Challenges

A. Data Heterogeneity

- Sensor Variability: Differences in gas sensor calibration (e.g., MOS vs. electrochemical) and spectral sensor resolutions lead to inconsistent feature spaces, complicating model generalization.
- Environmental Noise: Fluctuations in lighting (for imaging) and ambient VOCs (for e-noses) introduce spurious correlations, requiring robust preprocessing (e.g., wavelet denoising).
- Labeling Inconsistencies: Subjective spoilage thresholds (e.g., "semi-fresh" vs. "spoiled") across studies hinder dataset interoperability.

B. Computational Constraints

- Edge Deployment: CNN/XGBoost models often exceed the memory and power budgets of IoT nodes (e.g., ARM Cortex-M4 devices with 256 KB RAM).
- Energy Costs: Training deep models on high-resolution hyperspectral data consumes 100 W/h, which is inconsistent with sustainability goals.

C. Interpretability and Trust

- Black-Box Decisions: Regulatory agencies (e.g., FDA) demand explainable spoilage predictions, but CNNs/ARFs lack intrinsic interpretability, delaying adoption in safety-critical applications.

TABLE II. COMPARISON OF MACHINE LEARNING ALGORITHMS FOR FOOD SPOILAGE DETECTION

Algorithm	Strengths	Limitations	Use Case	Performance Metrics	Optimization Strategies
CNN	Superior spatial feature extraction; Robust to translational invariance in images; State-of-the-art for visual spoilage detection	High computational load (GPU dependency); Requires large labeled datasets; Poor interpretability	Image-based fruit/vegetable grading [56,93] Accuracy: 92–98%; F1-score: 0.89–0.94	Model pruning, quantization, MobileNet architectures	
XGBoost	Handles missing/sparse data; Feature importance rankings; High speed on structured data	Overfitting on small datasets (¡1,000 samples); Limited to tabular data; Hyperparameter sensitivity	Microbial growth prediction in meats [71]; Food waste forecasting [92]	RMSE: 1.2 days; Accuracy: 98%	Early stopping, regularization (λ, γ), synthetic data generation
SVM	Effective in high-dimensional spaces; Robust to outliers; Versatile via kernel tricks	Kernel selection impacts performance; Scalability issues with large datasets; Memory-intensive for multiclass tasks	VOC classification using e-noses [103]; Spectral data analysis [101]	Accuracy: 85–89%; Precision: 0.88	Linear kernels for scalability, PCA for dimensionality reduction
Adaptive Random Forest (ARF)	Handles concept drift in streaming data; Parallelizable for distributed systems; Robust to noise	High memory footprint; Slower inference than static models; Complex hyperparameter tuning	Real-time IoT monitoring in supply chains [107]	Precision: 92%; Recall: 89%	Feature hashing, dynamic ensemble resizing
Logistic Regression	Simple, interpretable; Low computational cost; Stable with small datasets	Limited to linear decision boundaries; Poor performance on imbalanced data; Assumes feature independence	Binary freshness classification [109]	Accuracy: 82–85%; AUC: 0.79	SMOTE for balancing, polynomial feature expansion
BPNN	Flexible architecture (adaptable layers); Suitable for non-linear patterns; End-to-end training	Vanishing/exploding gradients; Slow convergence; Risk of local minima	Spectral spoilage staging in poultry [101]	Accuracy: 88–91%; MSE: 0.12	Batch normalization, Adam optimizer

- Stakeholder Skepticism: Farmers and suppliers distrust models trained on lab data, citing domain shift (e.g., controlled vs. field conditions).

D. Scalability and Integration

- Cross-Domain Generalization: Models trained on specific foods (e.g., poultry) fail on others (e.g., leafy greens) due to divergent spoilage biomarkers.
- Legacy System Compatibility: Integration with existing SCADA/WMS platforms requires API standardization, which is lacking in proprietary IoT frameworks [107].

E. Mitigation Strategies

Although CNN and XGBoost dominate current research, their real-world efficacy depends on addressing sensor noise, energy efficiency, and stakeholder trust, as shown in Table III. Hybrid approaches (e.g., CNN-SVM cascades) and lightweight edge AI frameworks offer promising pathways. Future work must prioritize reproducibility through open-source benchmarks (e.g., FSLab) and industry-academia partnerships to bridge lab-to-field gaps.

VI. COMPUTER VISION IN FOOD SPOILAGE DETECTION

Computer vision is a pivotal technique for analyzing food spoilage in both the food and agricultural sectors, as it evaluates external and internal quality attributes. External attributes, such as color, size, and surface texture, are assessed through image analysis, while internal parameters, including defects and texture, are detected using advanced techniques like X-rays and hyperspectral imaging [114]. A standard computer vision system typically includes a camera, a light source, image processing software, and a computer (Fig. 3). For hyperspectral or multispectral systems, additional components such as wavelength dispersion devices (e.g., spectrographs or filters) are required [115]. Since spoilage is often manifested as changes in color and texture, precise calibration of the light source is crucial to minimize software misinterpretation of normal versus defective produce.

The implementation of computer vision technology follows a systematic process:

1) Image Acquisition: Images of food products are captured using cameras or imaging devices.
2) Pre-processing: These images undergo enhancements like resizing [116], [117], noise reduction for X-ray images

[117], and transformations from RGB to alternative color spaces, such as Lab, to improve quality and ensure consistency [118], [119].

3) Segmentation: Segmentation techniques are employed to isolate individual objects, such as fruits or vegetables, for focused analysis. Techniques include thresholding, edge detection, and region-based methods.
4) Feature Extraction: Key features such as color, texture, and shape are extracted from segmented images. Some studies also incorporate statistical features such as mean and standard deviation for a comprehensive analysis [118].
5) Classification and Detection: Advanced algorithms analyze the extracted features to detect defects, anomalies, or discolorations indicative of spoilage. Deep learning models such as CNNs have become predominant in these tasks, supported by traditional machine learning algorithms such as SVM, Random Forest, KNN, Decision Trees, and Linear Regression [118] [119] [120] [121].

A. *Systematic Process of Computer Vision Technology*

Implementation of computer vision technology, as illustrated in Fig. 5, follows a structured approach:

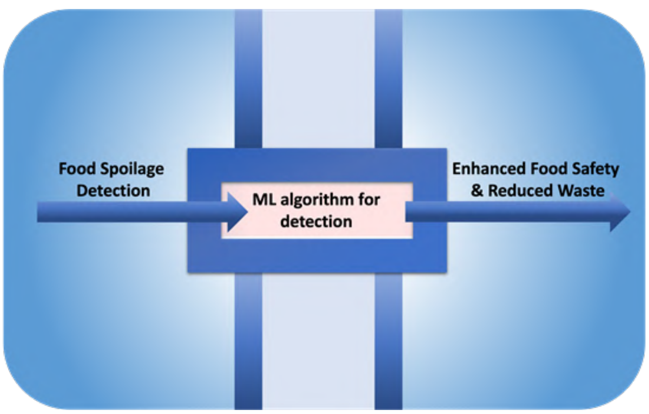

Fig. 5. Machine Learning-Based Food Spoilage Detection Framework

1) Image Acquisition: Images of food products are captured using cameras or imaging devices.
2) Pre-processing: These images undergo enhancements such as resizing [116], [117], noise reduction for X-ray images [117], and transformations from RGB to alternative color spaces, such as Lab, to improve quality and ensure consistency [118], [119].
3) Segmentation: Segmentation techniques are employed to isolate individual objects, such as fruits or vegetables, for focused analysis. Techniques include thresholding, edge detection, and region-based methods.
4) Feature Extraction: Key features such as color, texture, and shape are extracted from segmented images. Some studies also incorporate statistical features such as mean and standard deviation for a comprehensive analysis [118].
5) Classification and Detection: Advanced algorithms analyze the extracted features to detect defects, anomalies, or discolorations indicative of spoilage shown in Fig. 6. Deep learning models such as CNNs have become predominant in these tasks, supported by traditional machine learning algorithms like SVM, Random Forest, KNN, Decision Trees, and Linear Regression [118],[119],[120],[121].

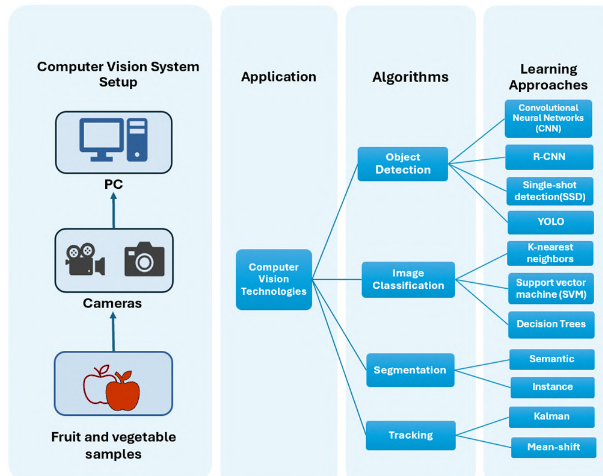

Fig. 6. A computer vision system application procedure. Systematic Process of Computer Vision Technology

B. *Advanced Methodologies in Computer Vision*

1) Pre-processing Techniques::

- Resizing: Standardizes image dimensions to ensure uniform input for algorithms [116], [117] .
- Noise Reduction: Enhances the clarity of X-ray images, particularly useful for detecting internal defects [117].
- Color Space Transformation: Converts images from RGB to Lab, which aligns more closely with human vision, facilitating better differentiation of spoilage indicators [118], [119].

2) Segmentation Techniques: Techniques such as thresholding and edge detection are used to isolate objects. Region-based segmentation is especially effective for analyzing grouped items, such as clustered vegetables.

3) Feature Extraction: Features like color (hue, saturation), texture (smoothness, roughness), and shape (roundness, irregularity) are analyzed. Statistical measures such as mean and standard deviation further enhance the detection accuracy [118].

4) Advanced Algorithms:

- Deep Learning Models: State-of-the-art models like ResNet and DenseNet have been deployed to improve classification and detection accuracy. Their architecture, leveraging residual learning and densely connected layers, outperform traditional CNNs in many tasks.

TABLE III. CHALLENGES AND TECHNICAL SOLUTIONS IN ML AND IOT FOR FOOD SPOILAGE DETECTION

Challenges	Technical Solutions	Industry Partnerships
Data Heterogeneity	Federated learning for multi-sensor data harmonization	Collaborate with sensor manufacturers (e.g., Figaro, AMS AG)
Computational Costs	TinyML frameworks (TensorFlow Lite for Microcontrollers)	Edge hardware vendors (Arduino, NVIDIA Jetson)
Interpretability	SHAP/LIME for model explainability	Regulatory bodies (FDA, EFSA)
Scalability	Transfer learning with domain adaptation (e.g., CORAL)	Cloud providers (AWS IoT, Google Cloud)

- Model Comparisons: Studies have shown CNNs to achieve higher accuracy compared to traditional machine learning models such as SVM, particularly in large datasets. Performance metrics such as precision, recall, and the F1 score further validate these findings.

5) Integration with IoT for Real-time Monitoring:

- IoT Sensors: Real-time data acquisition from IoT-enabled sensors, combined with computer vision algorithms, enables continuous monitoring of food quality.
- Data Fusion: Integrating data from multiple sensor types (e.g., visual, thermal, hyperspectral) enhances detection accuracy and provides a more comprehensive assessment of spoilage.

VII. ELECTRONIC NOSE

The AI protocols provide additional capabilities to rapidly test, identify and visualize complex data sets that could be associated with the generation of a broad range of analytes that stimulate the ripening or spoilage processes, or visual, mechanical and physical factors related to the changes in food in inappropriate storage conditions. In particular, one of the methods, so-called gas multisensory arrays or electronic noses (e-noses), enables us to identify spoiled stages according to gas/volatile molecule profiles related to bacterial or fungal metabolism in the food environment [122]. An electronic nose, or e-nose, is a device that mimics the operation of a mammalian olfactory system. It comprises an array of cross-sensitive sensors and an algorithm. An e-nose delivers a smell pattern, which is used to distinguish various, often complex smells. Here, for estimating the activities of microbial communities in the ripening and spoilage processes, the different volatiles associated with metabolism might be observed and detected by such sensing arrays. Particularly, the following volatile compounds were identified in the processes at the post-harvesting stages as spoilage markers:

1) Aliphatic biogenic amines such as putrescine and spermidine, released from spoiled meat [123, 124, 125].
2) Acids, alcohols, and sulfurous compounds as major metabolites of microbial fermentation [126, 127].
3) Volatile compounds associated with fungal production, including 2-methyl-1-propanol, 3-methyl-1-butanol, 1-octen-3-ol, 3-octanone, 3-methylfuran, ethyl acetate, 2-methyl-isoborneol, and geosmin [128, 129, 130].
4) Inorganic gases including H_2S and NH_3, related to high-protein food decomposition, as well as CO_2, CO, CH_4, and NH_3 [131].

The diversity of the spoilage markers demonstrates the complexity and labor intensity of their identification by standard analytical methods, e.g., GC-MS, due to complicated sample preparation and discrimination of individual analytes in the gas mixtures. Here, the combination of sensor array and AI protocol looks promising to minimize the sample preparation step and to help to interpret the output multidimensional data. Currently, E-nose applications in the food industry include the analysis of fruit and vegetable ripeness, spoilage or freshness evaluation, storage management [132], shelf-life management [133], and the detection of oxidation and environmental impacts. It is also used in food packaging, food production, and contaminant identification [134]. Other interesting applications are food processing and preparation [135]. Several reviews consider e-nose as a tool for food analysis [136, 137]. Some reviews evaluate spoilage, off-flavors, and fermentation [138]. A recent review by Mingyang Wang & Chen discusses existing commercial solutions, algorithms employed with e-noses, and highlights studies on freshness assessment of olives, kiwifruits, strawberries, and the drying and fermentation of green tea, garlic, ginger, and peppermint leaves [139]. The review also discusses the use of an e-nose in processing grapes and ginger, testing flavors of various fruits and vegetables like lemon, kiwifruit, pumpkin, zha-chili, and tomato, and the authenticity of crab apples. In most studies, metal oxide-based sensors have been used, with about 10 sensors in the array, up to 16, 18, or 32 sensors. Quality control is highlighted as an application for sweet potato, garlic, and olives. The authors discuss origin traceability and pesticide residue detection for apples, ginger, cherries, mint, and potatoes.

Additionally, studies on spinach, pepper, onion, and broccoli have been discussed in a review by H. Anwar, T. Anwar, and M. Sh. Murtaza [140]. They highlighted using e-noses for freshness/spoilage, selenite effect, cultivar difference, fungus detection, disease detection, variety differences, soft rot detection, classification as sweet or spicy, and treatment effect, indicating that many studies use self-made e-nose devices. Several reviews discuss fruit quality assessment and emphasize the importance of data fusion at different levels, such as combining e-nose and computer vision techniques [141 - 143].

Specifically, the e-nose has been used to evaluate the smell of green coffee [144] to address mycotoxins from Aspergillus spp. contamination. Numerous studies have focused on tomato spoilage, such as cherry tomatoes spoiled by fungi [145], and the detection of spoilage due to microbial contamination [146]. Fresh-cut green bell pepper (Capsicum annuum var. grossum) stored at 7 ± 1 °C [147] has been examined with an e-nose. These studies suggest that the pepper stays fresh for up to 5 days and spoils by the 7th day, particularly as evidenced by a surge in aerobic plate count and malondialdehyde content on subsequent days. The authors showed that the e-nose data combined with hierarchical cluster analysis (HCA) could distinguish between fresh (days 0, 1, 3, and 5) and spoiled (days 7 and 9) samples. The ripening and spoilage classification of green and yellow mangos has been achieved using a wireless electronic nose [148]. The microbial quality in edible seaweed was evaluated using FT-IR sensors, multispectral imaging, and e-nose [149]. A combination of methods is gaining popularity. For instance, an e-nose combined with GC-MS, sensory evaluation, and microbiological tests. Strawberries in food containers have been assessed using an e-nose, GC-MS, and sensory evaluation for edibility [150]. To reveal the potential relationship between the bacterial community and quality attributes of vacuum-packaged peeled potatoes, the bacterial community dynamics, visual quality, organic acids, flavor, and volatile organic compounds (VOCs) during 12 days of storage under 10° C were studied, and a correlation analysis was performed between the bacterial community and VOCs [151]. The effects of controlled atmosphere packaging with 3% O2 and 7% CO2 on changes in the nutritional quality, taste, and volatile compounds of fresh-cut cucumber caused by Pseudomonas plecoglossicida were studied by using electronic tongue, electronic nose, and gas chromatography-mass spectrometry [151]. The sensory quality and volatile profile of Spanish-style table olives inoculated with different strains of spoilage molds were analyzed using an e-nose. Pasteurized olives with brine were inoculated with nine spoilage mold strains: 1 strain of Galactomyces (G. geotrichum, G.G.2). 4 strains of Penicillium (3 P. expansum, P.E.3, P.E.4 and P.E.20; and 1 P. glabrum P.G.19). 3 strains of Aspergillus (A. flavus A.F.9, A.F.18 and A.F.21). 1 of Fusarium (F. solani F.S.11). Sensorial and volatile compound analysis showed the table olives inoculated with the strains of Aspergillus flavus A.F.18 and Penicillium expansum P.E.20 to be the most altered. E-nose, sensory analysis, and GC were used in this study [152].

Electronic nose was applied to successfully analyze varieties of fruits, edible and rotten, with 100% success of discrimination for New Hall oranges, Golden apples, Kiwis, and William pears, and with 97.2% success for the Starking apples [153]. It is suggested that without forming fruit variety subsets, discrimination between edible and rotten fruit was achieved with 95% success. Additionally, the aroma and spoilage of apples have been analyzed by detecting key compounds using gas chromatography and mass spectrometry. The differences were observed after 6 days of exposure to artificially induced damage in the form of a cut. The authors detected the differences in the volatile compounds between undamaged and damaged apples four or more days after the cut. Several cuts also had some effect on volatile compound emissions [154]. The spoilage of apples by Penicillium expansum was traced using enose, GC-MS, and correlated to HPLC quantification of patulin to develop a prediction model for patulin concentration in apples that can be used for apple juice, prediction of mycotoxin. In this study, the authors compared the results of the control sample with those treated by surface inoculation and core inoculation with P. expansum [155]. Also, regarding apple transportation and storage, Aspergillus niger, Penicillium expansum, Penicillium chrysogenum, and Alternaria alternata, were inoculated on apple samples [156]. An e-nose has been applied for quality testing of Royal Delicious apples by detecting pathogen contamination. This study revealed the presence of Staphylococcus, Salmonella, and Shigella bacteria species. GC–MS spectra of contaminated samples confirmed the presence of bacterial spoilage markers namely acetone, ethyl acetate, ethanol, and acetaldehyde [157].

The e-nose has been used for assessing the spoilage of bananas, peaches, carrots, and grapes operating at low temperatures, particularly in the refrigerator using a PCA – K Nearest Neighbors method [158]. Banana fruit spoilage has been tested [159]. An e-nose was applied for the detection of the freshness of carrot salad and the evaluation of the smell of rotting bananas [160]. Studying fungal contamination by an e-nose often includes inoculation. For example, peaches' storage was studied by inoculating with three common spoilage fungi, Botrytis cinerea, Monilinia fructicola, and Rhizopus stolonifera; then the peaches were stored for various periods [161]. Grape spoilage stages were investigated using infrared spectra of their volatiles and an e-nose [162]. A shelf-life considering outdoor aerobic storage has been tested for tomato puree-emitted gas samples with varying shelf life [163]. The freshness of kiwifruit, pork, and beef was tested with a sensor array [164].

While the e-nose is a self-sustained tool, studies have often combined various methods including GC-MS, sensory evaluation, microbiological analysis, metagenomics, and computer vision. Moreover, the current limitations of these devices are also interconnected to the capabilities to produce the identical sensors with low sensor-to-sensor variation [165], stability of sensor elements [166], sufficient selectivity towards the broad range of gas mixtures [167], and identification of individual volatiles [168].

VIII. Critical Analysis of Technological Limitations in Food Spoilage Detection Systems

The integration of advanced technologies into food spoilage detection has yielded significant progress, yet persistent challenges impede scalability, reliability, and adoption. This section critically evaluates key limitations across machine learning, sensor systems, and blockchain frameworks, supported by empirical evidence and contextualized within real-world constraints.

A. Machine Learning: Data Dependency and Computational Barriers

1) Challenge: ML models, particularly deep learning architectures like convolutional neural networks (CNNs), rely on extensive labeled datasets and high-performance computing resources. Overfitting risks escalate with small or imbalanced datasets, compromising generalization to diverse food types or environmental conditions.

2) Evidence: CNNs applied to fruit spoilage detection demand thousands of annotated images for robust training [93], while XGBoost models predicting microbial growth require structured datasets with precise microbial counts [71]. Resource-constrained settings often lack infrastructure for data acquisition (e.g., hyperspectral imaging) or GPU-powered computation.

3) Significance: These limitations disproportionately affect small-scale enterprises, widening the gap between experimental prototypes and deployable solutions. For instance, a CNN achieving 98% accuracy in lab-controlled environments may fail in field conditions due to dataset bias or hardware limitations [56].

B. Standardization: Methodological Fragmentation

1) Challenge: The absence of uniform protocols for data pre-processing, model evaluation, and performance reporting undermines reproducibility and cross-study comparisons.

2) Evidence: Studies on electronic nose (e-nose) systems report accuracy metrics ranging from 85% to 94% for similar spoilage tasks, yet discrepancies in gas sensor calibration, feature extraction methods, and validation splits obscure direct comparisons [103].

3) Significance: Methodological heterogeneity stifles consensus on optimal practices, delaying regulatory approval and industrial adoption. Standardized benchmarks, similar to ImageNet for computer vision, are urgently needed to harmonize research efforts.

C. Practical Deployment: Environmental and Operational Vulnerabilities

1) Challenge: Real-world environmental variability—such as fluctuating temperatures, humidity, and lighting—degrades sensor accuracy and model performance.

2) Evidence: In IoT-based frameworks, temperature shifts exceeding ±2°C introduce noise in gas sensor readings, reducing the precision of the VOC classification by 15% [105]. Similarly, computer vision systems for produce grading exhibit 20% accuracy drops under suboptimal lighting [56].

3) Significance: Such vulnerabilities erode stakeholder trust, particularly among farmers and logistics providers seeking consistent performance across diverse operational environments.

D. Computer Vision: Contextual and Technical Constraints

1) Challenge: Vision-based systems for food spoilage detection are constrained by their reliance on controlled imaging environments (e.g., uniform lighting, high-resolution cameras) and superficial visual features (e.g., color, texture), which often do not correlate with internal biochemical spoilage indicators such as pH changes or accumulation of microbial metabolites.

2) Evidence:

- Surface vs. Internal Spoilage: Although CNNs achieve 95% precision in detecting surface mold in strawberries under laboratory conditions [93], they do not identify internal spoilage in packaged meats or fruits (e.g. bacterial contamination in vacuum-sealed chicken breasts) without integrating X-ray or near-infrared (NIR) imaging [94].
- Dataset Scarcity: Publicly available food spoilage image datasets are limited to 10,000 annotated images across repositories like Kaggle and ImageNet, compared to 1 million images for generic object detection [110]. For example, the ”SpoiledFruits-1K” dataset contains only 1,200 images of apples and tomatoes, which is insufficient to train robust models for diverse produce [112].
- Environmental Sensitivity: A field trial in 2023 revealed that vision systems trained in laboratories suffered 25 to 30% accuracy drops when deployed in outdoor markets due to variable lighting (e.g., shadows, glare from sunlight) and occlusions (e.g., dirt, packaging wrinkles) [113].

3) Significance: This overreliance on external characteristics limits the applicability of computer visionputer vision to foods with non-visual spoilage(for example, shifts in dairy pH,e, shifts in dairy pH, fish biogenic amines). For SMEs, the high cost of auxiliary technologies such as hyperspectral cameras (20,000–20,000–50,000/unit) further exacerbates adoption barriers.

E. Electronic Noses: Stability and Maintenance Costs

1) Challenge: E-nose sensors suffer from drift due to environmental exposure, which requires frequent recalibration. Cross-sensitivity to nontarget VOCs further complicates spoilage detection.

2) Evidence: Metal-oxide semiconductor (MOS) sensors in e-noses exhibit baseline resistance shifts of 10–15% after 100 hours of operation, requiring weekly recalibration to maintain 90% classification accuracy [103]. Humidity variations ¿60% RH exacerbate false positives in meat spoilage detection [102].

3) Significance: Recalibration costs and downtime render e-noses economically unviable for small-to-medium enterprises (SMEs), which constitute 85% of global food suppliers [107].

F. Synthesis and Mitigation Pathways

While ML and IoT technologies hold transformative potential for food spoilage mitigation, their real-world impact hinges on resolving data quality, environmental robustness, and cost-effectiveness shown in Table IV. Prioritizing open-source toolkits for dataset generation (e.g., SpoilageNet), sensor fusion standards, and policy incentives for SME adoption will bridge these gaps. Future research must align with industrial pain points, ensuring technologies evolve from academic curiosities to field-ready solutions.

IX. Future Research Directions in Food Spoilage Detection and Supply Chain Management

The advancement of food spoilage detection and supply chain management requires multidisciplinary innovations across data science, sensor technology, and decentralized systems. Below, we outline critical research directions to address current limitations and enable scalable, reliable solutions.

A. Data Infrastructure Development

1) Standardized Dataset Creation: A foundational challenge lies in the scarcity of high-quality, diverse datasets. Future efforts should prioritize the development of open-access datasets encompassing varied food products, spoilage conditions (e.g., microbial growth, chemical changes), and environmental parameters (temperature, humidity). Standardized annotation protocols and metadata structures are essential to ensure cross-study reproducibility and benchmarking.

2) Unified Methodological Frameworks: The establishment of universal standards for data acquisition, preprocessing (e.g., noise filtering, normalization), and evaluation metrics (accuracy, sensitivity, computational efficiency) is critical. Harmonized methodologies will enhance comparability between studies and accelerate the translation of research into industrial applications.

B. Algorithmic Advancements for Edge Computing

1) Lightweight Machine Learning Models: Optimizing machine learning (ML) architectures for edge deployment—such as pruning, quantization, and knowledge distillation—can reduce computational overhead while maintaining accuracy. Prioritizing resource-efficient models (e.g., TinyML) will enable real-time spoilage detection on IoT devices, smartphones, and low-cost sensors, particularly in resource-constrained environments.

2) Hybrid Model Architectures: Integrating deep learning with traditional ML techniques (e.g., SVM, decision trees) or physics-based models may balance performance and interpretability. For instance, convolutional neural networks (CNNs) could extract spectral features from hyperspectral imaging, while simpler classifiers categorize spoilage stages, reducing inference time.

C. Multimodal Sensor Systems

1) Enhanced Electronic Nose (E-Nose) Technologies: Investments in advanced sensor materials (e.g., graphene oxide, metal-organic frameworks) could improve e-nose selectivity toward volatile organic compounds (VOCs) associated with spoilage. Concurrently, self-calibrating mechanisms leveraging reference gas chambers or onboard ML algorithms would mitigate sensor drift, enhancing long-term reliability.

2) Fusion of Sensing Modalities: Multimodal systems integrating computer vision (e.g., browning detection), gas sensors, spectroscopic analysis (NIR, Raman), and RFID-based temperature logs can provide holistic spoilage assessments. Cross-modal data fusion techniques, such as attention-based neural networks, may improve detection robustness in dynamic environments.

D. Blockchain-Enabled Supply Chain Traceability

1) Energy-Efficient Consensus Protocols: Transitioning from proof-of-work (PoW) to lightweight consensus algorithms (e.g., proof-of-authority, directed acyclic graphs) is crucial to minimize blockchain's energy footprint. This shift will enhance scalability for large supply chains while maintaining immutability.

2) AI-Driven Data Validation: Automated validation of sensor data—using anomaly detection models or digital twin simulations can ensure the integrity of blockchain records. Smart contracts may enforce predefined quality thresholds, triggering alerts for non-compliant shipments.

3) Privacy-Preserving Architectures: Hybrid blockchain designs (e.g., private sidechains for sensitive data, public chains for audit trails) combined with zero-knowledge proofs or homomorphic encryption will safeguard stakeholder privacy without compromising transparency.

E. Scalable Deployment Strategies

1) Cost-Optimized Hardware-Software Co-Design: Deploying spoilage detection systems at scale demands hardware innovations, such as paper-based microfluidic sensors or frugal spectroscopic tools, paired with optimized ML pipelines. Modular designs will allow customization for diverse food types and supply chain nodes.

TABLE IV. SYNTHESIS OF FOOD SPOILAGE DETECTION TECHNIQUES, INTERCONNECTIONS, AND ECONOMIC FEASIBILITY

Detection Technique	Key Limitations	Interconnections & Trade-offs	Scalability & Economic Feasibility
Machine Learning (ML)	• High dependency on large, well-labeled datasets. • High computational resource demands (e.g., GPU-powered computation). • Overfitting risks in controlled environments versus diverse field conditions.	• Can be fused with data from e-noses and computer vision systems. • Balances computational cost against compensating for sensor errors (e.g., e-nose drift).	• Extensive data and hardware requirements raise costs. • May not be cost-effective for SMEs without efficient or subsidized solutions.
Electronic Noses (E-Noses)	• Sensor drift due to environmental exposure. • Frequent recalibration requirements. • Cross-sensitivity to non-target VOCs.	• Provide real-time chemical detection that can complement ML predictions. • Integration challenges arise from the need to account for sensor drift.	• High maintenance and recalibration costs reduce viability for SMEs. • Increased downtime and labor costs hinder economic feasibility.
Computer Vision	• Reliance on controlled imaging conditions (e.g., uniform lighting, high resolution). • Limited to surface-level indicators; fails to capture internal spoilage. • Vulnerability to environmental variability.	• Often integrated with ML for enhanced feature extraction. • Requires supplementary technologies (e.g., hyperspectral or NIR imaging) which complicate system design.	• High costs associated with advanced imaging hardware. • Increased complexity limits deployment in uncontrolled, real-world environments, especially for SMEs.
Standardization & Methodological Uniformity	• Lack of consistent protocols for data preprocessing, calibration, and evaluation. • Hinders reproducibility and cross-study comparisons.	• Harmonized standards can facilitate the integration of ML, e-nose, and computer vision data. • Reducing fragmentation can mitigate trade-offs between high-tech approaches.	• Establishing standardized benchmarks could lower long-term costs. • Enhanced adoption potential for SMEs.
Practical Deployment in Field Environments	• Environmental variability (fluctuating temperature, humidity, lighting) impacts sensor and imaging performance. • Significant lab-to-field performance gap.	• All techniques are impacted by environmental challenges. • Integrated systems must address these external variables for robust operation.	• Robust, cost-effective solutions are essential for consistent performance in uncontrolled settings. • Overcoming environmental sensitivities is critical for scalable SME adoption.

2) Industrial Pilot Programs: Collaborative trials with food producers, retailers, and logistics providers are needed to validate system robustness under real-world conditions. Economic analyses should quantify waste reduction and ROI to drive adoption.

The comparative analysis of ML models for food spoilage detection highlights distinct strengths and limitations across methodologies. Convolutional neural networks (CNNs) and hybrid deep learning architectures (e.g., CNNs+LSTM) demonstrate superior accuracy (often ¿95%) in processing spectral or image-based data, such as hyperspectral imaging of microbial growth or produce browning. However, their computational complexity and reliance on large, annotated datasets limit deployment in resource-constrained environments. In contrast, traditional models like SVMs and gradient-boosted trees achieve moderate accuracy (80–90%) but excel in scenarios with limited data or low-cost hardware, particularly for time-series sensor data (e.g., pH, gas sensors). While deep learning models are promising for real-time, high-resolution spoilage detection, their practicality hinges on addressing critical challenges: mitigating data heterogeneity across food types, reducing computational costs for edge deployment, and improving interpretability for stakeholder trust.Addressing these priorities will require interdisciplinary collaboration among material scientists, data engineers, and supply chain experts. By advancing standardized datasets, efficient algorithms, resilient sensor systems, and secure traceability frameworks, the food industry can mitigate spoilage risks, reduce economic losses, and improve global food security. Future work must also consider regulatory alignment and stakeholder education to ensure seamless implementation.

X. CONCLUSION

This review article underscores the profound potential inherent in integrating advanced technologies—such as ML, electronic noses (e-noses), and computer vision for the detection of food spoilage. However, despite these promising advances, several critical challenges remain that may impede their real-world application, particularly for SMEs. A significant limitation is the high computational cost associated with ML models. Deep learning architectures, including CNNs, require extensive labeled datasets and powerful hardware, which not only increase the overall cost but also increase the likelihood of overfitting when models are developed in controlled laboratory settings. This inconsistency between laboratory performance and field robustness can lead to considerable prediction errors when deployed in environments characterized by variability in temperature, humidity, and lighting. Similarly, while e-noses provide rapid and non-destructive detection of spoilage through the monitoring of VOCs, their practical utility is constrained by issues of sensor drift and cross-sensitivity. The necessity of frequent recalibration to maintain detection accuracy introduces further operational costs and complexity. These factors collectively make e-nose-based systems less economically viable for resource-constrained SMEs, which constitute the backbone of the global food supply chain. In addition, the review highlights the lack of standardized methodologies in data acquisition, pre-processing, and performance evaluation. This methodological fragmentation not only complicates cross-study comparisons but also hinders the integration of complementary technologies. For example, while computer vision systems can detect external indicators of spoilage with a flair, they often fail to identify internal biochemical changes, necessitating a fusion with other sensing modalities. However, such integration introduces additional trade-offs in terms of cost, complexity, and scalability. In addition to these technical challenges, the ethical and operational ramifications of deploying blockchain for traceability must not be overlooked. Energy-intensive consensus mechanisms and data privacy concerns pose significant barriers to large-scale adoption in the food industry, where sustainability and cost-effectiveness are paramount. Meanwhile, computer vision frameworks, when combined with IoT sensors, create immutable records of environmental conditions, enhancing transparency and accountability across decentralized supply chains. In general, while advances in smart detection technologies have considerable promise in reducing food waste and improving food safety, their real-world impact will depend on the surmounting of these critical limitations. Future research should focus on developing lightweight and resource-efficient models, establishing unified protocols, and creating adaptive sensor fusion strategies that can operate reliably under diverse, real-world conditions. By addressing these challenges, the field can transition from academic prototypes to scalable and cost-effective solutions that meet the practical needs of the food supply chain.

ACKNOWLEDGMENT

This work was carried out with financial support from the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant AP19680157).

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