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Artificial intelligence for prediction of shelf-life of various food products: Recent advances and ongoing challenges

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Abstract

Background:

Accurate estimation of shelf-life is essential to maintain food safety, reduce wastage, and improve supply chain efficiency. Traditional methods such as microbial and chemical analysis, and sensory evaluation provide reproducible results but require time and labor and may not be suitable for real-time or high-throughput applications. The integration of artificial intelligence (AI) with advanced analysis techniques offers a suitable alternative for rapid, data-driven estimation of shelf-life in dynamic storage environments.

Approach and Scope:

The current review assesses the application of AI-based techniques such as machine learning (ML), deep learning (DL), and hybrid approaches in food product shelf life prediction. This study highlights how AI can be utilized to examine data from non-destructive testing methods like hyperspectral imaging, spectroscopy, machine vision, and electronic sensors to enhance predictive performance. The review also describes how AI-based techniques contribute to managing food quality, reduce economic losses, and enhance sustainability by ensuring optimized food distribution and reducing waste.

Key Findings and Conclusions:

AI techniques overcome conventional techniques by considering intricate, multi-sourced information capturing microbiological, biochemical, and environmental factors influencing food spoilage. Meat, dairy, fruits and vegetables, and beverage case studies illustrate AI techniques' superiority in real-time monitoring and quality assessment. It also identifies limitations such as data availability, model generalizability, and computational cost, constraining extensive applications. Cloud and Internet of Things (IoT) platform integration into future applications has to be considered to enable real-time decision-making and adaptive modeling. AI can be a paradigm-changing tool in food industries with intelligent, scalable, and low-cost interventions in food safety, waste reduction, and sustainability.

Key words: Artificial Intelligence, Machine learning**,** Food quality, Food products, Digitalization, Intelligent sensors

1. Introduction

Accurate prediction of the shelf life of food products is one of the most important concerns in the food industry worldwide for food safety,quality control and to maintain economic stability. With the increased demand for high quality food products with a long shelf life, there is a growing demand to practically and accurate predict when produce will expire (Cui et al., 2023). Food spoilage not only leads to considerable economic losses on the part of producers and retailers but also causes a lot of food to be wasted worldwide with associated negative environmental damage (Gao et al., 2020). It is estimated that up to 1.05 billion tonnes of food was lost across households, food services, and for retail it is approximately 132 kg per person per year (FAO, 2022). In this respect, the minimization of such losses, without compromising consumer safety, makes shelf-life prediction a very important topic for technological innovation.

Traditionally, food shelf life has been estimated using microbial analysis, chemical testing, and sensory evaluation (Marin et al., 2021; Shi et al., 2023). While these methods are effective, they are labor-intensive, time-consuming, and may not fully account for the dynamic environmental conditions, such as fluctuations in temperature, humidity, and microbial load during storage and transportation (Cui et al., 2023; Goyal et al., 2024; Cui et al., 2024). To address these challenges, mathematical models have been introduced to predict shelf life based on data obtained from either destructive or non-destructive analytical techniques. The reliability of these models depends heavily on the quality and precision of the analytical methods used for data collection. Destructive methods, including microbial culturing and chemical assays, provide highly detailed information but are impractical for real-time monitoring and large-scale applications (dos Santos Formiga and Júnior, 2024; Nguyen et al., 2024). In contrast, advanced non-destructive analytical methods such as spectroscopy, hyperspectral imaging, and electronic sensors, allow for real-time, high-throughput monitoring of food quality without compromising the integrity of the sample. These techniques provide comprehensive data on physicochemical changes in food, including microbial growth, biochemical transformations, and environmental influences, offering a more accurate and adaptable basis for predictive modeling. However, traditional mathematical models often rely on simplified assumptions that fail to fully capture the complexities of spoilage mechanisms, leading to potential inaccuracies in real-world applications (Gao et al., 2020; Marin et al., 2021; Cui et al., 2023). Therefore, integrating advanced analytical methods with artificial intelligence-driven approaches is essential to enhance the accuracy, scalability, and adaptability of shelf-life prediction, ultimately improving food safety, reducing waste, and optimizing supply chains.

Among the challenges in modeling and prediction, artificial intelligence (AI) has emerged as a potential solution, (Shi et al., 2023). AI can, through machine learning (ML) and deep learning, analyze large volumes of data and find patterns that may be hard to perceive under more traditional models (Wang et al., 2022; Lin et al., 2023). AI-based methods can include all kinds of variables including biochemical composition, conditions of storage, and microbial activity (Cui et al. ,2023). This capacity and predictive power make AI an ideal tool with which to understand with the very roots of food spoilage and extend shelf life.

AI techniques have great potential for food shelf-life prediction of a wide array of products, such as meat and poultry (Cui et al., 2024; Esposito et al., 2024; Saeed et al., 2025), dairy (Sunithamani et al., 2024; Golzarijalal et al., 2024; Wang et al., 2025), fresh fruit and vegetables (Goyal et al.,2024; Kanjilal et al., 2025; Zhang et al., 2025) and, soft drink and beverages (Harris et al., 2023; Gao et al., 2024; Zhou et al., 2024). Each of these categories was subject to different forms of spoilage mechanisms, which, in turn, are under the influence of specific environmental and biological factors. AI flexibility in modeling these variable parameters is yet another evident advantage over traditional methods in terms of gaining higher accuracy and efficiency (Chhetri, 2024).

AI application in predicting food shelf-life is a paradigm shift from traditional methods, with more accurate, real-time, and scalable predictions. Unlike traditional chemical and microbiological tests with high labor inputs and in many situations impossible in dynamic storage environments, AI-based models can evaluate enormous amounts of information from non-destructive analysis techniques and give rapid and adaptive predictions. This integration is very useful in food industries, as it maximizes shelf life to enhance quality control, reduce economic losses, and avert wastage of food (Cui et al., 2024; Zhang et al., 2025). Food wastage being a global issue with enormous environmental and economic implications, AI-based shelf-life prediction is a high-social value technological innovation. Through real-time monitoring and predictive evaluation, AI enables manufacturers, retailers, and consumers to make intelligent choices, reducing unnecessary disposal and ensuring food safety (Chhetri, 2024; Sunithamani et al., 2024; Saeed et al., 2025). This review particularly emphasizes AI's application in such a situation, systematically describing its potential, limitations, and future scope in reshaping food sustainability and supply chain management.

A number of reviews detailing the application of machine learning in food safety are available in the literature (Wang et al., 2022; Lin et al., 2023; Feng et al., 2023; Chhetri, 2024). However, no review (to the best of our knowledge) exclusively focuses on the application of AI in the prediction of shelf life in food products. The novelty of the manuscript is that it focuses on the integration of AI with advanced analytical methods, gives a critical review of AI applications across diverse food categories, and addresses critical challenges and future opportunities. Unlike other reviews, this article puts the focus on actionable insights for food-specific applications and shows the practical and transformative potential of AI for the food industry. This article reviews the potential for AI in the prediction of shelf life for food products. on the article will present some key AI approaches, together with their applications in smart systems like machine vision and spectroscopic techniques. This paper also presents AI applications across different categories of food and assesses the major economic and sustainability impacts. These sustainability impacts were addressed through examples in various case studies, such as the reduced wastage of fruits and vegetables due to accurate ripening predictions and energy savings in the meat industry through optimized refrigeration. It also considers contemporary challenges and limitations to the implementation of AI for shelf life prediction. The last section discusses the future directions of this approach and then outlines a vision of how this area of food shelf-life prediction will continue to evolve with AI.

2. Traditional methods for predicting shelf life

The traditional methods used to assess shelf life of food include chemical and microbiological analyses. The microbial growth studies have been the most instrumental since they monitor the increase of spoilage and pathogenic organisms with time. Bacteria, yeasts, and molds commonly act as spoilage indicators of foods (Chhetri, 2024). Parameters monitored to predict shelf life include lipid oxidation, protein degradation in meats and poultry (Saeed, et al., 2022), ethylene production and organic acid production in fruits and vegetables (Li, et al., 2024), lactic acid, pH, and acidity in dairy products (Freire et al., 2024) and alcohol content in beverages (Kyaw et al., 2024). Trained sensory panels regularly test at pre-defined intervals throughout the life cycle of the product. In most literature reviewed, it was stated that sensory methods require a large amount of operations and are costly to be run, hence they are usually less practical for routine use in large-scale shelf life prediction (Saeed et al., 2022; Cui et al., 2023; Chhetri, 2024). Although these techniques are highly valued in shelf life predictions, their dependency on periodical testing and specific markers affects their efficiency and adaptability to dynamic storage conditions. Within the past few years, various mathematical modeling approaches have been developed in order to enhance predictiveness and to account for the food spoilage complexity involving different circumstances.

Predictive microbiology models extend conventional microbial growth studies to develop mathematical relationships between microbial growth and environmental factors (Cui et al., 2023). Most predictive microbiology models make use of kinetic equations in predicting the trends of microbial growth, therefore, predictive microbiology models can be useful in evaluating how products will respond to different storage environments. Prediction of shelf life for various food products available in the literature use first-order kinetic and Weibull models to predict chemical degradation processes and microbial survival curves (Gao et al., 2020; Tuly et al., 2023; dos Santos Formiga and Júnior, 2024; Cheng et al., 2025). Empirical data has been analyzed using pathogen modelling methods, together with model predictions for several microorganisms. While these empirical models provide quantitative predictions, most of them are bound within the limited scope of data collected and decrease the generalisation of a model across variable conditions.

Although both empirical and kinetic models have a wide range of applications in traditional shelf life prediction, there are quite a number of limitations in their use. The most important of these is the dependency on historical data, specified for a product, which restricts generalization to new formulations or variable storage conditions(Bhagya Raj and Dash,2022; Shi et al., 2023). This is because most of them are based on fixed parameters that cannot fully capture diverse environmental and composition factors affecting spoilage. In addition, these models normally work on simplified assumptions like linear or exponential reaction rates-outside the real-world food systems in which most factors are dynamic in microbial interactions and interplay (Cui et al., 2023; Rashvand et al., 2023; Taiwo et al., 2024). Considering these limitations, novel approaches have been attracting more interest. Literature has shown that AI could overcome some of these constraints imposed by traditional methods toward faster, more adaptable, and perhaps more accurate predictions (Gonzalez Viejo and Fuentes, 2020; Wang et al., 2022; Harris et al., 2023; Yıkmış et al., 2024; Zhang et al., 2025).

Interactions among microorganisms, such as competition, synergy, and antagonism, are very prominent and can affect the dynamics of food spoilage and thus the accuracy of predictions (Dantigny, 2021; Cui et al., 2023). Cui et al . (2023) stated competitive interactions between bacteria and fungi may alter spoilage rates because some bacteria act to inhibit fungal growth or vice versa. There can also be synergistic interactions whereby metabolic by-products of one microorganism provide favorable conditions for the proliferation of another, accelerating spoilage. These complex dynamics, thus, are an illustration of constraints on developing traditional models of microbial growth in their descriptions, since such models often involve assumptions of one single dominant organism.

Yeast, mold, and bacteria differ in characteristics that affect spoilage and hence the prediction of spoilage, its accuracy, and the approach to it (Dantigny, 2021). Yeasts cause spoilage in foods high in sugar or acids. They form volatile compounds and can be detected with intelligent sensors such as spectroscopy devices. Molds are aerobic and dominate in drier environments; they are often found on fruits, vegetables, and cheese. They also produce spores and secondary metabolites including mycotoxins, which have a bearing on safety and shelf life. Snyder et al. (2024) reported bacteria represent the most important spoilage agents in high-moisture foods. Rapid growth under favorable conditions often makes them the focus of traditional predictive methods. This justifies using advanced models of AI that are better positioned in handling such multi-dimensional data and interactions. Real-time data on microbial communities' interactions can be fed into AI methods for more robust, more accurate predictions under natural conditions.

Figure 1 represents the overall frame of foods' shelf-life assessment and prediction as a function of various factors, indicators, and modeling techniques. The progress of freshness quality indicator (FQI) could be described as a function of time, passing through a stochastic path depending on the environmental conditions, until it crosses a failure threshold corresponding to the conclusions of shelf life. This is the maximum acceptable level beyond which quality degradation was no longer acceptable and defines remaining shelf life from any given observed point (Chen et al., 2023). In addition, the figure indicates that ecological factors like temperature, illumination, humidity, and gas concentration drive the chemical reactions and microbial growth on meats that constitute spoilage. Shelf life was monitored by sensory, physicochemical, and microbiological indices that assessed critical thresholds of quality deterioration and established predictive shelf life models (Ren et al., 2022). Advanced statistical and kinetic models, such as zero-order kinetics and Arrhenius equations, were applied to understand dynamics in quality variation with time. The most accurate prediction of shelf-life could be achieved by an integrated model combining statistical models, quality dynamics models, and algorithms from AI for capturing complex interactions among the multiple factors

(Cheng et al., 2025). This integrated modeling approach will support quality management and, therefore, will allow producers to monitor the shelf life of various perishable foods more precisely and predict and extend it.

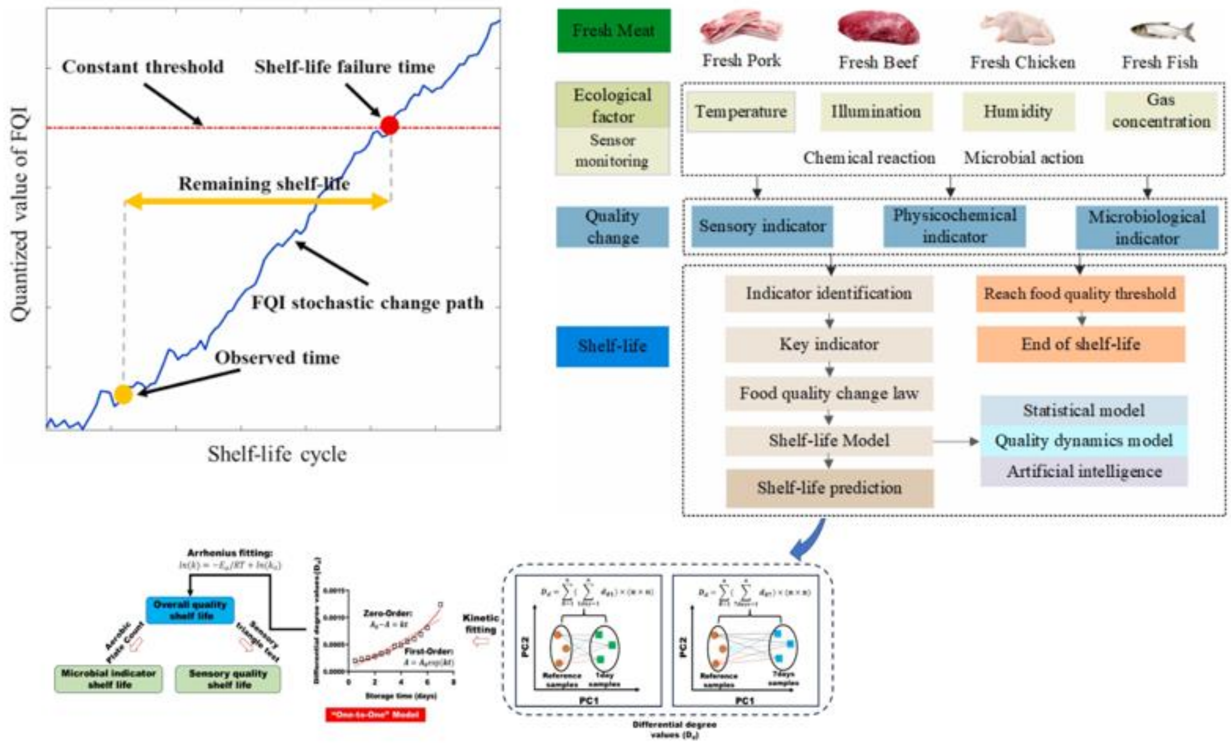

Figure1. Integrated framework for shelf-life prediction and quality assessment of food products using ecological factors, quality indicators, and advanced modeling techniques (Reproduced from Ren et al., 2022; Chen et al., 2023, Cheng et al., 2025).

Similar to meat products, respiration is a critical factor in the shelf life of plant-based products because it is among the fundamental metabolic processes in fruits and vegetables after their harvest. Pieczywek et al. (2024) and Yin et al (2024) demonstrated that the process of respiration includes degradation of stored carbohydrates and other substrates by cellular biochemical transformations to produce energy, which will be dissipated as carbon dioxide, water, and heat. This is very dependent on temperature, humidity, and the concentration of oxygen. Overall, literature have combined information on respiration rates with numerical modeling, using environmental conditions and alterations in metabolic activities to make better predictions in plant-based commodities (Wang et al., 2021; Rashvand et al., 2023, Yin et al., 2024).

3. Fundamental of Artificial Intelligence methods for shelf life prediction

The accuracy and reliability of AI models for shelf-life prediction are highly dependent on the quality of data generated by analytical methods. Advanced analytical techniques play a crucial role in ensuring that the data fed into AI systems are precise, reproducible, and representative of real-world conditions. Inaccurate or low-quality data can lead to flawed predictions, underscoring the need for selecting superior analytical approaches that consistently provide reliable information across various food categories and storage environments (Eş and Khaneghah, 2024). Both destructive and non-destructive analytical methods contribute significantly to AI-driven shelf-life modeling. Non-destructive techniques, such as hyperspectral imaging and Raman spectroscopy, enable real-time monitoring of food quality by capturing biochemical and structural changes without damaging the samples, making them ideal for continuous assessment and industrial applications. In contrast, destructive methods, including microbial enumeration and chemical assays, offer highly precise and detailed measurements of spoilage indicators but are invasive and impractical for large-scale or real-time monitoring. A comparative discussion of these techniques will be presented in the following sections, highlighting their respective advantages and limitations in enhancing the predictive power of AI-based shelf-life estimation.

Besides this, the features extracted by such analytics methods, which are relevant in nature, such as the production of ethylene in fruits or variations of pH in dairy products, must be strongly related to the variation in shelf life if the AI models are to provide practical predictions.ML is a powerful tool capable of handling enormous data volumes include food chemical composition, storage temperature, humidity, and non-destructive evaluation sensors for highly accurate predictions of product shelf life(Çetin et al., 2022; Do et al., 2024; Haghbin et al., 2023). Various traditional and novel ML models have been developed and applied in the food industry. The traditional ML models usually require structured and hand-engineered features, interpretable, and suffer from high-dimensional and unstructured data. While deep learning has been designed to automatically learn feature representations from raw data using multiple layers of computation, performing exceptionally well on unstructured data like images (Chen et al., 2023). The key difference lies in their complexity and feature extraction. While classical machine learning involves manual feature engineering, deep learning models learn from raw data hierarchically and are hence flexible but, at the same time, computationally expensive. However, some of them have been utilized in the shelf life prediction of food product. In the following, common models that have been applied and developed in the literature were described.

3.1. Traditional machine learning

3.1.1. Linear models

Linear models consist of Multiple linear regression (MLR), Generalized linear models (GLM) and Partial least squares regression (PLSR). These algorithms are well-suited for straightforward, structured datasets, such as those obtained from chemical analysis. For example, MLR has been effectively applied to correlate shelf-life indicators in dairy products where relationships between features and outcomes are largely linear (Golzarijalal.et al., 2024). However, these models fall short when non-linear interactions such as microbial growth dynamics, or high-dimensional datasets are involved. MLR is a widely applied regression method assuming a linear relationship among predictors and the response variable. Since MLR illustrates how changes in the predictors influence the dependent variable by fitting a linear equation to the observed data, MLR models are straightforward to implement and interpret the linear relationships between the variables. MLR has been applied to correlate quality data with the shelf life indicators for a variety of food products(Çetin et al., 2022; Dulger Altıner et al., 2024). However, some of the drawbacks to MLR models are non-linearity, inflated standard errors, unstable coefficient estimates, and overfitting to the data.

GLM extend traditional linear regression to accommodate a wider range of data types and distributiosn that might not follow a linear relationship. They can modelvarious probability distributions for the dependent variable and therefore can be modeled with a variety of link functions such as an identity link in normal distribution, a logit link in binomial distribution, and a log link in Poisson distribution. According to Çetin et al. (2022) and Nturambirwe and Opara (2020), this was indicative that GLMs could become flexible in correlating a variety of data types. They also provide a unified framework for various regression models such as linear regression and logistic regression . However, the interpretation of coefficients in GLMs is less intuitive on many aspects when compared to linear regression analysis (Fan et al., 2019).

PLSR is designed to model the relationships of independent and dependent variables and this method is considered an efficient tool in both dimensionality reduction and predictive modelling (Ren and Sun, 2022). PLSR build upon the extraction of new latent variables that are highly correlated with the dependent variables such that this approach is particularly useful when the number of predictors is large and highly collinear or for the case when the number of observations is smaller than the number of predictors. It is such challenges that are quite common in datasets that are intrinsically complex, which also relates to datasets associated with predicting the shelf life of food items (Çetin et al., 2022; Goyal et al., 2024; Jiang et al., 2023; Pieczywek et al., 2024; Sharma et al., 2023). It has also been observed a number of times that PLSR had the tendency to overfit when dealing with highly complex models or small datasets, because it works on maximum covariance between the variables rather than pure prediction accuracy. Therefore, the other developed ML methods in this regard have been preferred by researchers (Xiao et al., 2024; Shao et al., 2024; Francis et al., 2025).

3.1.2. Decision trees (DT) and random forests (RF)

DT and RF algorithms are exceptionally good at dealing with diverse data from multiple sources, such as sensory, microbial, and environmental information. RF is much more effective on fruits and vegetables whose spoilage depends on several related factors, which interact with one another, such as those related to the production of ethylene, temperature, and moisture (Goyal.et al., 2024; Kanjilal et al., 2025). RF even prevents overfitting, enabling its application in real conditions. However, DT and RF are computationally intensive when dealing with extensive datasets, considering that optimization is necessary in such cases. DT operate by recursively splitting data into subsets based on their input features and makes a tree-like structure of decisions. In regression tasks, the model predicts the character of the new incoming data point by navigating the tree starting from the root node down to a leaf node (Hassan et al., 2024). RF is an ensemble learning method based on many decision trees to boost the accuracy of models and reduce overfitting. The methodology ensembles multiple decision trees to yield a more generalizable model. RF improves general model accuracy and robustness by averaging the predictions in the case of regression tasks or via a majority vote in case of classification tasks.

One of the key strengths of decision trees is their interpretability. Nturambirwe and Opara (2020) and Palumbo et al. (2024) mentioned that the model structure gives one obvious visual information about how the model makes decisions, thus, it becomes easily understandable. Furthermore, applied DT are good at describing complex and nonlinear relationships between data without any need for transformation of features, normalizing, or scaling. By nature, they are versatile in handling continuous and categorical data, hence suitable for a wide range of datasets (Çetin et al., 2022; Do et al., 2024; Nturambirwe and Opara, 2020; Palumbo et al., 2024; Sharma et al., 2023). On the other hand, DT and RF are prone to overfitting by the training data, especially in DTs with deep tree structures. Oliveira Chaves et al. (2023) found that with just a little change in the data, sometimes quite dramatic changes in the tree structure would result, meaning it was a less stable model. Therefore, RF reduces the risk of overfitting by taking an average of several decision trees' predictions and is less sensitive to outliers and noisy data; hence, they have the capability to handle large datasets with high-dimensional feature space(Oliveira Chaves et al., 2023; Goyal et al., 2024; Kanjilal et al., 2025).

3.1.3. Support vector machines (SVM)

SVM are supervised ML algorithms applied to establish regression models. The major goal of SVM is to find a decision boundary, normally referred to as the hyperplane, which splits various classes within data with maximum separation. Different from the other algorithms, which apply all data points to create decisions, SVM relies solely on the data points that might be closest to the decision boundary or hyperplane (Wang et al., 2022). For this purpose, it is highly suitable for nonlinear data, generally obtained in the spectroscopy or sensor-based analysis of volatile organic compounds in meat and poultry products (Esposito et al., 2024; Liang et al., 2024). The computational performance of SVM greatly depends on the choice of kernel-for example, radial basis function-that involves adapting kernel selection to fit the complexity of the dataset. Although highly accurate, SVM suffers from high computational cost with large datasets, hence presenting limitations to real-time applications. Manthou et al. (2020) demonstrated that it was computationally more efficient and more robust to outliers, hence, possibly reducing overfitting. Further, Manthou et al. (2022) and Haghbin et al. (2023) applied different kernel functions for SVM, which can handle both data of linearly and nonlinearly separated classes; it is thus flexible for most calibration modeling tasks. One of the disadvantages of SVM presented in the literature was that the performance of the SVM depends on the choice of the kernel and associated tuning of the kernel parameters. Besides, the computational load of an SVM increases with dataset size, hence not always suitable for the analysis of large datasets (Çetin et al., 2022; Huang et al, 2023; Jiang et al., 2023;Nturambirwe and Opara, 2020).

3.2. Deep learning and neural networks (NNs)

3.2.1. Multilayer perceptron (MLP)

MLPs can be considered one of the most used neural network architecture types in both classification and regression. Typically, MLP have more than three layers of nodes that are fully connected to each subsequent layer. Shi et al. (2023) and Deng et al. (2024) fully described the basic architecture of an MLP. The learning process in an MLP occurs through backpropagation and gradient descent. During the process of training, internally, the MLP adjusts internal parameters like weights and biases by going forward with every step of the training data, computing loss and backpropagation so that for every MLR, the error between predicted and actual outputs gets minimized. MLP can be configured with respect to nonlinear relationship modeling. Moreover, works done by Anwar et al. (2023), Shi et al. (2023), and Karimi, (2025) have documented that this increase in the number of hidden layers gave the chance for an MLP to made deep representations of features that enhanced its generalization to new unseen data. The addition of more hidden layers however carries an added risk which could result in overfitting of MLPs against a training set. Training MLP is often a resource intensive process that always requires high processing and memory. In addition selecting the optimal hyperparameters of the model is often time-consuming and use methods such as grid searchers (Do et al., 2024; W. Huang et al., 2023; Jiang et al., 2023).

3.2.2. Recurrent Neural Networks (RNN)

RNNs represent a class of ANNs which was specially designed to process sequential data. Unlike the traditional feedforward neural networks, such as MLP, these process their inputs independently. RNNs consist of directed cycles and this architecture can process any input sequences in a step-by-step manner (Nayak et al., 2020; Ma et al., 2024). Such architectures will possibly allow information to be kept over time and the information from the previous inputs is preserved, hence, the best-suited applications for RNNs include time-series forecasting tasks. Dhiman et al. (2021) and Kanjilal et al. (2025) evaluated a general-purpose multi-fruit system for the quality assessment of fruit by applying a recurrent neural network. They realized that in RNNs, the hidden state was a sort of memory that got updated at every input, and each hidden state at every time step got revised.

3.2.3. Convolutional neural networks (CNN)

The CNN is a special kind of neural network used to process data with grid-like topology. In particular, image and spectra data come as two important means of the effective prediction of shelf life. With the ability to detect significant features from raw input data using a convolutional filter, CNNs do an extremely good job in the identification of spatial patterns such as edges, textures, and shapes in images, hence being very powerful in performing tasks which concern visual data (Shi et al., 2023; Cui et al., 2023). While traditional feed-forward neural networks form the basis for a CNN, the convolutional layer applies a set of filters to the input data. For that reason, the researchers applied ANN, FNN, and CNN and then selected the best topology for use in their model to predict shelf life (Wu et al., 2022; Nayak et al., 2020; Goyal et al., 2024). CNN consists of an element-wise product of a filter with a portion of the input data, followed by a sum of products. Each filter then slides over the input data detecting specific features such as edges, corners, and textures. This process is repeated as the filter moves across the entirety of the input, thus creating a feature.

Figure2 illustrated a comparison of the architectures of classical ML and DL, with the main methods in both. In Figure2a, the procedure of regression by SVM was presented, where a hyperplane could optimally predict with regard to features for a certain item. Critical data points near the decision boundary in that hyperplane were marked as support vectors. Single DT model represents the split of data at each internal node based on features, tracing down the tree through branches to leaves, and giving the final output of regression by majority voting or averaging, whichever applies (Figure2b). This concept is extended in Figure 2.c to an ensemble of such trees, where multiple trees are making independent estimates for a dataset, the final prediction being given by majority vote among the results of these individual trees, further enhancing robustness (Lin et al., 2023). Figure 2d depicts an RNN with an input x< t > as a time-series flowing into time-step-dependent hidden layers to model in temporal relationships (Dhiman et al., 2021). Figure 2.e shows a feedforward neural network architecture with input, hidden, and output layers was defined; neurons will be interconnected and process inputs via weighted summation and activation functions. Figure 2.f shoes spectral-spatial feature learning in CNN - based models, for hyperspectral image analysis (Wang et al., 2024). Features were first extracted by convolutional filters in the layers and then the attention mechanisms sharpen both the spatial and spectral representations. These subfigures together present the evolution from the classical ML model to state-of-the-art deep learning architectures. These are suited to different levels of complexity and types of data.

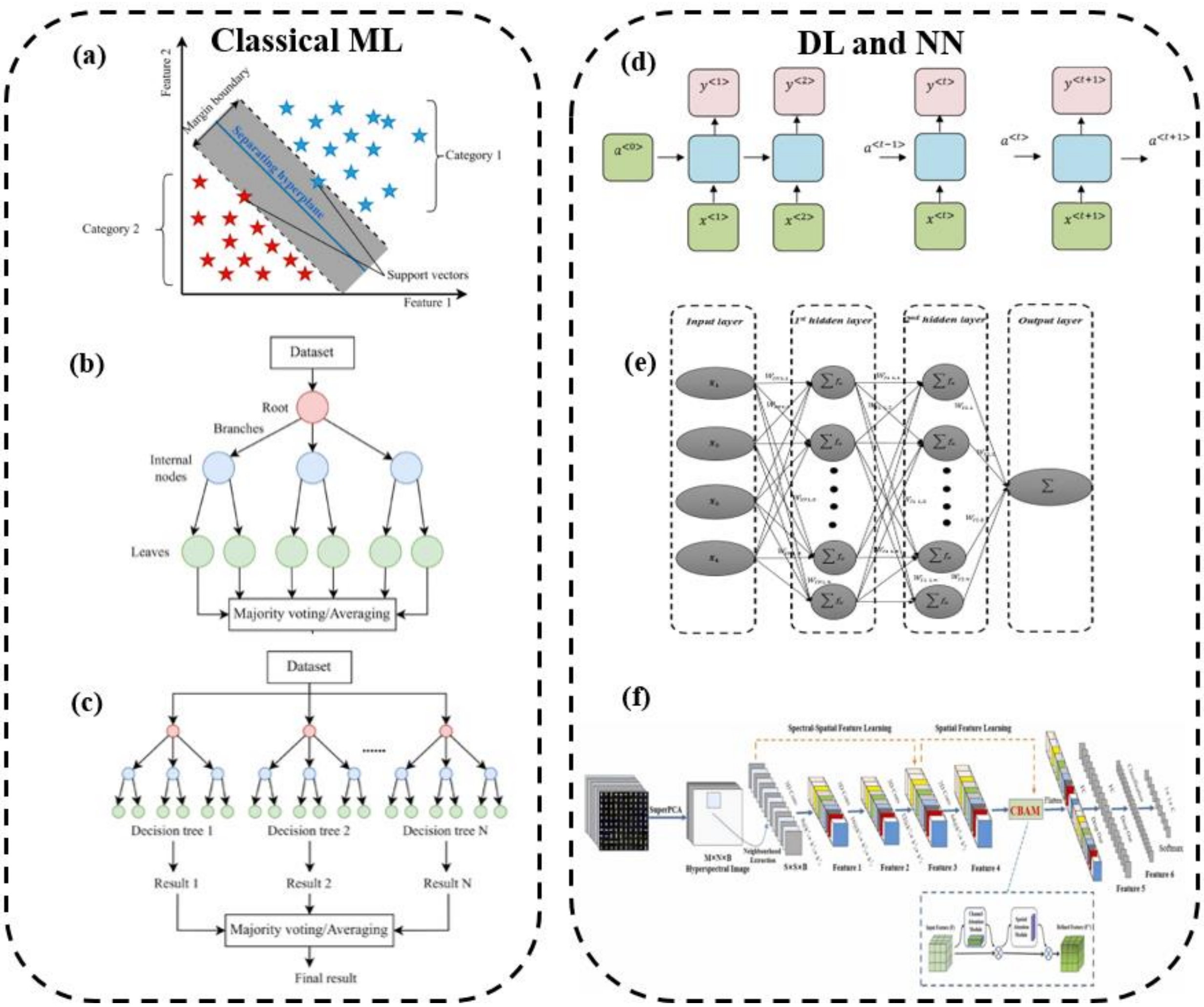

Figure2. Comparison of Classical Machine Learning and Deep Learning Architectures: (a) Support Vector Machine (SVM) classifier illustrating decision boundary and support vectors; (b) Decision Tree model with hierarchical data splits; (c) Random Forest ensemble model combining multiple decision trees for robust prediction (Reproduced from Lin et al., 2023); (d) Recurrent Neural Network (RNN) for sequential data processing (Reproduced from Dhiman et

al., 2021); (e) Feedforward Neural Network with multiple hidden layers; (f) Convolutional Neural Network (CNN) (Reproduced from Wang et al., 2024).

3.2.4. Transfer learning (TL)

TL involves transferring knowledge gained from a source task to a new target task where limited data and computational resources exist. In fact, it aims at exploiting a model already developed for a particular task in performing well on another related but different task (Deng et al., 2024). This would be really useful in applications because training a deep neural network right from scratch would be computationally prohibitively expensive, or even impossible, given that there is no large labeled dataset available. Similar transfer learning was done by Kim et al. (2022) and Razavi et al. (2024) for predicting the shelf life and quality of egg and rice, respectively. They explained that through transfer learning, pre-trained models allow the reuse of features and representations previously learned, hence enhancing performance while reducing training times and data size.

3.2.5. Hybrid models

In addition to MLP, RNN, CNN, and transfer learning, which are widely used, other identified ANN architectures include radial basis function neural networks, autoencoders, and generative adversarial networks, all of which have great potential for application in predicting product quality and shelf life. These algorithms may provide higher prediction accuracy and faster convergence in predications regarding the shelf life of food (Haghbin et al., 2023; W. Huang et al., 2023). Hybrid models generally refer to the integration of two or more different algorithms into ML; in this way, the strengths developed with one approach complement the weaknesses found in another, and a more robust system is achieved. Hybrid models come into play especially when the performance by mono-models turns out to be unsatisfactory. Hybrid models combine algorithms in both parallel and/or sequential ways (Huang et al., 2023).

4. Data processing and model development

4.1. Data Collection and Processing

Data collection and exploratory data analysis are the first step of any ML model development aimed at shelf life prediction, as they have an impact on the further quality and relevance of data input for model training and optimisation. Some ML methods may also require different types of input data, such as historical shelf life, environmental factors, intrinsic product characteristics, and conditions of packaging(Wang et al., 2022; Lin et al., 2023). It is observed from the literature that in traditional ML, data collection mostly focuses on key predictive features such as time-temperature abuse and microbial counts obtained from experimental studies and controlled laboratory conditions (Gonzalez Viejo et al., 2018; Zhang et al., 2022; Ren et al., 2023; Yıkmış et al., 2024). Furthermore, Yudhistira et al. (2024), Liao et al. (2023), Cui et al. (2024), and Esposito et al. (2024) applied preprocessing methods including feature standardization or normalization to ensure that all features were on a comparable scale, making them suitable for models sensitive to feature scale.

Advanced ML techniques, such as neural networks and ensemble methods, require more sophisticated data quality and preprocessing since they are able to process complex nonlinear relationships among the input data (Ma et al., 2024). Most researchers outlook for capturing such subtle patterns, which could not be identified with simple models, these advanced ML algorithms had to be fed with large datasets. It was the sensor and IoT-generated data that provided real-time updates on the existing storage conditions and spoilage indicators(Nayak et al.,2020; Bhagya Raj and Dash, 2022; Shi et al., 2023; Ma et al., 2024). Further, it was the resultant sensor and IoT-generated data which provide real-time updates regarding existing storage conditions and spoilage indicators. Wu et al. (2022) applied convolution neural network combines with long short-term memory NN methods for predicting the shelf life of salmon with fluctuating temperature. Current microbial kinetic equations could predict freshness for certain conditions where temperature was fixed; once the temperature fluctuated, they became ineffective. They employed deep learning to determine the inherent relationship of variable temperature during storage and proposed a new model called CNN_LSTM. Overall, every ML technique therefore demands a specific process for data collection and treatment pertinent to their specific requirements as documented in the literature (Ropelewska and Noutfia, 2024; Pieczywek et al., 2024; Cheng et al., 2025; Francis et al., 2025). Using preprocessed, engineered, and augmented data, researchers were confident that robust models of shelf life prediction emerged on a variety of food products and diverse storage environments could be achieved.

4.2. Model training and validation

Model training and validation include some of the key steps involved in the process when a ML model is developed to create an effective prediction model for food shelf life. Data partitioning, hyper-parameters tuning, and model performance evaluation are required for model reliability and generalizability (Lin et al., 2023). linear regression, DTs, and SVR perform training, usually by the selection of the most informative features from those that best correlate with shelf life, and optimization of model parameters in order to minimize the prediction errors (Huang et al., 2023; Rong et al., 2024; Liao et al. 2023; Gonzales Viejo and Fuentes). Harris et al. (2023) tried hyperparameter tunning with the purpose of making sure that the model was well-calibrated against the datasets by using methodologies such as a Grid Search or a Random Search.

Also, complex optimizers can be applied together with regularization techniques in the training process of deep models to avoid overfitting, according to Nayak et al. (2020), Dhiman et al. (2021), and Ma et al. (2024). K-fold cross-validation in this context was used quite a lot for performing both types of cross-validation in order to make sure each subset of data was used both as a train and a test set to make the model more generalizable by testing across a variety of parts of the data.

Performance metrics in general add up model structure and target objectives. When comparing this to the conventional ML model used by Liao et al. (2023), Yıkmış et al. (2024), and Esposito et al. (2024), very simple-type metrics were measured in these approaches. Additional verification of predictive validity was also pursued inside the derived models in the literature regarding performance measures characterized by values like R-squared, precision and recall, and F1-score (Bhagya Raj and Dash, 2022; Ropelewska and Noutfia, 2024; Francis et al., 2025). The extant literature further tends to suggest that robust and transferable models must entirely exploit the available validation metrics and techniques. In detail, training, tuning, and validation for each model type may provide the researchers with an ability to produce an accurate and robust model for shelf-life prediction suitable for a wide variety of foods and conditions.

5. Intelligent systems

5.1. Machine vision

Machine vision has been one of the most widely applied techniques to predict the shelf life of various food commodities, mainly based on changes in color, texture, shape, and surface of the commodity over time, as captured by any form of imaging technique. In meats and poultry products, machine vision displays color and surface texture changes that were associated with microbial growth and shelf life (Sánchez et al., 2023; Albano-Gaglio et al., 2025). It is possible for vision systems to detect parameters of shelf life for fruits and vegetables, including ripening, bruising, decaying, by imaging the external color shifts and surface deformation (Goyal et al., 2024; Shanthini et al., 2025). In the case of dairy products, machine vision helps monitor mold growth and discoloration(Bosakova-Ardenska, 2024; Loddo et al., 2025). These visual features, when processed through ML models, suggest effective non-destructive ways of predicting shelf life across a wide range of food categories as documented in scientific studies.

Applications of machine vision systems can be automated for many uses to realize high-throughput assessments in real-time environments like production lines in various food industries. However, these have been limited in real world application due to varied lighting conditions, noise in the background, and the complexity of product textures(Saeed et al., 2022; Oliveira Chaves et al., 2023; Peveler, 2024). The same type of food products comes in a variety of shape, size, and color, which introduce inconsistencies that have to be preprocessed extensively in order to calibrate the model for reliable results. Sánchez et al. (2023), Goyal et al. (2024) and Loddo et al. (2025) worked on the prediction of shelf life of beef, tomato and cheese, respectively and they identified inconsistencies problem with the computer vision system coupled ML. They indicated, that although machine vision worked quite well for external changes in quality, it was inadequate to point out internal spoilage indicators that did not show up as visual features, such as the chemical changes in the case of beef or even microbial growth in cheese, hence necessarily needing other complementary techniques such as spectroscopy for a more holistic prediction model.

5.2. Spectroscopy devices

Spectroscopic methodologies span a wide application domain in the prediction of the shelf life of food products, considering their measurement is based on changes in chemical and molecular composition related to spoilage. Near infrared spectroscopy (NIR) has been used for the detection of protein degradation, lipid oxidation, and microbial growth-all factors to explore food freshness and shelf-life determination(Gonzalez Viejo et al., 2018; Bisutti et al., 2024; Albano-Gaglio et al., 2025). While Raman spectroscopy is effective in monitoring the oxidation of lipids and degradation of proteins, measurement of acidity and sugar content increases, among other changes in compositions, can also indicate the shelf life status of foods. This makes it a versatile tool in several other food categories(Campos et al., 2024; Zhao et al., 2025). Other spectroscopy methods such as Fourier Transform (Gao et al., 2024), Mid-Infrared (Lan et al., 2022), fluorescence (Venturini et al., 2024), ultraviolet (Joshi et al., 2022), electrical impedance

(Huang et al., 2023) and hyperspectral imaging (combining computer vision and spectra data) (Francis et al., 2025) has been coupled with ML to predict the shelf life of various products.

These methods have some drawbacks when it comes to food shelf life prediction. A major limitation that spectroscopy methods had in the past was the fact that they dealt with very complex data, requiring advanced preprocessing. Baseline correction, de-noising, and normalization were required for the removal of variabilities brought about either by sample variability and/or environmental conditions using techniques such as Savitzky Golay algorithm (SGA) and Standard normal variate (SNV) used by Lan et al. (2022), Bisutti et al.(2024), Venturini et al. (2024), and Zhao et al. (2025). In these regards, another important factor that influences the measurement outcomes is related to the fact that spectroscopic equipment is sensitive to changes in environmental conditions concerning temperature and moisture changes. The literature expressed that further improvement through the parallel development of both spectroscopic hardware and data treatment is needed as a way of developing technology that will be increasingly unobtrusive and easy to use for ordinary shelf-life prediction applications.

5.3. Miscellaneous sensors

Advanced sensing technologies along with different data integration approaches were used in the prediction of the shelf life of food products with very high accuracy. An electronic nose has been employed in the prediction of the shelf life of food products through the detection of volatile organic compounds released during spoilage of the food (Anwar et al., 2023).Gonzalez Viejo and Fuentes, (2020) and Wijaya et al. (2023) investigated the pattern of volatile organic compounds profiles of beer and seafood using machine learning algorithms and an electronic nose. Likewise, during microbial growth, specific gases such as carbon dioxide and ethylene were emitted, hence gas sensors had also been applied for the prediction of shelf life in some food products. It could provide data input for AI models by monitoring the gas sensors for concentration and rate of change of those gases associated with spoilage (Liang et al., 2024). The miscellaneous intelligent systems such as RGB-colourimetric resazurin assay (Thanasirikul et al., 2023), and DNA sensor array (Wang et al., 2025) have been improved food quality control thanks to better estimates of the residual shelf life due to fluctuating environmental and biological conditions.

Table 1 presents an overview of several ML models for a diverse range of sensors and imaging systems applied for the shelf-life prediction. Dts, SVM, NN, RF, and Linear Regression have been some of the models most generally in use, with optimized hyperparameters for the tasks at hand, such as kernel selection in the case of an SVR, or a limit on the depth of the decision tree. Data preprocessing techniques vary by sensor type, specifically image normalization and color channel separation for machine vision; spectral smoothing and SNV transformation for hyperspectral imaging; and baseline correction for spectroscopy-based systems. Each model-sensor combination suffers from limitations, mostly due to environmental and sample variability factors. For example, Sánchez et al. (2023) and Zhang et al. (2025) stated that good lighting was required in the precision of their models since the basis of machine vision system and hyperspectral imaging is sensitive under conditions related to lighting and sample variability. Other disadvantages include recalibration upon the use of different products (Goyal et al., 2024) whereas other problems regard low detectability of compositional changes of lower magnitude, in general, for fluorescence spectroscopy (Venturini et al., 2024). These references draw a comparative look whereby, advanced ML models are improving the predictive accuracy of robust preprocessing, maintaining experimental conditions in such a manner as to reduce possible limitations in different applications.

Table1. Overview of Machine Learning Models, Data Preprocessing Techniques, and System Limitations Across Sensor-Based Analytical Applications

Smart systems and sensors	Utilized devices	Applied ML models	Hyper parameters and model settings	Data pre-processing	Limitation of applied system coupled ML models	References
Machine Vision	Sony DSC W830 (compensating the exposure brightness to +1.0 in all cases), two LED light, t keep the interior light of the booth constant at 640 lm	Decision tree, multivariate normal distribution, logistic regression	Color histogram bin count, resolution	Image normalization, color channel separation (RGB to grayscale)	Accuracy dependent on color uniformity and controlled lighting	Sánchez et al. (2023)
	One Plus AC2001 mobile camera, LED lights (9 W)	Support vector regression, decision tree, random forest, neural network,	SVR kernel, decision tree depth limit	Mean centering, standardization, principal component analysis	Susceptible to lighting variations, requires re-calibration for different produce	Goyal et al.(2024)
	Nikon D750	Neural network, support vector regression, random forest, multiple linear regression	Split criteria for decision tree, kernel selection for support vector regression	Image resizing, Gaussian noise filtering	Generalizability limited across product types; sensitive to light interference	Loddo et al. (2025)
Hyperspectral Imaging	ImSpector V10E, Specim (380–1030 nm), two 150w tungsten halogen lamps (Fiber-Lite DC950 Illuminator, Dolan Jenner Industries Inc, USA), a 12-bit CCD camera	Support vector regression, deep learning	Layer count, regularization	Savitzky-Golay smoothing, multiplicative scatter correction, standard normal variate, successive projections algorithm, competitive adaptive reweighting sampling, and iteratively retains	Sensitive to lighting and sample variability	Zhang et al. (2025)

				informative variables		
	Specim IQ camera (400–1000 nm)	Deep neural networks	Rank setting, layer configuration	Spectral smoothing, standard normal variate, principle component analysis	Sensitive to lighting, high computation for spatial variability	Francis et al. (2025)
	Spectronon, Resonon (wavelength range of 386–1015 nm, encompassing 300 wavebands at 2 nm intervals), Four 50 W tungsten-halogen lamps	Robust regression	Spectral bandwidth, calibration with standards	Spectral filtering , 1st and 2nd derivative preprocessing	Calibration needed across sources; limited in detecting subtle textural changes	Albano-Gaglio et al. (2025)
	HySpex-VNIR-1800 camera (00 nm to 1000 nm and a spectral sampling interval of 3.18 nm)	Support vector regression, neural network ,decision trees, random forest	Regularization Parameter, Kernel, n_ neighbors, Max Depth, n_ estimators	Spectral smoothing, standard normal variate, Mean centering	Sensitive to lighting; high computational power required	Shanthini et al. (2025)
	microPHAZIR™ RX Analyzer (1600–2396 nm)	Linear regression, neural network	Learning rate for neural network, feature standardization	Baseline correction, Savitzky-Golay filter	Limited for complex product, influenced by foam and turbidity variations	Gonzalez Viejo et al. (2018)
Multi spectroscopy	Bruker Optics® (12500 to 4000 cm−1), horizontal attenuated total reflectance (4000 cm−1 to 800 cm−1), Confocal Raman Microscope Senterra II spectrometer (50 to 3650 cm−1)	Linear regression	Number of components, spectral region selection	Spectral smoothing, Savitzky-Golay, principle component analysis	Limited in correlating complex textural traits; sensitive to sample preparation	Lan et al. (2022)
	NIR 256-2.5, Ocean Optic-QR400-7-VIS-BX	Support vector regression	Regularization parameter, kernel, degree	Standard Normal Variate, Multiplicative Scatter Correction , Savitzky Golay	Limited accuracy for high-variation samples,	Joshi et al. (2022)

				derivatives, principal component smoothing, and Gaussian smoothing.	affected by external lighting	
Infrared spectroscopy	MilkoScan FT6000 (5011 to 925 (cm−1)	Random forest, deep learning	Number of latent variables, spectral resolution	Model's weights	Limited to specific minerals, impacted by milk quality variations	Bisutti et al. (2024)
Raman spectroscopy	Bruker RFS 100, Peltier-cooled CCD camera and coupled to a Leica Microscope (DM2500 M)	Linear regression	-	-	Less accurate for irregular shapes, sensitive to surface variations	Campos et al. (2024)
Fourier-transform infrared spectroscopy	PerkinElmer Frontier Optical (5005–1000 cm−1	Linear regression	-	Fourier smoothing, principle component analysis	Limited to certain compounds of product	Gao et al. (2024)
Fluorescence spectroscopy	-	Linrear regression, random Forest	Cluster count, number of estimators in random forest	background subtraction, spectral filtering	Limited in detecting subtle composition changes	Venturini et al. (2024)
Electrical impedance spectroscopy	TH2816A, Tonghui Electronic Co	Random forest, support vector regression	Number of estimators, discriminant function	Standardization, normalization	Limited in distinguishing close profiles, affected by sample consistency	Huang et al. (2023)
Electronic nose	MQ136, MQ137, MQ5, MQ8	Random forest	Number of estimators, max depth	Data augmentation	Sensor drift, influenced by environmental odors	Wijaya et al. (2023)
	Designed and fabricated by the authors	Neural network	Number of neurons, hidden layers, transfer function	Standardization, noise filtering, Gaussian smoothing	Limited in detecting subtle flavor compounds; sensor drift over time	Gonzalez Viejo and Fuentes, (2020)
Gas sensor	MQ136, MQ137, MQ138, TGS2612, TGS822, and TGS26006	Support vector regression, multiple regression	Feature selection, stacking layer settings	Spectral normalization, baseline correction	Susceptible to ambient odors, influenced by humidity	Liang et al. (2024)

RGB-colourimetric resazurin assay	ISL29125 colour sensor, SMD LED LiteOn LTW-150TK	Support vector regression	Kernel type	Mean centering, RGB to grayscale transformation	Sensitive to temperature, limited by colorimetric detection	Thanasirikul et al. (2023)
DNA sensor array	-	Multiple regression, neural network	Hidden layer configuration for multiple regression	Standardization, spectral smoothing	Limited by probe specificity; sensor sensitivity constraints	Wang et al. (2025)

6. Case studies of AI in predicting shelf life

6.1. Fruit and vegetables

Shelf-life prediction of fruits and vegetables has great potential to reduce food losses, ensure quality, and improve supply chain management. Such methods integrated multiple data sources including but not limited to visual appearance, physicochemical indicators, volatile composition, and environmental conditions. Using these state-of-the-art computational models, the main issues to be solved by researchers are non-destructive testing, speed classification, and resource efficiency; applications can reach both the industrial and consumer levels. These AI-driven applications, further, can analyze big datasets, anything from physical and chemical environmental parameters to those affecting ripeness and spoilage of the produce itself (Ren et al., 2023).

Image-based machine learning applications have been inducted towards development of predictive systems which analyze appearance quality signals of fruits and vegetables. Adoption of several imaging techniques involving CCD camera (Knott et al., 2023; Han et al., 2022), hyperspectral (Logan et al.,2021; Shanthini et al., 2025), thermal imaging (Bhole and Kumar, 2021; Melesse et al., 2022), and Specialized modality like MRI (Yakatpure et al., 2022) . Knott et al. (2023) showed the great potential of pre-trained Vision Transformers, which could attain high classification accuracy with much smaller datasets on tasks such as apple defect detection and banana ripeness estimation. Similarly, Bhole and Kumar (2021) have highlighted the potential use of thermal imaging with CNN-based models for mango shelf-life prediction, which resulted in an accuracy above 98%. Likewise, thermal imaging has also been harnessed in creating a digital twin for bananas that provides optimum storage insight (Melesse et al., 2022). Logan et al. (2021) further made the comparison between traditional CCD camera and hyperspectral imaging and they revealed that hyperspectral imaging, when used as an input, outperforms the RGB method on freshness classification and age prediction of a number of products like potatoes and bananas. In contrast, Han et al. (2022) used only RGB datasets combined with ResNet and DenseNet architectures for freshness classification, with the results being robust, considering challenging factors such as data imbalance.

Non-destructive analytical methods have been widely applied in relation to machine learning for the shelf-life prediction of fruits and vegetables by measuring texture, color, chlorophyll content, and water loss without damaging the product (Ren.et al., 2023). Hyperspectral imaging has been done to estimate biochemical changes such as sugar levels and acidity in strawberries (Do et al., 2024) and mandarins (Zhang,et al., 2025) while the machine vision systems estimate visual cues of freshness in bananas (Kanjilal et al., 2025)and tomatoes (Goyal.et al., 2024). These non-invasive techniques enable real-time monitoring, thus offering good data for ML models to predict spoilage. On the other hand, destructive techniques include various chemical assays to observe ethylene output and organic acid levels of the commodity. These are really less suitable for continuous assessment. The potential integration of different non-destructive tools with AI fuels sustainability and improves precision in postharvest segments of the produce supply chain at all levels.

Various techniques, such as machine vision coupled with AI for color and texture analysis (Dhiman et al., 2021; Ropelewska and Noutfia, 2024; Palumbo et al., 2024), and spectroscopy for the detection of changes in the molecular composition (Xiao et al., 2024; Shanthini et al., 2025; Francis et al., 2025), detect changes in quality, including internal bruises that may cause further decay. Recently, Shanthini et al. (2025) and Zhang et al. (2025) used hyperspectral and NIR spectroscopy for the detection of internal biochemical changes in fruits like strawberries and mandarins by capturing spectral data about water content, sugar levels, acidity, and chlorophyll degradation. Mukhiddinov et al. (2022) extended the application of image-based models to classify fruits and vegetables as fresh or rotten by incorporating YOLOv4 with enhanced activation functions. Their system was designed for operation in various lighting conditions and targeted industrial applications, such as supermarkets, and assistive technologies, like smart glasses for visually impaired persons. Applications can also reach as far as real-world tools, for instance, the mobile application suggested by Tata et al. (2022) makes use of CNNs for quality grading. Using a dataset of 2000 images per category of produce, their system rapidly provides scalable analysis of fruits and vegetables in marketplaces for bridging gaps between producers and consumers, hence smoothing the quality assessment processes. However, these tools must be adapted to the specific target group in view of their particular needs and the usability and interface design requirements of the tools in question (Senge et al., 2025).

6.2. Meat and poultry

AI has refined the preciseness of the applications used in the prediction of the shelf life of meat, fish, and poultry in food quality control. Recently, huge datasets derived from sensory, microbial data, chemical, and environmental ones have been used to train models for AI applications with high accuracy regarding spoilage and freshness level predictions (Wu et al., 2022; Saeed et al., 2025). By applying this knowledge in real time from the conditions of storage-tasked parameters, such as gas composition, AI is capable of predicting how these variables will affect microbial proliferation and enclave chemical changes that may appear in products. Several researchers developed machine learning algorithms for color, texture, and volatile organic compounds among several other spoilage indicators for real-time assessment of meat quality (Gong et al., 2023; Cui et al., 2024; Esposito et al., 2024). AI-based shelf-life prediction is further applied for perishable seafood like Rainbow trout (Saeed et al., 2025), Salmon (Wu et al., 2022), Balsa fish (Cao et al., 2025), and pacific white shrimp, cuttlefish, squid, and octopus (Wijaya et al., 2023).

The methods for forecasting the shelf life of meat and poultry have both destructive and non-destructive techniques, which are now integrated with ML. Nondestructive tools include an electronic nose and hyperspectral imaging that have been applied on routine basis to detect the volatile compounds, color changes and surface texture-assumed as vital signs from spoilage (Esposito.et al., 2024). Electronic noses detect ammonia and carbon dioxide gases produced by spoilage in rainbow trout (Saeed et al., 2025), while hyperspectral imaging detects the change in composition of fat and protein in pork and beef (Sánchez et al., 2023; Albano-Gaglio et al., 2025).These were complemented by more accurate, yet destructive, approaches-microbial culturing and chemical analysis of lipid oxidation and protein degradation-provide high-accuracy data to train the ML models. While destructive tests are still indispensable in some applications, there is an increasing trend towards the non-destructive technique in the field of real-time and continuous monitoring due to the reduction in waste and efficiency improvement on predictability.

Some key parameters, as chemical indicators in estimating quality and shelf life with the help of digital technologies combined with ML are pH, water activity, lipid oxidation, or protein degradation. These were monitored with a high frequency to estimate spoilage processes for various items that were stored or shipped (Albano-Gaglio et al., 2025). On this aspect, microbial load, which expresses the presence and rate of development of spoilage organisms, has also been pointed out independently by Wu et al. (2022), Gong et al. (2023), and Luo et al. (2025) as another main factor in the determination of shelf life. For this reason, advanced sensors of environmental conditions like temperature and gas composition were used, while ML models against them were employed for the creation of smart monitoring (Esposito et al., 2024; Saeed et al., 2025; Cao et al., 2025). Digital imaging technologies determine colors, texture, and changes in the appearance of the products (Gong et al., 2023; Sánchez et al., 2023; Albano-Gaglio et al., 2025), while electronic noses detect volatile organic compounds released during spoilage (Wijaya et al., 2023, Cui et al., 2024). The data supplied through these sensors are then fed into ML models where, with the correlation of those parameters with the rate of spoilage, real-time prediction about shelf life is done. A combination of digital measurement technologies with machine learning forms a generic data-driven approach toward managing the quality of perishable meats.

6.3. Dairy products

AI models have been used to predict the shelf life of dairy products by analyzing microbial growth, storage conditions, and chemical composition to obtain a closer approximation of the product's longevity (Freire et al., 2024). Thus, ML algorithms use real-time data from temperature, humidity, and packaging to predict the rate of spoilage and the shelf life of varieties of cheese, milk, and yogurt (Bi et al., 2022; Golzarijalal et al., 2024; Wang et al., 2025).

Precise prediction of shelf life of milk products is highly important for such extremely perishable products, due to susceptibility to microbial growth and changes caused by enzymatic and chemical activity (Mhapsekar et al., 2024; Sunithamani et al., 2024). Therefore, various new-generational technologies have been coupled with ML for the current study, including matrix-assisted laser desorption/ionization time-of-flight mass spectrometry (Zhang et al., 2022), Fourier-transformed MIR spectroscopy (Bisutti et al., 2024), electrical impedance spectroscopy (Huang et al., 2023), and a colorimetric device (Thanasirikul et al., 2023). AI could, therefore, predict, based on the microbial data analysis, when the bacterial levels will reach spoilage thresholds, enabling the accurate estimation of remaining shelf life. With ML, the real-time prediction is dynamic, improving the quality of the product through optimization of production with shelf-life forecasting, thus making it indispensable in the AI of perishable milk.

The same applies to the dairy sector, which has applied a mix of non-destructive and destructive methods coupled with ML in order to predict shelf life. Examples of such non-destructive methods are FTIR spectroscopy and electrical impedance spectroscopy. Indeed, both are among the most popular techniques to analyze changes in pH, protein degradation, and mineral content in milk and cheese (High et al., 2021; Bisutti.et al., 2024). In general, instruments based on this principle will provide a rapid, nondestructive test for indicators of spoilage. Other destructive methods of microbial enumeration or chemical analysis of the proteolysis have been used in the prediction of spoilage of Mozzarella and Cheddar cheese (Golzarijalal et al., 2024). For example, though destructive, Thanasirikul et al. (2023) reported RGB-colorimetric assays yield more accurate microbial data which the ML models can utilize for dynamic predictions of shelf-life. Coupling AI with nondestructive tools has proved to offer sustainable monitoring of spoilage in real time with reduced loss during testing of the product.

AI also predicted the shelf life of a variety of cheeses by analyzing their complex physical and chemical properties, including pH, salt concentration, and microbial activity (Rocha et al., 2020; Chaturvedi et al., 2020; High et al., 2021; Loddo et al., 2022). Rocha et al. (2020) have applied ML models to process large datasets of both historical and real-time data. They explained how those factors affect the growth of spoilage organisms and associated biochemical changes, including breakdowns of proteins and fat in minas cheese. Further, Golzarijalal et al. (2024) applied ML modeling to develop a relationship between proteolysis and observed spoilage rates of Mozzarella and Cheddar cheese, and finally, AI might give exact predictions for the shelf life of the cheese. Besides, sensory data such as color, texture, and odor changes were combined with chemical markers like levels of proteolysis to fine-tune predictions (High et al., 2021; Loddo et al., 2022). Literature indicated that the AI approach provides quality assurance in the dairy industry for optimized conditions of processes and storage with improved product shelf-life management.

6.4. Soft drink and beverages

AI transforms the beverage industry by making several improvements to the production process for greater customer satisfaction. Shelf-life forecasting of vegetable fruit beverages is one of the most complex challenges facing repetitive formula adjustments and continuous process optimization that impede rapid intervention. These diversified beverage demands are stretching the traditionally employed research and development methods to high costs and long development cycles. Researchers have been addressing the development of models for the integration of novel sensors with machine learning with the aim of predicting the shelf life and processing parameters of vegetable-fruit beverages (Liu et al., 2022; Ren et al., 2023; Liao et al., 2023; Yıkmış et al., 2024). Advanced data processing techniques, such as data fusion and imputation further increase the possibility of analysis by the model. For example, Ren et al. (2023) used RF and deep neural networks while predicting processes and shelf life based on the electronic sensing technologies for sea buckthorn-passion fruit juice beverages. They suggested that in future research, one might investigate the process of transfer learning, where parameters of a trained model can be transferred into new models, which then make it easier to predict processes for other kinds of beverage processes, such as fermentation.

Fermentation levels and periods that the juice will survive are interlinked as it may generally impact its stability, safety, and quality over time. In non-pasteurized or poorly stored juices, fermentation can occur so rapidly that spoilage occurs, thereby reducing the product's shelf life, whereas, for pasteurized juices, this may not be the case

(Niu et al., 2024). Liao et al. (2023) and Zou et al. (2024) investigated the fermentation characteristics of blueberry and pomegranate juices, respectively, using regression modeling and ML optimization to predict the shelf life of these products. To investigate the relationship between fermentation characteristics and juice shelf life, 9 machine learning models were used to develop regression models. The linear models considered in this case included linear regression and ridge regression, with comparison to other non-linear models consisting of k-nearest neighbor, SVR, RF, adaptive boosting, gradient boosting, bootstrap aggregating, and ANN (Zou et al., 2024). Similarly, Liao et al. (2023) illustrated that ML was able to predict the blueberry juice shelf life based on the presence of *S. thermophilus* with *L. fermentum* or *L. plantarum*, along with total phenolic content. Further, ML has been used to predict the impact of non-thermal treatments such as ultrasound (Yıkmış et al., 2024) and high-pressure processing (Liu et al., 2022) on the quality of juice and, thus, its shelf life. The bioactive compounds and treatment parameters in both the referred studies were optimized using various ML techniques such as ANFIS and BPNN. The results showed that there was a high correlation between the empirical data and the predictions of the ML models, with residual values being very small. These ML models have also been efficient in predicting the shelf life and characteristics, such as bioactive and volatile compounds, of other beverages like beer and wine (Gonzalez Viejo et al., 2018; Gonzalez Viejo et al., 2020; Harris et al., 2023; Gao et al., 2024; Zhou et al., 2024).

Quality attributes and shelf-life evaluation in wine is usually an expensive and time-consuming process as it is majorly carried out in a well-equipped laboratory containing several complex chemical and sensory analyses. Harris et al. (2023) assessed Shiraz wine for shelf life using NIR spectroscopy with an integrated low-cost electronic nose combined with ML models. The developed ML approach predicts wine shelf life with good accuracy while detecting specific flavor compounds in wine samples. In a similar direction, Gao et al. (2024) and Zhou et al. (2024) suggested that beer shelf life is related to its volatile compounds quantification through FTIR and multi-spectroscopies techniques such as Raman and NIR combined into ML approaches. Three different modelling methodologies consisting of partial least squares, least squares SVM, and ANNs were applied to divided datasets. These studies conclude that the use of spectroscopic methods coupled with ML models provides a quick and low-cost way of predicting the shelf life of beers. In any case, one of the main challenges for these models is the development of representative databases. The researchers consequently suggested increasing the sample size and enhancing the algorithms, while applying developed models to other food products (Gonzalez Viejo et al., 2020; Gao et al., 2024; Zhou et al., 2024).

Literature diversifies AI into this area of shelf-life prediction by examining large datasets of sensory and chemical measurements that help identify spoilage markers or quality indicators. Applications of AI and sensor technology to predict the quality and shelf-life of various food products are presented in Table 2. It points out that tools such as e-noses, hyperspectral imaging, and FTIR spectroscopy, in combination with ML models ANN, SVR, and RF, enable successful prediction based on the estimation of properties such as moisture, gas levels, volatile compounds, etc. SVR and MLR were habitual in the case of continuous data, such as gas levels and pH, where quality parameters were quantified with high precision by Huang et al. (2023), Goyak et al. (2024), Kanjilal et al. (2025), and Francis et al. (2025). Deep learning neural network models can only consider large datasets with complex patterns, making them ideal in wide ranges assessing both chemical and microbial properties (Ren.et al., 2023; Gong et al., 2023; Bisutti et al., 2024; Zhang et al., 2025). Additionally, decision tree-based models, such as RF and gradient boosting, are very good at multi-feature analysis, thus being effective basically for all variants of food, whether fresh produce or beverages (Ropelewska and Noutfia, 2024; Francis.et al., 2025; Zou et al., 2024). Therefore, AI has proved itself in the integration of data emanating from a wide variety of sensors toward more robust and proactive shelf-life management of the food industry.

Table2. Overview of ML models and sensor technologies for shelf life prediction in food products

Category	Products	Physicochemical parameters for Shelf Life prediction	Applied device and ML	ML Performance	Reference
Fruit and vegetables	Fresh sea buckthorn, passion fruit	Chemical properties	E-nose and E-tongue; RF and DNN	R^2: 0.91, RMSE: 0.055, MAE: 0.031	Ren et al. (2023)
	Tomato	texture, taste, nutritional content, defects, and ripeness	Machine vision; SVR,RF,DTs	R^2: 0.73, RMSE: 1.14, MAE: 0.87, MSE: 1.3	Goyal et al. (2024)
	Banana	CO_2 and O_2 gas levels	Gas sensor; MLR, RF, SVR	R^2: 0.958, RMSE: 0.206	Kanjilal et al. (2025)
	Mandarin	anthracnose, black spot, decay, and scarring	Hyperspectral imaging; SVR and DNN	R^2: 0.929, RMSE: 0.377, RPD: 3.765	Zhang et al. (2025)
	Strawberries	volatile organic compounds	Mass spectrometry; MLR, ANN	R^2: 0.984, RMSE: 0.390	Do et al. (2024)
		Internal texture	Hyperspectral imaging;RF, SVR and DTs	R^2: 0.901, RMSE: 0.665	Shanthini et al. (2025)
	Apple	respiration rate	laser speckle imaging; DTs	R^2: 0.801, RMSE: 0.249	Pieczywek et al. (2024)
	Grape	texture parameters of the fruit outer structure	Machine vision; MLR, RF	Overall accuracy: 0.91	Ropelewska and Noutfia (2024)
	Potato	firmness, moisture content , and soluble solids content	Hyperspectral system; SVR	R^2:0.897; RMSE: 0.036; RPD: 2.262	Xiao et al. (2024)

	Watermelon	Soluble Solids Content	Hyperspectral system; SVR, MLR, DT,RF	R^2: 0.982, RMSE: 0.132	Francis et al. (2025)
	Winter Jujube	Soluble Solids Content	Hyperspectral imaging; SVR	R^2: 0.837, RMSE: 0.810, RPD: 2.47	Shao et al. (2024)
	Date	Moisture content	Dielectric spectroscopy; SVR, MLR	R^2: 0.87, RMSE: 9.4	Karimi. (2025)
	Apple, Banana, Pear, Guava, Grape, Mango, Pomegranate, Orange and Tomato	Colour and texture	Machine vision; RNN	Overall accuracy: 0.98	Dhiman et al. (2021)
	Blueberry	Water loss rate, pH, and VC content	Gas and ethylene sensors; NN, RF, SVR	R^2:0.994, RMSE:0.035; MAE: 4.51	Huang et al. (2023)
	Fresh cut Papaya	Weight loss and titratable acidity	E-nose and E-tongue; SVR	R^2: 0.991; RMSE: 0.13	Rong et al. (2024)
	Rocket leaves	Chlorophyll and ammonia content	Computer vision; MLR	R^2: 0.83; RMSE: 20.27	Palumbo et al. (2024)
Meat, fish and poultry	Marine fish species	Total volatile base nitrogen	E-nose; NN	R^2: 0.991, RMSE: 0.127; MSE: 0.016, MAE:0.096	Cui et al. (2024)
	Chicken	Nicotinamide, anserine, carnosine, and Biogenic amines	Analysis sensors; SVR	Overall accuracy: 0.96	Esposito et al. (2024)
	Rainbow trout	trimethylamine, ammonia, carbon dioxide	artificial sensory system, ANN	RMSE: 1.512, MSE: 2.29, MAE: 0.783	Saeed et al. (2025)
	Fish	Methacryloyl	Machine vision; DNN	Overall accuracy: 0.974	Gong et al. (2023)
	Salmon	Microbial parameters	Designed sensor; RNN	R^2: 0.99, RMSE: 0.1	Wu et al. (2022)
		Ammonia, formaldehyde, ethyl alcohol	Gas sensor; MLR and SVR	R^2: 0.966, MSE: 3.151	Liang et al. (2024)

	Beef	Color and texture	Machine vision; DTs	Overall accuracy: 0.98	Sánchez et al. (2023)
	Pork	Firmness, fatness, and compositional properties	Visible and near-infrared spectroscopy;	R^2:0.90; RMSE: 4.37; RPD: 2.34	Albano-Gaglio et al. (2025)
		Microemulsions	Fourier-transform infrared spectroscopy; NN	Overall accuracy: 0.913	Luo et al. (2025)
	Pacific white shrimp, cuttlefish, and squid, octopus	Microbial parameters	E-nose; RF, ANN and SVR	R^2: 0.995, RMSE: 0.03	Wijaya et al. (2023)
	Balsa fish	Color and texture	ATP/PI NFAs-based colorimetric sensor array;RF	R^2: 0.966, RMSE: 0.859,RPD: 3.89	Cao et al. (2025)
Dairy Products	Milk	Peptidomic profiling	laser desorption time-of-flight mass spectrometry; SVR and RF	Overall accuracy: 0.97	Zhang et al. (2022)
		Mineral elements	Fourier-transform infrared spectroscopy; RF and DNN	R^2: 0.78, RMSE: 7.38, RPD: 2.33	Bisutti et al. (2024)
		pH and total soluble solids	Electrical impedance spectroscopy; SVR and RF	R^2: 0.88; RMSE: 0.3464	Huang et al. (2023)
		Microbial concentrations	RGB-colourimetric resazurin assay; SVR	Overall accuracy: 0.96	Thanasirikul et al. (2023)
		Foodborne pathogenic and spoilage bacteria	DNA sensor array; MLR, NN, SVR,RF	Overall accuracy: 0.984	Wang et al. (2025)
		Microbial concentrations	E-nose; SVR	R^2: 0.874	Cheng et al. (2025)

	Mozzarella and Cheddar cheese	Coagulating enzyme concentration and calcium content	The data was collected from literature; SVR,MLR and RF	R^2: 0.92, RMSE: 0.08, MAE: 0.13	Golzarijalal et al. (2024)
	Pecorino cheese	Color and texture	Computer vision; DL	Overall accuracy: 0.964	Loddo et al. (2022)
	Indian Cheese	Biochemical content and microbial counts	Sensory instruments; ANN	R^2: 0.987, RMSE: 0.0091	Chaturvedi et al. (2020)
	Blue cheese	Volatile compounds	Mass spectrometry; MLR	Overall accuracy: 0.94	High et al. (2021)
	Fresh cheese	Texture features	Computer vision; SVR, RF and MLR	Overall accuracy: 0.99	Loddo et al. (2025)
	Yogurt	Sensory attributes	Sensory instruments; hybrid NN and SVR	Overall accuracy: acceptable	Bi et al. (2022)
Soft drink and Beverages	Gilaburu juice	Total monomeric anthocyanin content and Total flavonoid content	Sensory instruments; ANN	R^2: 0.998, RMSE: 0.004, MAE: 0.003	Yıkmış et al. (2024)
	Blueberry juice	Total phenolic, ferulic acid, rutin	Sensory instruments; MLR	Overall accuracy: acceptable	Liao et al. (2023)
	Pomegranate juice	Chemical properties	Sensory instruments; SVR, RF and ANN	R^2: 0.912, MSE: 0.024, MAE: 0.123	Zou et al. (2024)
	Parsley Juice	Total chlorophyll and ascorbic acid	Sensory instruments; MLR	R^2: 0.99, RMSE: 1.11	Dulger Altıner et al. (2024)
	Beer	Physical Parameters	E-nose and near infrared spectroscopy; ANN	R^2: 0.95; MSE: 0.02	Gonzalez Viejo and Fuentes (2020)
		Total soluble solids, alcohol and pH	Near infrared spectroscopy; ANN	R^2: 0.93, RMSE: 5.05	Gonzalez Viejo et al. (2018)

	Total phenols and sugar	Raman and Near infrared spectroscopy; NN and SVR	R^2: 0.998, RMSE: 0.862, RPD: 0.959	Zhou et al. (2024)
	Volatile compounds	Fourier-transform infrared; MLR	Overall accuracy: 0.998	Gao et al. (2024)
Wine	Physicochemical measurements	E-nose and near infrared spectroscopy; ANN	R^2:0.99, MSE: 0.09	Harris et al. (2023)
	Physicochemical measurements	The data was collected from literature; SVR and ANN	R^2: 0.779, RMSE: 0.267, MAE: 0.142	Dahal et al. (2021)

Note: RMSE, MAE, and MSE retain the same units as the predicted variable in each study (days for shelf life, % for moisture content, °C for temperature). R^2 and RPD are unitless indicators of model performance.

Table 2 in the manuscript shows that AI models achieve accuracies exceeding 90% in most cases, with some models reaching 95-99% accuracy ($R^2 > 0.90$, RMSE < 0.5, and MAE < 0.1 in several instances), which were significantly better than the 70-85% typical in conventional microbiological and chemical predictions of shelf-life (Bhagya Raj & Dash, 2022; Cui et al., 2023).It shows that AI-based models not just compete with, but even outperform conventional predictive performance. AI's performance surpasses conventional methods because it continuously tracks real-time factors such as biochemical transformation, microbiological growth, and environmental fluctuations compared to conventional methods that depend on periodic sampling and static parameters. Such findings confirm AI's potential to make food shelf-life estimation a more precise, scalable, and flexible tool to ensure food safety, reduce waste, and enhance supply chains.

7. Economical and sustainable impacts

AI-powered models in shelf-life forecasting provide value from an economic point of view (Krupitzer and Stein 2021) but, more importantly, contribute to sustainability by the reduced waste of end products within the meat and poultry industries since the models further streamline the supply chain. That would most likely be through proper spoilage rate forecasting through microbial growth, temperature, and pH. Besides, avoiding overproduction tendencies means the extension of freshness and a reduction in economic loss on account of expired stock (Grassi et al., 2023; Jia et al., 2023). Cui et al. (2023) and Viancy et al. (2024) have also identified that, through optimized logistics of storage and transportation strategies, energy was conserved due to reduced excessive refrigeration and, hence, the generation of greenhouse gas emissions from waste disposal. Yudhistira et al. (2023) investigated how the integration of AI with processing methods can further enhance process optimization, leading to additional reductions in energy consumption and greenhouse gas emissions. They proved that AI optimization in heat drying can save about 15-25% in energy, which translates to 0.6 to 1.0 tons of CO_2 equivalent annually per ton of food processed. In further study by Yudhistira et al. (2024), the researchers claimed that AI, by enhancing the shelf-life predictions, would reduce food waste by 10-

20%. That is considerable since disposal of 1 ton of food waste results in about 2.5 tons of CO_2-equivalent emissions. The better the AI forecasts the shelf life, the more value it will carry for sustainability by reducing the amount of meat that goes directly to trash, therefore reducing overall environmental impact arising from livestock production (Esposito et al., 2024).

AI will affect the economic and sustainability metrics linked to the fresh fruit and vegetable sector, as it hopefully will make highly accurate forecasts of spoilage and ripening rates to improve inventory management and reduce post-harvest losses (Li et al., 2024). AI models can be helpful in making decisions concerning supply chain (Krupitzer and Stein 2024), with variables such as ethylene production, humidity, temperature, and transport time, hence reducing waste and delivering only the supplies that match the demand (Pieczywek et al., 2024; Do et al., 2024; Kanjilal et al., 2025). Decrease in carbon dioxide emission and water use resulting from post-harvest processes through reducing economic costs caused by the spoilage of agricultural products. Besides this, AI-driven storage conditions insights support sustainable practices through extended resource use in the process of preservation and distribution because of reduced rates of spoilage (Lin et al., 2023; Opara et al., 2024; Noutfia and Ropelewska, 2024).

AI in the dairy industry also predicts the shelf life of products, and an important contribution is economic saving due to the avoidance of waste such as those products. It maintains inventories at an optimum level. Freire et al. (2024) has indicated that the AI model may analyze biochemical features that represent dairy sensitivity, such as fat and protein degradation and also with temperature and humidity factors that may have allowed producers to more precisely pinpoint the date of expiration (Zhang et al., 2022; Thanasirikul et al., 2023; Mhapsekar et al., 2024). It lessens financial losses by reason of wasted goods and ensures fresher products to the consumer. The energy and water footprint of dairy farming and processing is reduced greatly on account of less spoilage, thus making a path further toward the sustainability model of dairy production.

Applications of AI in forecasting shelf life for soft drinks and beverages have gone hand in hand economically, ensuring sustainability by extending product quality and improving storage practices. In the ML models, the inclusion of chemical variables such as rate of carbonation and efficiency of preservatives among others, added to environmental conditions, performs predictions of optimum shelf life and distribution guidance (Gonzalez Viejo and Fuentes, 2020; Gao et al., 2024). Such data might be included into approaches for digital physico-chemical twins (Krupitzer et al. 2022; Henrichs et al. 2022). Correct projections of expiration dates translate directly into producers' reducing expired products, thereby reducing financial losses as well as resources spent on cooling and storing beverages. This further cuts the waste disposal impacts, and the beverage manufacturing industry is closer to attaining sustainable production and consumption of goods (Peveler, 2024; Kyaw et al., 2024).

8. Challenges and limitations of AI in shelf life prediction

Although AI coupled with new sensors has tremendous potential to improve the precision in the shelf-life prediction of food products, several technical, organizational, and economic challenges impede its complete deployment. The application of AI, machine vision, and spectroscopy to food products has been seriously challenged by their inherent complexity and variability (Wang et al., 2022). Each variety has specific physical, chemical, and microbial characteristics that affect the rate of spoilage of each commodity, as modified by handling practices such as storage conditions, packaging, and distribution. Most of the literature reports that machine learning algorithms need large and varied datasets to make an accurate model of the spoilage dynamics (Lin et al., 2023; Chhetri, 2024; Peveler, 2024). On the other hand, it may be difficult to generalize across samples due to various environmental and product characteristic variabilities in some cases. Besides, the spoilage processes depend on complex interactions among various biochemical and microbial factors, it is often so little understood that the establishment of correct, comprehensive models is hard to achieve (Cui et al., 2023). From this viewpoint, this variability will make it necessary to carefully calibrate any AI model, and its transferability might be limited even across different food types or even batches within one type.

Traditional and hyper machine vision systems rely on surface-level indicators of spoilage, such as color change, surface mold, and variation in texture. However, this is a limited approach to the analysis of food products, in light of the fact that spoilage is often produced directly inside many food products or even at a microbial level that may not be well indicated until its development is quite advanced (Gong et al., 2023; Ropelewska and Noutfia, 2024). There are foods that spoil from the interior outwards, making it quite hard for normal machine vision to reveal early signs of spoilage. Besides, depending on lighting conditions, surface reflectance, and natural varieties in appearance, can add noise, making the analysis of images more difficult and thus probably leading to wrong predictions (Goyal et al., 2024). Also, the integration of machine vision systems within the food processing environment is a not-so-easy task from a technical point of view and can be pretty costly, especially for small and medium enterprises. Lastly, those techniques cannot support the analysis of foods in opaque packages, such as milk boxes or juice packages.

Using spectroscopy for the determination of the chemical composition, internal spoilage factors in foods, such as pH, water activity, and microbial growth in food, can be established. These methods may be vulnerable to a variety of ambient conditions, such as moisture content, particle size, and sample thickness, that will interfere with the accuracy and consistency of spectral readings. For instance, high moisture content in dairy or meat reduces the clarity or strength of the signal, while a high variation in the level of sugar or pigment gives inconsistent analysis in fruits (Cozzolino et al., 2024). Besides being expensive, spectroscopy equipment is also burdensome due to the lack of in-depth training in proper data analysis. These limitations suggest that while spectroscopy can be highly useful for detailed chemical analysis, the application to rapid, real-time shelf-life prediction may be more limited (Zhao and Xu,2025;Francis et al., 2025).

The work flow integration of AI and equipment necessary for data intake in either food processing or food distribution is still very logistically and economically burdensome, especially when this needs to be done in real time. Many technologies require very expensive infrastructures, including high-quality cameras, spectral sensors, and computers with a high performance capacity for data processing. For many small-scale producers, initial costs, as well as later maintenance and calibration, are a significant barrier. Apart from that, the management and analysis of real-time multi-source data require complex systems in data integration (Henrichs and Krupitzer, 2022), which may be a bit hard to establish if there is no particular expertise. For businesses, balancing the benefits of these advanced methods with their costs and operational impact remains a key limitation, particularly in cost-sensitive industries where traditional methods of shelf-life assessment are still the norm.

9. Future directions and opportunities

AI-based development in the prediction of food shelf life will be more closely interlinked with data and modeling techniques with increased accuracy in the future. These models will increasingly tie together data sources from a broad range, including environmental sensors, into one integrated real-time analysis of the factors that affect shelf life. While the prediction accuracy could be further improved by the identification of complex nonlinear patterns of multi-source data, deep learning and reinforcement learning-based emerging machine learning algorithms are conceptualized. Moreover, advances in IoT technology can enable continuous monitoring of storage and ambient conditions, and this can provide a real-time feedback loop that AI systems can use to dynamically update their shelf-life predictions. The integrated approach has the potential to further enhance the granularity of the predictions, thereby helping in the reduction of food waste and improvement in product quality. Especially, sensors integrated into packaging might support the dynamic analysis and determination of shelf life. Such concepts exists, e.g., Müller and Schmid (2019) or Henrichs et al. (2025). However, they have several open challenges, such as energy provision for the sensors, the required connection between sensors in packages for data collection and the computational devices for analysis, and the recycling of empty packages with sensors. Equally promising is developing non-destructive, real-time analysis techniques that can tell food freshness without affecting the product. In connection with this, new approaches using AI in combination with machine vision and spectroscopy are likely to be further refined so that one can have accurate internal quality evaluations based on actual internal rather than surface indices. Techniques like hyperspectral imaging, which identifies a wider range of wavelengths, will give increasingly detailed chemical profiles that enable AI models to identify early markers of spoilage on a molecular level. Improvement in portable spectroscopy devices and miniaturized sensors may even bring these technologies directly into retail and distribution environments for immediate shelf-life assessments for consumers and suppliers. Therefore, such innovation could accelerate the change to better, clearer expiry labeling, reducing the environmental impact of wasteful disposal of safe food.

The future of AI in food shelf-life prediction will be further ensured once these technologies become more attainable and reasonably priced for more food producers, at least for SMEs. Advancement and scaling of cloud-based AI solutions may even enable much smaller companies to tap the benefits of sophisticated algorithms and high-performance computing resources by paying for the usage of software and computational capacities, rather than owning it themselves. With AI systems also becoming easier to use with less specialized knowledge required for operating them, the rate of adoption is expected to go up at all levels of the food industry. Democratization of AI technology in shelf-life prediction could improve food sustainability and reduce waste across each stage of the food supply chain, starting from production to the consumer.

10. Conclusion

This review presents how AI is used in the prediction of shelf lives for food products, which represents a new but innovative approach to enhancing food safety, improving the quality control approach, and ensuring economic viability within the food industry. Most traditional methods of estimating shelf life vary from microbial analysis to chemical and sensory evaluations and are usually labor-intensive, time-consuming, and limited in adaptability under variable conditions. Contrarily, AI-based models can process even highly complex datasets of biochemical, environmental, and microbial variables much more rapidly. AI-driven shelf-life prediction may completely revolutionize the food industry with real-time, nondestructive, and precise food-quality predictions of high accuracy for a wide category of products. Also, this innovation solves crucial challenges in the industry, reduction of food waste, optimization of supply chain efficiency, and a reduction in operational costs. In any case, when combined with advanced analysis devices such as spectroscopy, machine vision, and IoT-based sensors, AI will contribute to the shift away from these conventional, labor- and time-consuming approaches toward more adaptive and data-driven ones. The benefits of using such technologies will also include reduced spoilage and carbon emissions while offering a high level of consumer satisfaction related to improved food quality management.

AI could integrate `these variables with a high degree of accuracy for predictions in real time with respect to spoilage dynamics, especially in conjunction with modern sensors and imaging systems. This synthesis of AI and sensor technology has been effective for various categories of foods, from meats to dairy, vegetables/fruits, and beverages, supporting major reductions in food waste and, therefore, greatly enhancing the food supply chain efficiency. Although there are certain drawbacks associated with data standardization, model transferability, and the costs of the technology, the future of AI for shelf life prediction is promising. In fact, the continuous development of IoT, data integration, and hybrid modeling certainly has the potential to support further refinement in predictive accuracy while maintaining the goal of overcoming current limitations and enabling scalable solution development for improving food quality management. In such a setting of challenging food industries that are increasingly adopting such advanced data-driven approaches, AI will lie at the core of underpinning sustainability to overcome global demands for safer, more durable foods.

Author contributions

Mahdi Rashvand: Writing – review & editing; writing—original draft; conceptualization; Methodology; Validation; Supervision. Yuqiao Ren: Writing – review & editing; writing—original draft; Resources; Methodology. Da-Wen Sun: Writing – review & editing; Visualization; Resources; Investigation; Supervision. Julia Senge: Writing – review & editing; writing—original draft; Methodology. Christian Krupitzer: Writing – review & editing; Visualization; Resources; Investigation; Supervision. Tobi Fadiji: Writing – review & editing; writing—original draft; Resources; Methodology; Marta Sanzo Miró: Writing – review & editing; writing—original draft; Resources; Methodology; Alex Shenfield: Writing – review & editing; Investigation. Nicholas J. Watson: Writing – review & editing; Visualization; Resources; Investigation. Hongwei Zhang: Writing – review & editing; Visualization; Resources; Investigation; Supervision.

Declaration of competing interest

The authors declare no competing interest.

Rights Retention Statement

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Data availability

No data was used for the research described in the article.

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