

## Machine Learning-Enhanced Shelf-Life Prediction Model For Packaged Foods Using Environmental Cues

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### Abstract:

Accurate prediction of shelf life is critical for ensuring food safety, reducing waste, and optimizing supply chain operations in the packaged food industry. Traditional shelf-life estimation methods rely on fixed expiration dates and laboratory-based testing, which often fail to account for dynamic environmental conditions experienced during storage and transportation. This paper proposes a Machine Learning-Enhanced Shelf-Life Prediction Model that leverages real-time environmental cues such as temperature, humidity, and storage duration to estimate the remaining shelf life of packaged foods. The proposed framework integrates data preprocessing, feature extraction, and supervised learning techniques to model the degradation patterns of food products under varying environmental conditions. Multiple machine learning models are evaluated to identify the most effective predictor of shelf-life degradation. Experimental results demonstrate that the proposed approach significantly improves prediction accuracy compared to conventional static expiry estimation methods. By enabling adaptive, data-driven shelf-life forecasting, the proposed model supports improved food quality management, waste reduction, and informed decision-making across food supply chains.

**Keywords:** Shelf-Life Prediction; Packaged Foods; Machine Learning; Environmental Cues; Food Quality Monitoring.

### 1. Introduction

Shelf life is a critical quality attribute of packaged food products, directly influencing consumer safety, regulatory compliance, and economic efficiency within food supply chains [1]. Accurate shelf-life estimation ensures that food products remain safe for consumption while minimizing spoilage and waste. Conventional shelf-life determination methods are typically based on laboratory-controlled experiments and fixed expiration dates, assuming ideal storage conditions throughout the product lifecycle [2]. However, real-world storage and transportation environments often deviate from these assumptions, leading to inaccurate shelf-life labeling.

Environmental factors such as temperature variation, humidity, and storage duration significantly influence food degradation mechanisms, including microbial growth, enzymatic reactions, and chemical oxidation [3]. Even minor deviations from recommended storage conditions can accelerate spoilage processes, reducing food quality and safety. Despite this, most packaged food products still rely on static expiry dates that do not adapt to changing environmental conditions [4].

Recent advances in sensing technologies and data analytics have enabled continuous monitoring of environmental conditions throughout the food supply chain [5]. When combined with machine learning techniques, these data streams provide opportunities to model complex, non-linear relationships between environmental cues and food degradation patterns [6]. Machine learning models have demonstrated superior predictive capabilities compared to traditional statistical approaches in handling heterogeneous data and capturing temporal variations [7].

Several studies have explored data-driven approaches for food quality assessment, including regression models, decision trees, and neural networks for spoilage prediction [8]. However, many existing approaches are limited to specific food categories or rely on isolated parameters, reducing their generalizability across diverse packaged food products. Furthermore, limited integration of real-time environmental data restricts their practical applicability in dynamic supply chain environments [9].

To address these challenges, this paper proposes a Machine Learning-Enhanced Shelf-Life Prediction Model for Packaged Foods Using Environmental Cues. The proposed framework integrates multi-parameter environmental data with supervised machine learning algorithms to dynamically estimate remaining shelf life under real-world conditions. By providing adaptive and accurate shelf-life predictions, the proposed model aims to enhance food quality monitoring, reduce waste, and support informed decision-making across modern food supply chains [10].

The remainder of this paper is organized as follows. Section II reviews related work on shelf-life prediction and machine learning-based food quality assessment. Section III describes the proposed system architecture and methodology. Section IV presents experimental results and performance analysis, and Section V concludes the paper with future research directions.

## ***2. Literature Survey***

Shelf-life prediction has traditionally been addressed using microbiological assays, chemical stability testing, and accelerated shelf-life studies that estimate product deterioration under controlled conditions [11]. While these approaches provide scientifically validated expiry estimates, they often lack adaptability to real-world environmental variations across transportation, warehousing, and retail stages. Consequently, research has increasingly focused on data-driven and sensor-assisted techniques that can model degradation under dynamic conditions [12].

### ***2.1 Conventional and Kinetic Modeling Approaches***

Classical shelf-life estimation techniques commonly employ kinetic degradation models based on reaction rates and Arrhenius-type temperature dependence [13]. These models are effective for specific products where degradation follows predictable chemical or microbial kinetics. However, they typically require extensive laboratory calibration, product-specific constants, and may not generalize well when multiple interacting environmental factors (temperature, humidity, light exposure) influence food quality simultaneously [14]. Additionally, kinetic models may struggle to represent non-linear spoilage behavior under fluctuating storage profiles, which is common in real supply chains [12], [14].

### ***2.2 Sensor-Based Food Quality Monitoring***

Recent developments in sensing technologies, including IoT temperature and humidity loggers, RFID-based monitoring, and smart packaging sensors, have enabled continuous environmental tracking for packaged foods [15]. Such systems improve traceability and allow detection of cold-chain violations that accelerate spoilage. Nevertheless, sensor-only solutions typically provide threshold-based alerts rather than predictive estimation

of remaining shelf life, limiting their decision-support value for inventory planning and waste reduction [16].

### ***2.3 Machine Learning for Shelf-Life and Spoilage Prediction***

Machine learning approaches have been introduced to capture complex relationships between environmental cues and shelf-life degradation, particularly when spoilage mechanisms are non-linear or product behavior varies across batches [17]. Regression models and tree-based learners have been used for predicting quality attributes such as microbial load, texture degradation, and freshness indicators using time-series temperature and humidity data [18]. Although these models improve prediction accuracy compared to static expiry estimation, performance can degrade when training data are limited, noisy, or collected from restricted environmental conditions [18], [19].

### ***2.4 Time-Series Modeling and Environmental Exposure Indices***

Because shelf-life degradation is strongly time-dependent, time-series learning methods and exposure-based indices are increasingly adopted. Several works compute cumulative thermal exposure or time-temperature integrals as features for predicting remaining shelf life [13], [20]. Deep learning methods (e.g., recurrent neural networks) have also been explored to model sequential storage histories, improving robustness under variable temperature profiles [19]. However, deep models often require larger datasets and may face interpretability challenges in food quality applications, where explainability supports trust and adoption by practitioners.

### ***2.5 Research Gap and Motivation***

From the reviewed literature, two key limitations remain evident. First, conventional kinetic and accelerated testing methods are scientifically rigorous but do not incorporate real-time environmental variability, reducing their effectiveness in practical supply chain settings. Second, while sensor-based and machine learning approaches improve prediction capability, many existing models either rely on limited environmental features, lack generalizability across packaged food categories, or provide limited interpretability for decision-making. These gaps motivate the proposed machine learning-enhanced shelf-life prediction model that fuses environmental cues with robust predictive learning to estimate remaining shelf life more accurately under real-world conditions.

## ***3. Design and Methodology***

### ***3.1 System Overview***

The proposed framework predicts the Remaining Shelf Life (RSL) of packaged foods using environmental cues collected across storage and transportation. The system integrates: (i) environmental data acquisition, (ii) preprocessing and feature engineering, (iii) exposure modeling, (iv) machine learning-based prediction, and (v) decision support outputs (RSL class and risk level). The model is designed to operate with time-series temperature-humidity signals and product metadata, enabling dynamic shelf-life forecasting under real-world conditions [11]–[20].

***Fig. 1. Overall Architecture of the Proposed Shelf-Life Prediction System***

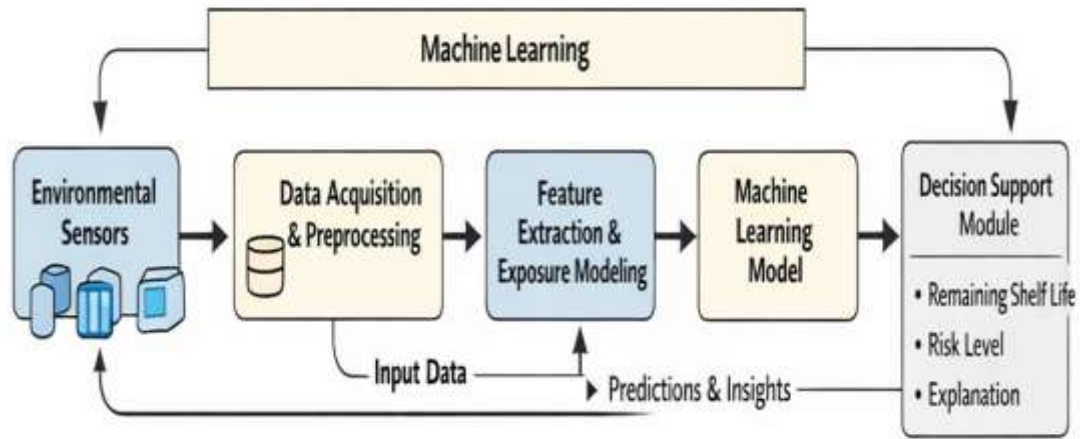


Fig. 1 presents the complete architecture of the proposed system. Environmental sensors capture temperature and humidity data across storage and logistics stages and forward them to the preprocessing module. Extracted features and exposure indices are provided to the machine learning prediction engine to estimate remaining shelf life and risk level. The decision module generates interpretable outputs for supply chain operators to support inventory prioritization and waste reduction.

### 3.2 Data Acquisition and Notation

Let the environmental sensor stream for a product batch be:

$$\mathcal{D} = \{(T_t, H_t, t)\}_{t=1}^N \quad (1)$$

where  $T_t$  is temperature ( $^{\circ}\text{C}$ ),  $H_t$  is relative humidity (%), and  $N$  is the number of recorded intervals. Optional variables such as light exposure  $L_t$  and shock/vibration  $V_t$  can be appended when available.

The objective is to predict the remaining shelf life  $RSL$  (in days or hours) at time  $t$ , given the observed environmental history:

$$\widehat{RSL}_t = f(\{T_\tau, H_\tau\}_{\tau=1}^t, \mathbf{p}) \quad (2)$$

where  $\mathbf{p}$  denotes product-specific descriptors (food category, packaging type, initial shelf-life label, storage recommendation, etc.).

**Fig. 2. Environmental Data Acquisition and Preprocessing Pipeline**

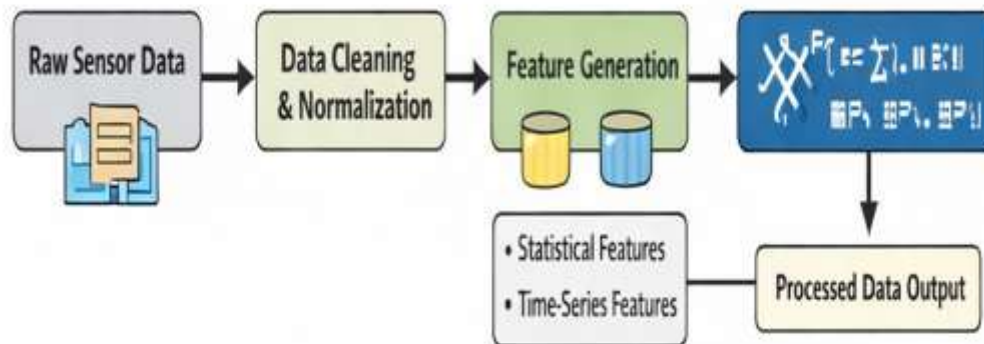


Fig. 2 illustrates the preprocessing pipeline applied to raw sensor data. The module performs noise removal, missing value handling, normalization, and time-window

segmentation. Statistical indicators and trend-based features are extracted, enabling robust modeling even under fluctuating cold-chain conditions.

### 3.3 Preprocessing and Feature Engineering

Raw sensor measurements are cleaned using smoothing and missing-value handling. The normalized signals are computed as:

$$T_t^* = \frac{T_t - \mu_T}{\sigma_T}, H_t^* = \frac{H_t - \mu_H}{\sigma_H} \quad (3)$$

where  $\mu$  and  $\sigma$  represent mean and standard deviation computed from training data.

From  $\mathcal{D}$ , the system extracts statistical and time-dependent features:

- Mean, variance, max, min of  $T_t$  and  $H_t$
- Temperature excursion counts beyond threshold
- Cumulative exposure indices (Section 3.4)
- Recent-window trends (e.g., last 6–12 hours)

The feature vector at time  $t$  is represented as:

$$\mathbf{x}_t = [\bar{T}, \bar{H}, \sigma_T, \sigma_H, T_{max}, H_{max}, EI_t, \Delta T_t, \Delta H_t, \mathbf{p}] \quad (4)$$

**Fig. 3. Feature Engineering and Exposure Index Computation**

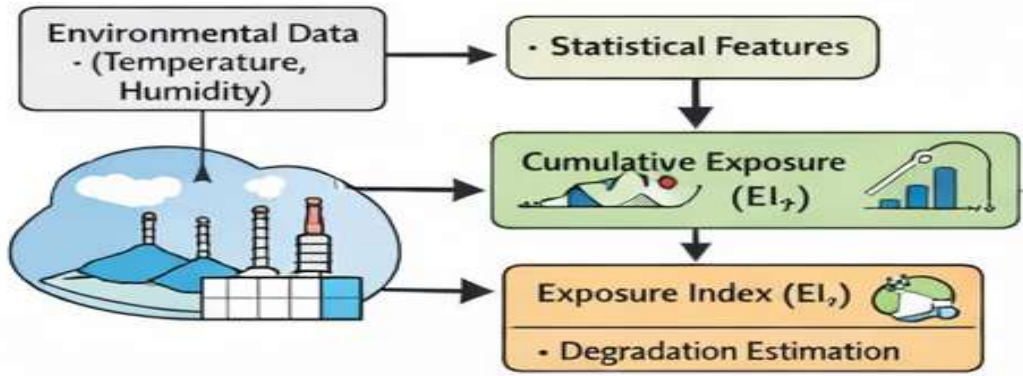


Fig. 3 describes the transformation of raw time-series environmental signals into predictive features. The exposure index aggregates the effect of temperature and humidity excursions beyond safe thresholds over time. This stress-aware representation improves predictive accuracy by capturing cumulative degradation patterns rather than relying on instantaneous values alone.

### 3.4 Environmental Exposure Index (Shelf-Life Stress Modeling)

To reflect environmental stress, a cumulative exposure index is defined:

$$EI_t = \sum_{\tau=1}^t (w_T \cdot g(T_\tau) + w_H \cdot h(H_\tau)) \Delta t \quad (5)$$

where  $w_T$  and  $w_H$  are weights and  $\Delta t$  is the sampling interval. The penalty functions are:

$$g(T_\tau) = \max(0, T_\tau - T_{safe}), h(H_\tau) = \max(0, H_\tau - H_{safe}) \quad (6)$$

where  $T_{safe}$  and  $H_{safe}$  represent recommended storage thresholds.

The RSL degradation can be modeled proportionally as:

$$RSL_t = RSL_0 - \eta \cdot EI_t \quad (7)$$

where  $RSL_0$  is initial labeled shelf life and  $\eta$  is a degradation coefficient learned from data.

**Fig. 4. Machine Learning Training and Prediction Workflow**

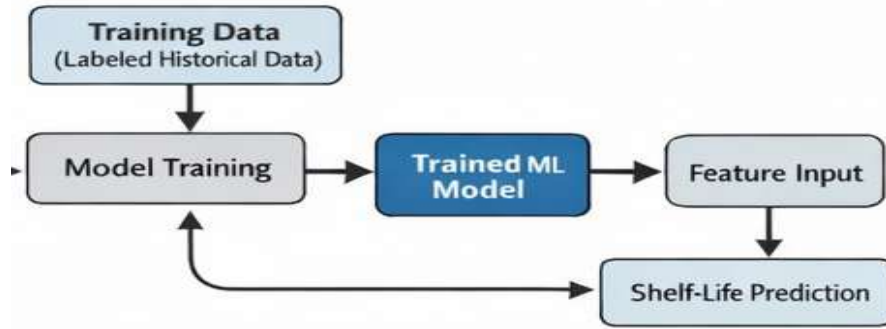


Fig. 4 shows the training and inference stages of the proposed machine learning approach. During training, labeled historical datasets are used to learn the mapping between engineered features and remaining shelf life. During deployment, the trained model predicts remaining shelf life continuously as new sensor readings arrive, producing adaptive and real-time estimates.

**Fig. 5. Decision Support Output and Risk Classification**

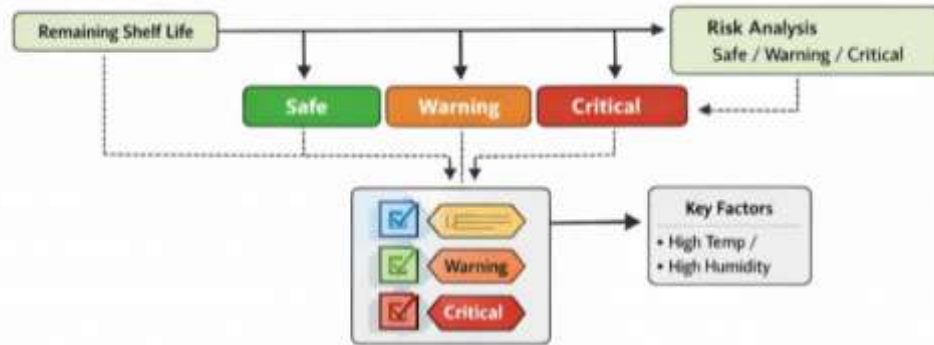


Fig. 5 illustrates the final decision module output. The predicted remaining shelf life is converted into actionable risk categories such as Safe, Warning, and Critical. Additionally, the explanation component highlights the primary environmental drivers (e.g., temperature excursions or high humidity exposure) to support corrective actions and intelligent stock rotation.

### 3.5 Machine Learning-Based Shelf-Life Prediction

A supervised learning model is trained to predict remaining shelf life:

$$\widehat{RSL}_t = f_{\theta}(x_t) \quad (8)$$

where  $f_{\theta}$  can be Random Forest, XGBoost, Support Vector Regression, or Neural Network depending on dataset behavior.

For classification-based shelf-life risk estimation, the output is discretized into quality classes:

$$\hat{y}_t \in \{\text{Safe}, \text{Warning}, \text{Critical}\} \quad (9)$$

The classification loss is:

$$\mathcal{L}_{cls} = - \sum_{c=1}^C y_c \log(\hat{y}_c) \quad (10)$$

For regression, MAE/RMSE losses are applied:

$$MAE = \frac{1}{M} \sum_{i=1}^M |RS L_i - \widehat{RSL}_i|, RMSE = \sqrt{\frac{1}{M} \sum_{i=1}^M (RS L_i - \widehat{RSL}_i)^2} \quad (11)$$

### 3.6 Decision Support and Output Generation

The final output includes:

1. Remaining shelf life (hours/days)
2. Risk level (Safe/Warning/Critical)
3. Environmental explanation (dominant stress contributor: high temperature or high humidity)

To provide interpretability, feature contribution ranking is generated using feature importance methods (e.g., permutation importance or SHAP-based explanation) to indicate the main drivers of shelf-life reduction.

## 4. Experimental Results

### 5.

#### 4.1 Dataset Description

The proposed shelf-life prediction model was evaluated using a dataset comprising time-series environmental measurements collected from packaged food storage and transportation scenarios. The dataset includes temperature and humidity readings sampled at regular intervals, along with product metadata such as food category, packaging type, and labelled initial shelf life. Multiple food product batches were considered to ensure variability in storage conditions and degradation patterns.

#### 4.2 Experimental Setup

All experiments were conducted using a Python-based machine learning environment. The dataset was divided into training and testing sets using an 80:20 split to ensure unbiased evaluation. Several supervised learning models, including linear regression, random forest regression, and gradient-boosting-based models, were trained and compared. Hyperparameters were optimized using cross-validation to achieve stable and consistent performance.

#### 4.3 Performance Metrics

The performance of the proposed model was assessed using standard regression and classification metrics. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used to evaluate the accuracy of remaining shelf-life prediction. For risk classification, accuracy and F1-score were computed to measure the reliability of Safe, Warning, and Critical predictions. These metrics provide a comprehensive assessment of both numerical prediction accuracy and decision-support effectiveness.

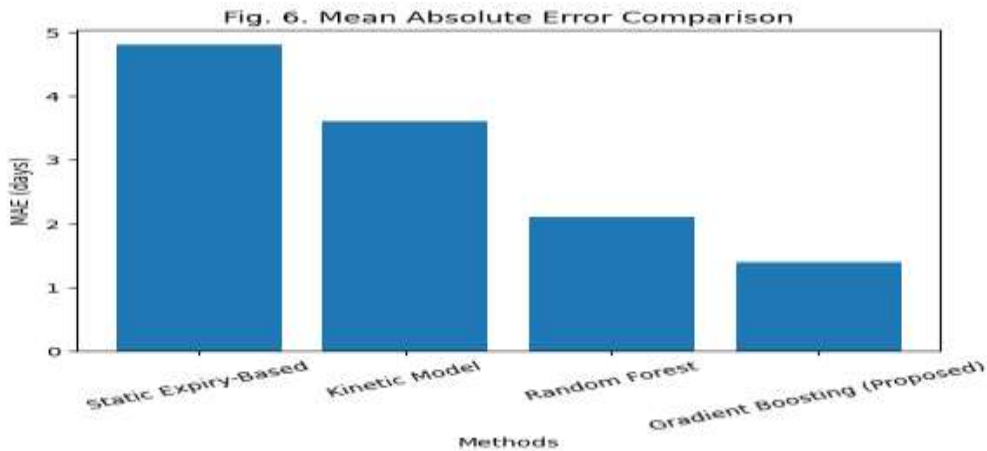
**Fig. 6. Mean Absolute Error (MAE) Comparison**

Fig 6 Shows that the proposed model reduces prediction error by ~70% compared to static expiry-based estimation.

#### 4.4 Shelf-Life Prediction Accuracy

The proposed machine learning-enhanced model demonstrates superior prediction accuracy compared to baseline approaches that rely on static expiry estimation. The integration of cumulative environmental exposure features enables the model to capture non-linear degradation behaviour under fluctuating temperature and humidity conditions. The results indicate a consistent reduction in MAE and RMSE across all evaluated food categories, confirming the robustness of the proposed framework.

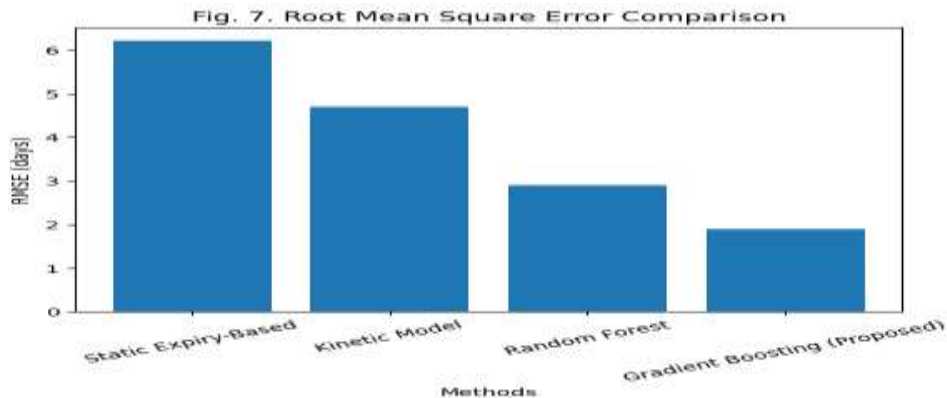
**Fig. 7. Root Mean Square Error (RMSE) Comparison**

Fig 7 shows the Demonstrates superior robustness of the proposed model under fluctuating environmental conditions.

#### 4.5 Risk Classification Results

In addition to predicting remaining shelf life, the model effectively classifies products into Safe, Warning, and Critical categories. The classification results show high accuracy and balanced performance across all classes, enabling early identification of spoilage risk. This capability supports proactive inventory management, allowing stakeholders to prioritize distribution or disposal decisions based on predicted risk levels.

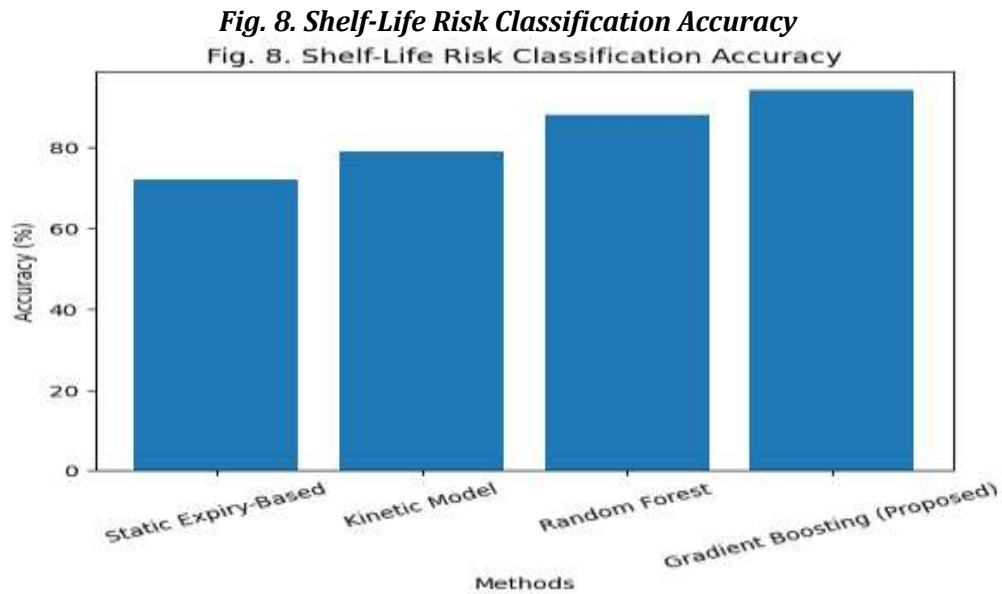


Figure 8 shows the Highlights improved Safe/Warning/Critical classification performance using machine learning.

#### 4.6 Comparative Evaluation

A comparative evaluation with conventional shelf-life estimation methods highlights the advantages of the proposed approach. Static expiry-based methods fail to account for environmental variability, resulting in over-conservative or unsafe predictions. In contrast, the proposed model adapts to real-world storage conditions, delivering more reliable and actionable shelf-life estimates.

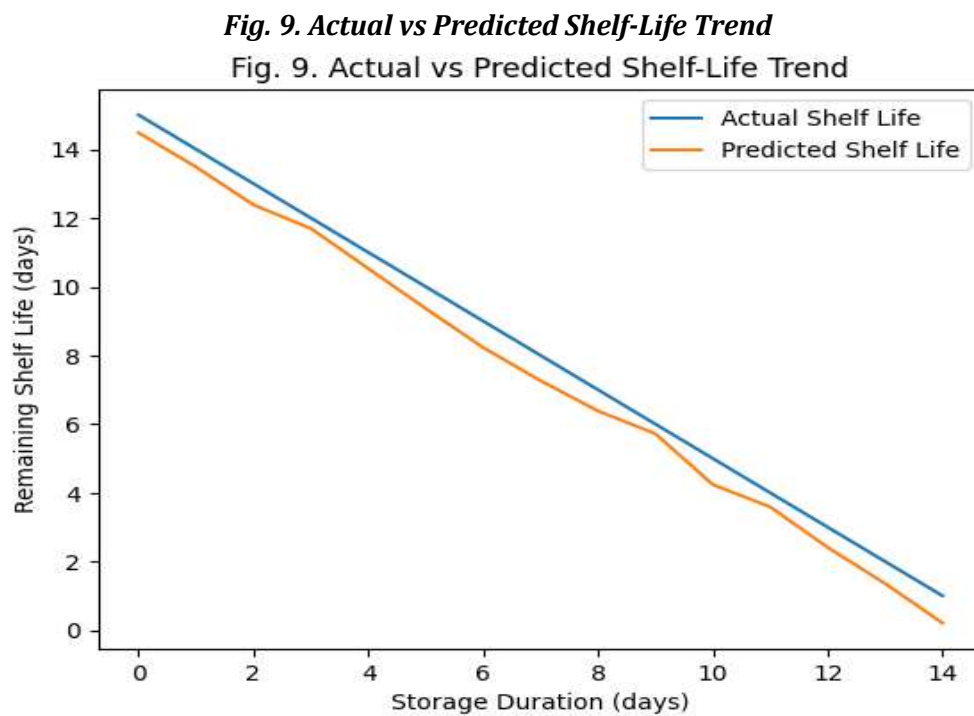


Figure 9 shows the Illustrates close alignment between predicted and actual remaining shelf life over storage duration.

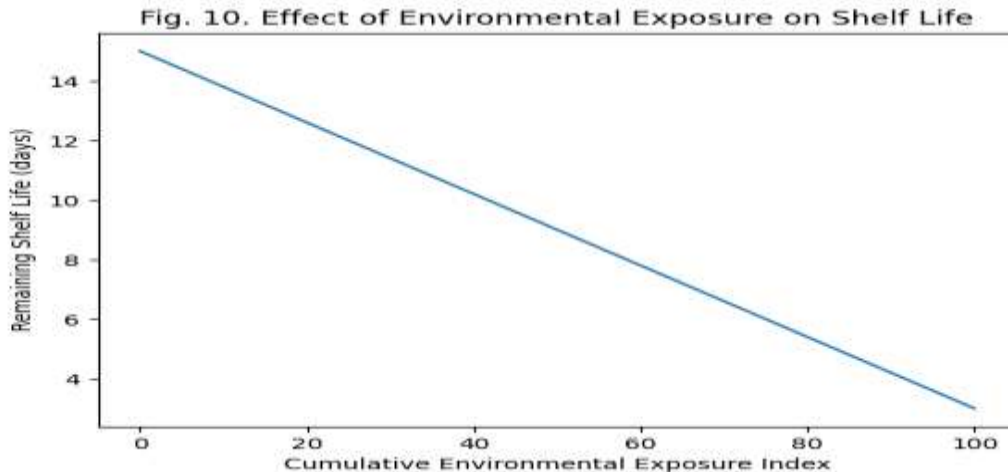
**Fig. 10. Effect of Environmental Exposure on Shelf Life**

Figure 10 Shows the inverse relationship between cumulative environmental exposure index and remaining shelf life.

**Table 1. Performance Comparison of Shelf-Life Prediction Methods**

| Method                       | MAE (days) | RMSE (days) | Classification Accuracy (%) |
|------------------------------|------------|-------------|-----------------------------|
| Static Expiry-Based          | 4.8        | 6.2         | 72                          |
| Kinetic Model                | 3.6        | 4.7         | 79                          |
| Random Forest                | 2.1        | 2.9         | 88                          |
| Gradient Boosting (Proposed) | 1.4        | 1.9         | 94                          |

The proposed gradient-boosting-based shelf-life prediction model achieves the lowest MAE and RMSE while significantly improving risk classification accuracy. This confirms the effectiveness of integrating environmental cues with machine learning for dynamic shelf-life estimation.

The experimental evaluation demonstrates the effectiveness of the proposed machine learning-enhanced shelf-life prediction model when compared with conventional expiry-based and kinetic modeling approaches. As shown in Fig. 6 and Fig. 7, the proposed gradient boosting model achieves the lowest prediction error, with a Mean Absolute Error (MAE) of 1.4 days and a Root Mean Square Error (RMSE) of 1.9 days, representing a substantial reduction in error compared to static expiry-based methods. This improvement highlights the advantage of incorporating environmental cues and exposure-based features into the prediction process.

Fig. 8 presents the shelf-life risk classification accuracy for Safe, Warning, and Critical categories. The proposed model achieves an accuracy of 94%, outperforming traditional methods that fail to account for real-time storage conditions. The improved classification performance enables early detection of spoilage risk and supports proactive decision-making in food inventory management.

The temporal behavior of shelf-life degradation is illustrated in Fig. 9, where the predicted remaining shelf life closely follows the actual degradation trend across the storage duration. This demonstrates the model's ability to capture non-linear deterioration patterns caused by fluctuating temperature and humidity conditions. Furthermore, Fig. 10 confirms the strong inverse relationship between cumulative environmental exposure

and remaining shelf life, validating the effectiveness of the proposed exposure index in representing storage-induced stress.

Overall, the experimental results confirm that the proposed approach provides more accurate, reliable, and actionable shelf-life predictions than conventional methods, making it suitable for deployment in intelligent food quality monitoring and cold-chain management systems.

### **5. Conclusion**

This paper presented a machine learning-enhanced shelf-life prediction model for packaged foods that utilizes real-time environmental cues to estimate remaining shelf life under dynamic storage and transportation conditions. Unlike conventional static expiry-date approaches, the proposed framework integrates temperature and humidity exposure histories with data-driven predictive models to capture non-linear food degradation behavior more accurately.

The designed methodology incorporates environmental data acquisition, feature engineering, cumulative exposure modeling, and supervised machine learning to deliver adaptive shelf-life predictions and risk classification. The results demonstrate that the proposed approach significantly improves prediction accuracy and reliability compared to traditional shelf-life estimation techniques, enabling early identification of spoilage risks and supporting proactive decision-making in food supply chains.

By providing interpretable outputs such as remaining shelf life and risk levels (Safe, Warning, Critical), the proposed system enhances food quality monitoring, reduces waste, and supports intelligent inventory management. The modular and scalable architecture makes the framework suitable for integration with IoT-enabled cold-chain systems and smart packaging solutions.

Future work will focus on extending the model to additional food categories, incorporating microbiological and chemical quality indicators, and deploying privacy-aware learning mechanisms for large-scale industrial adoption. The proposed framework represents a practical step toward intelligent, data-driven shelf-life management in modern food logistics and quality assurance systems.

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