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Research article

Real-time monitoring and freshness classification of fresh bananas: practical insights

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Abstract: Fresh foods are essential products in the global food industry, offering consumers vital nutrients and health benefits worldwide. Despite advancements in freshness classification using image-based data, the literature lacks exploration of quantitative data in this field. In this study, we collected a real-world sensor dataset for food freshness classification during runtime by monitoring and recording environmental and chemical variables that affect food quality, using bananas as a case study. The collected dataset was pre-processed and used to train and test six machine learning models: logistic regression, random forest, support vector machine, K-Nearest Neighbor, decision tree, and gradient boosting. These models were employed for the automatic classification of banana freshness into three health classes: fresh, ripening, and spoiled. The results revealed that the random forest model outperforms other models in predicting banana health class, achieving an average accuracy of 95%. Additionally, we critically analyzed the collected data and provided actionable insights for stakeholders and professionals in the food industry, enabling them to make informed decisions that maintain product quality and reduce food waste.

Keywords: food freshness; classification; machine learning; sensor data; food waste

1. Introduction

Fresh foods are vital products in the global food industry, providing essential nutrients and health benefits to consumers worldwide. As the global population continues to grow, preserving the freshness of perishable food items throughout the supply chain stages has become a significant issue [1]. The freshness of perishable food items, such as dairy, fruits, vegetables, and meat, is crucial for ensuring their quality and safety. Food safety and public health have gained increasing attention and have attracted researchers and professionals from the food industry to develop effective and practical methods for food freshness monitoring and classification [2]. By accurately assessing food freshness, stakeholders can make informed decisions that extend shelf-life periods, reduce waste, and provide customers with safe and healthier products.

Food freshness is crucial in reducing food waste at various supply chain stages. Food products are sensitive to changing environmental conditions that might deteriorate their quality during storage, transportation, and while on retailers' shelves, leading to significant food waste [3]. Monitoring food quality in real time and employing appropriate approaches to classify freshness, determine remaining shelf life, and communicate this up-to-date information to all stakeholders significantly impacts maintaining quality and ensuring sustainability. Consequently, the field of food freshness monitoring and classification has received substantial attention in recent years [4,5].

Researchers have utilized machine learning (ML) and deep learning (DL) to detect and classify food freshness and quality. Specifically, these studies employed computer vision and image processing techniques combined with convolutional neural networks (CNNs) to classify food items based on their visual characteristics, such as color and shape [6–9]. For instance, Liu, Zhao [10] developed an integrated method utilizing the simple linear iterative clustering (SLIC) and support vector machine (SVM) classifier to detect the freshness of red apples using color and shape features. Ganeshan Mudaliar [11] utilized a CNN to develop a model for classifying tomatoes into ripe and rotten classes. Fu, Nguyen [12] proposed a hierarchical approach for grading fruit freshness utilizing computer vision and deep learning. A neural network You Only Look Once (YOLO) model was first employed to extract the region of interest from digital images. Then, the CNN used the extracted images for grading food freshness. Kazi and Panda [13] classified the freshness of three fruit types, including apples, oranges, and bananas, utilizing the CNN model's classical and residual architectures. Mukhiddinov, Muminov [14] proposed a deep-learning system utilizing the YOLOv4 model for classifying fruits and vegetables into two classes: fresh or rotten. While the proposed models effectively classified food items' freshness and achieved high accuracy, they relied on image-based datasets and required substantial computational power and resources to run the DL models. Additionally, most researchers have used offline images to classify food items, which limits their practical applicability in real-world scenarios.

Some researchers have explored the potential of utilizing numerical data, such as sensor data, for food freshness classification. Leveraging the Internet of Things (IoT) sensors to monitor food quality and freshness is crucial in ensuring food safety and reducing waste [15]. The integration of IoT sensors enables the real-time collection of critical variables that affect food quality, such as temperature, humidity, and gas emissions [16,17]. For instance, selecting the appropriate temperature and humidity levels prevents deterioration by inhibiting the critical metabolic processes of fruit. Additionally, gas concentration is an essential indicator of the ripening stages of fresh foods, making it a crucial parameter for monitoring food freshness [18,19]. Feng, Zhang [20] proposed an IoT-enabled monitoring system to assess the freshness of salmon and detect nose spoilage under several cold storage conditions. Torres-Sanchez, Teresa Martinez-Zafra [21] developed a monitoring system to record the quality of lettuce under various temperature conditions during storage and transportation. The authors utilized the recorded temperature to develop a multiple non-linear regression (MNLR) model to predict optimal temperature conditions that extend lettuce shelf life. Huang, Wang [22] proposed a monitoring platform to record gas concentration parameters at various temperatures using IoT sensors. The authors then used the collected sensor data to develop prediction models based on a

BP neural network, a radial basis neural network (RBF), an SVM, and an extreme learning machine (ELM).

Despite advances in integrating IoT sensor data, few researchers have used sensor-related parameters to classify food freshness. There is a need for real-time monitoring systems that record vital parameters during runtime and use the recorded data to support timely freshness classification and decision-making. We utilize a quantitative sensor-based real-world dataset for real-time food freshness monitoring and classification. Using real-time sensor data enables early detection of spoilage signs, giving an early warning to take actions that help reduce food waste. The real-world dataset is collected through real experiments performed on bananas to monitor their quality. It includes readings of environmental and chemical variables, as well as manually labeling their freshness (health classes). The dataset is thoroughly analyzed using several preprocessing approaches to derive critical insights and prepare for model training, which automatically classifies food freshness. However, given that the dataset is collected on a small scale, we further develop a synthetic dataset using the real one to address this limitation, maintaining the same statistical distribution while expanding its size.

To bridge the research gaps and considering the lack of real-world validation, we adopt the following methodology: (1) Preprocessing and analyzing a dataset collected from real-world experiments within the food retailer sector to derive practical insights, (2) developing a synthetic dataset using the same distribution patterns as the real sensor-based dataset, (3) applying six machine learning models to classify the health class of bananas using the developed dataset, and (4) establishing a comparative analysis between the models to assess their performance in accurately predicting the health class using several evaluation metrics. Using the proposed approach, we aim to provide practical recommendations on the models for classifying food products. Additionally, we aim to provide actionable insights to professionals and stakeholders in the food industry to help them make informed decisions.

The remainder of this paper is organized as follows: In Section 2, we present the research methodology. In Section 3, we provide and discuss the experimental results. Finally, in Section 4, we conclude the paper and recommend future directions.

2. Research methodology

In this section, we describe the methodology adopted in this study. The proposed methodology leverages a real-time environmental and chemical sensor dataset to classify food freshness, using bananas as a case study. Experiments are first conducted to record banana temperature, ethylene gas concentration, volatile organic compounds (VOCs), and humidity. Recording these critical parameters in real time enables early spoilage detection, facilitating timely, informed decisions. Bananas are manually inspected and labeled, providing reliable labeling for ML models' training, testing, and further analysis.

Section 2.1 describes the data, Section 2.2 explains the preprocessing steps applied to the data, and Section 2.3 presents the analysis and key findings.

2.1. Data description

In this section, we describe the dataset collected through real-world experiments. The experiments are conducted to monitor the conditions of bananas stored on retailers' shelves by collecting critical variables from environmental and chemical sensors in real time. The collected data is processed, and features are generated and fed to several ML models to classify health classes into fresh, ripening, and spoiled.

Several real experiments are conducted to monitor the freshness of bananas placed in boxes on retailers' shelves, which experience complete spoilage with visible rot. Inside each box, two types of sensors are installed. The first type, environmental sensors, monitors and collects essential data on environmental conditions, including temperature and humidity. The second type includes chemical sensors that track and record voltage readings of the Ethylene gas, providing critical insights into their concentration. The MQ3 alcohol sensor measures ethylene gas concentration, while the BME280 sensor measures temperature and humidity, both of which are critical factors in monitoring the condition of stored fruits. Sensor data are recorded every 10 minutes, and the bananas are visually inspected to assess their freshness and labeled with a health class score. The health score ranges from 1 to 3, as follows: Class 1 (Fresh), Class 2 (Ripening), and Class 3 (Spoiled).

The dataset comprises 8158 observations from five experiments, corresponding to five banana boxes. Each observation reflects sensor readings of the parameters recorded every 10 minutes for each box included in the dataset. Table 1 describes the included variables.

Table 1. Description of variables.

Variable name	Description
Box ID	The current banana box ID
Timestamp	The current time of the observation
Index	A 10-minute period of observation
Temperature	The recorded temperature for each box
Humidity	The recorded humidity for each box
Alc-voltage	An alcohol voltage level for each box
VOC	The volatile organic compounds measured for each box
Box health-class	The health class of the tested box

2.2. Data pre-processing

Visual data preprocessing is crucial to preparing the dataset for modeling. It involves several iterative steps, including understanding data characteristics and variable distributions, identifying potential anomalies, detecting outliers, checking for missing values, applying the appropriate transformations, creating additional features, and determining the correlation between variables [23].

Several preprocessing approaches are utilized to clean and prepare the sensor-based datasets collected for each banana box. The individual experiments are then merged into a single comprehensive file, indicating a dataset that captures readings from the five boxes. Dataset variables are checked for missing values and anomalies, and statistical analysis indicates potential outliers in some VOC values. After carefully examining the detected outliers, some values are retained because they represent real observations, while the unnecessary outliers are removed using the Z-score trimming method. Additionally, the logarithmic transformation is applied to variables with positive skew, while the Box-Cox transformation is used for those with negative skew. Finally, numeric variables such as humidity, temperature, and alcohol voltage are normalized and scaled using the Min-Max normalization method to a common range between 0 and 1.

After cleaning and processing the real sensor-based datasets, we use them to generate synthetic samples by employing Gaussian noise, increasing the volume and diversity of the data while preserving the underlying distribution patterns. This approach is utilized to reduce overfitting and enhance generalization when working with limited sensor-based datasets. Figure 1 illustrates the distribution of the target variable using the developed dataset. As shown, the synthetic dataset maintains the same overall distribution as the real dataset, confirming that the applied Gaussian noise expands the dataset size without altering the underlying data characteristics.

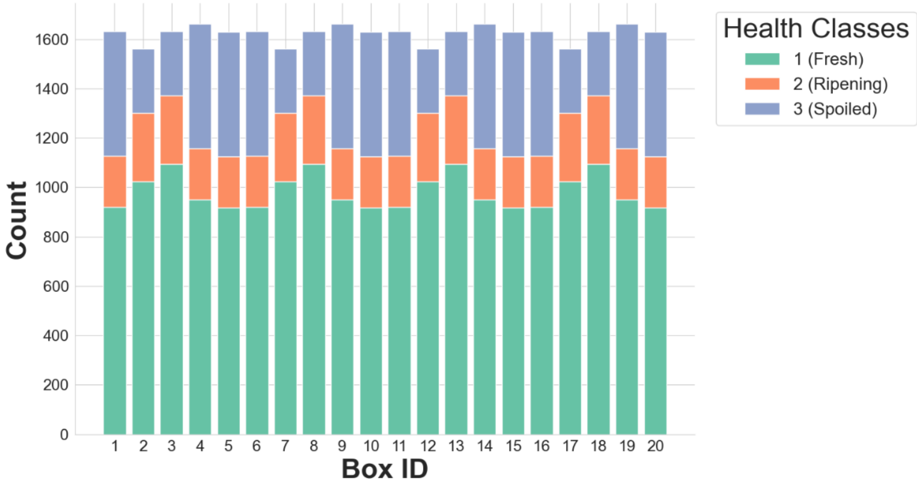

Figure 1. Distribution of health classes across the tested banana boxes.

To visualize relationships among features and to facilitate feature selection before model training, a correlation heatmap is generated in Figure 2. The heatmap reveals a strong positive relationship between the variables (alc-voltage and index) and the target variable (health class), indicating that the most impactful variables are alc-voltage and index, with correlation measures of 0.77 and 0.61, respectively. Conversely, a weak relationship is observed between the target variable and other variables such as humidity, temperature, and VOC. Although factors such as temperature are generally considered major contributors to food deterioration, their impact is not reflected in the results. This is mainly due to the controlled experimental conditions, which result in a stable temperature throughout the monitoring period and prevent the model from capturing the expected correlation between temperature and perishability.

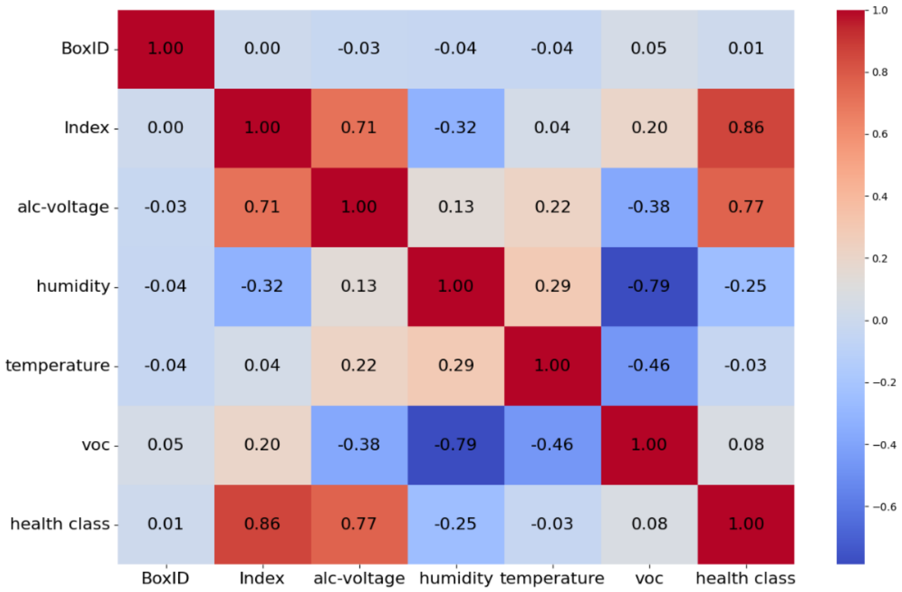

Figure 2. Heatmap of Pearson's correlation.

2.3. Data analysis and key findings

Data analysis is conducted on the clean final dataset, which contains observations from five real boxes, as they reflect realistic conditions and facilitate the extraction of meaningful insights. First, the data analysis reveals that higher humidity is associated with lower VOC levels across observations from the 5 boxes. This leads to the derived hypothesis:

"There is a strong negative correlation between humidity and VOC readings, where an increase in humidity readings leads to a decrease in VOC values".

This hypothesis is supported and proven based on the conducted data analysis, as follows:

1) From the heatmap in Figure 2, the correlation between the two variables is calculated as -0.79, indicating a strong negative relationship.
2) From plotting the two variables using line graphs, Figure 3 reveals a strong relationship between the two variables.

Additionally, it is revealed that the progression of bananas' health class over time, from fresh to ripening to spoilage, is primarily related to the alcohol gas voltage (alc-voltage) variable. This observation suggests that the alc-voltage variable significantly impacts the health class readings. Based on that, we hypothesize that:

"The voltage readings of alcohol gas are directly impacting and leading to the decrease of the products' freshness level from fresh to ripening to spoilage".

This hypothesis is supported and proven based on the conducted data analysis, as follows:

1) From the heatmap in Figure 2, the correlation between the two variables is calculated as 0.77, indicating a strong positive relationship.
2) The relation between the two variables is plotted using line graphs in Figure 4. The results confirm a strong positive correlation, indicating an increase in alc-voltage with some fluctuations over time.

From the data analysis, it is revealed that bananas remain in the fresh class for a longer period compared to other classes, as illustrated in Figure 4. However, once bananas start to ripen, their freshness deteriorates much more rapidly. It is further observed that bananas take approximately 12 to 13 days to spoil from being fresh, with visible signs of rot. These findings suggest proposing a time window for bananas' shelf life, as shown in Figure 5.

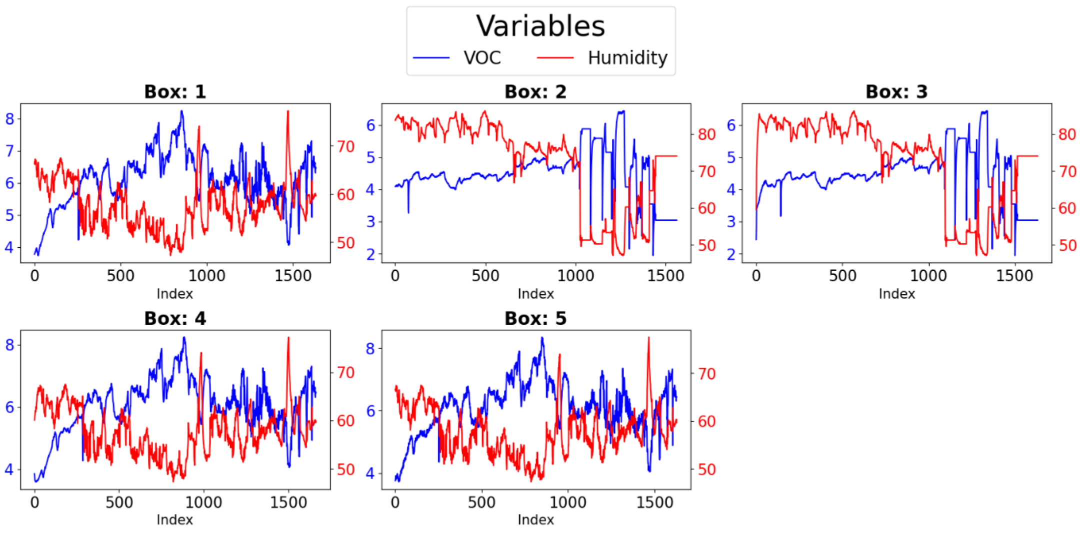

Figure 3. Correlation between humidity and VOC variables for the five banana boxes.

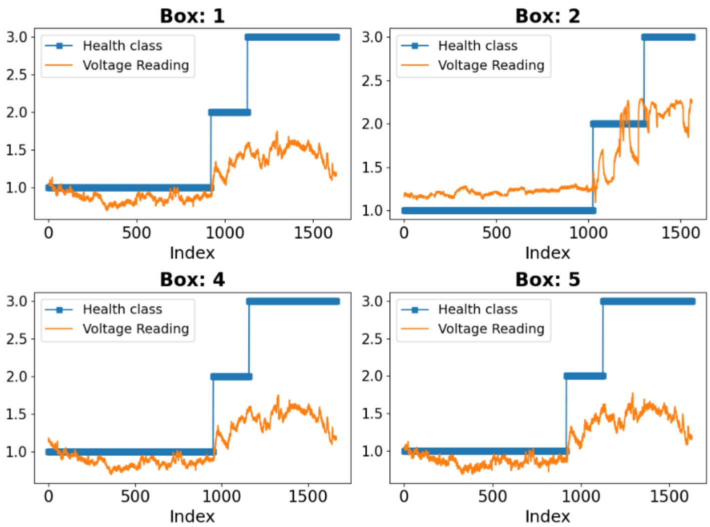

Figure 4. Correlation between alc-voltage and health class variables for the five banana boxes.

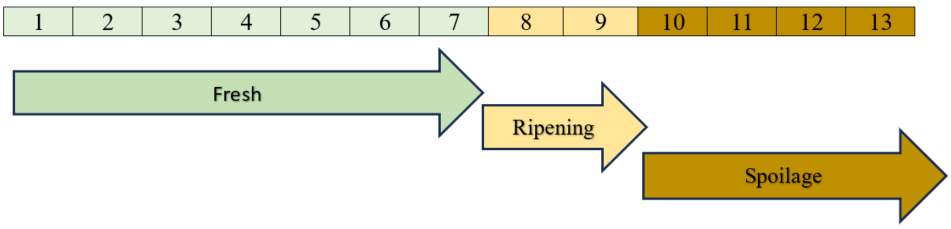

Figure 5. Time window of bananas' shelf life.

According to the proposed time window of bananas' shelf life, we recommend the following observations:

1) Bananas remain fresh for up to 7 days.
2) Bananas are observed in the ripening stage for 2 days.
3) Bananas typically take 3 to 4 days to spoil. This period represents the spoilage timeline from the initial signs of spoilage until it becomes unsuitable for sale or consumption due to visible rot.

To maintain the proposed timeline for bananas' shelf life, storing them at a controlled temperature between 24 °C and 27 °C and a humidity level between 65% and 80% is recommended. Additionally, a trigger action should be initiated on the first day of the spoilage stage, and action should be taken by the second day. This strategy enables informed decisions that reduce waste, such as optimizing product processing, offering discounts, and implementing labels for expedited delivery.

3. Experimental results

A comparative analysis is conducted to assess the performance of six ML models, including logistic regression (LR), support vector machine (SVM), random forest (RF), K-Nearest Neighbor (KNN), decision tree (DT), and gradient boosting (GB), for the classification of banana freshness into three classes: fresh, ripening, and spoiled. The processed dataset, which combines real and synthetic records, is split into training and testing sets using the implemented grid search cross-validation approach to ensure reliable model validation and testing.

A nested cross-validation approach is employed, consisting of an outer loop and an inner loop. The outer loop employs a group 5-fold cross-validation to split the dataset into training and testing sets based on the Box ID variable (presented in Table 2), ensuring readings of the same group are included in the training or the testing sets. For each dataset split, another 10-fold cross-validation with grid search is employed within the training dataset to optimize hyperparameters, validate models, and select the best models. During the validation stage, the accuracy of the applied models is computed ten times and averaged, and the models with the highest accuracy are selected as the best models. The regularization strength (C) and the optimization algorithm (Solver) parameters are optimized for the LR model. For the RF, we fine-tune the maximum depth of decision trees (max_depth) and the number of trees (n_estimators). The number of nearest neighbors (n_neighbors) and the maximum depth of decision trees (max_depth) are optimized for the KNN and DT models, respectively. For the SVM, we optimize the regularization parameter (C) and the kernel function (kernel). The learning rate (learning_rate) and the number of boosted trees (n_estimators) parameters are optimized for the GB model. Table 3 presents all parameter settings of the tested models for each dataset split.

The best models from the grid search are tested on unseen data in the test dataset. We assess and compare model performance across dataset splits using the common classification metrics, including accuracy, recall, precision, and F1-score.

Accuracy is calculated as the proportion of correct predictions to the full sample size, as in Eq (1). Precision measures the proportion of true positives among all instances that have been predicted as positive, as in Eq (2). Recall measures the correctly predicted positive instances from all actual positive samples, as in Eq (3). F1-Score measures the harmonic mean of the precision and recall, as in Eq (4).

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TS}}, \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}, \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}}, \tag{3}$$

$$\text{F1}-\text{Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}, \tag{4}$$

where TS is the total samples, TP (true positive) indicates the correctly predicted positive samples, TN (true negative) indicates the correctly predicted negative samples, FP (false positive) refers to the incorrectly predicted positive samples, and FN (false negative) indicates the incorrectly predicted negative samples.

Table 4 presents the evaluation metrics returned by each model for the five dataset splits. Among the six included models, RF achieved the best performance with the first, third, and fourth dataset splits, while DT performed best with the second and fifth datasets. However, LR returned the poorest performance when tested using the five dataset splits. Figure 6 plots the evaluation metrics for the models that achieved high performance on each dataset split, highlighting their relative performance.

Additionally, Figure 7 plots the confusion matrix for the best-performing model on each dataset split. The confusion matrix is an effective tool for evaluating the performance of the best models. It plots the distribution of true and predicted values for each class, reflecting the model's accuracy in predicting each class.

From Figure 7, it is observed that the RF model correctly predicted 97.8% of class 1, 90% of class 2, and 97.2% of class 3 observations for the first dataset split. When tested on the second dataset split, the DT model achieved the best performance, correctly predicting 99.4% of class 1, 76.5% of class 2, and 83% of class 3 observations. The RF model achieved the highest performance for the third dataset split (correctly predicting 97.8% of class 1, 95.4% of class 2, and 96.9% of class 3) and for the fourth dataset split (correctly predicting 96.9% of class 1, 90.1% of class 2, and 98% of class 3). The

DT model achieved the highest performance when tested on the fifth dataset split, correctly predicting 99% of class 1, 72.8% of class 2, and 84.5% of class 3.

Table 2. Dataset splits from Group 5-fold cross-validation.

Dataset splits	Boxes included in the training and validation sets	Boxes included in the testing set
Dataset 1	2,3,5,6,8,9,10,11,13,15,16,17,18,19,20	1,4,7,12,14
Dataset 2	1,2,4,5,6,7,9,10,11,12,14,15,16,18,19	3,8,13,17,20
Dataset 3	6,7,8,9,10,11,12,13,14,15,16,17,18,19,20	1,2,3,4,5
Dataset 4	1,2,6,4,5,7,8,12,13,14,15,17,18,19,20	3, 9, 10, 11, 16
Dataset 5	1,2,3,4,5,6,9,10,11,12,14,15,16,17,20	7,8,13,18, 19

Table 3. Parameter settings.

	Model	Parameter settings
Dataset 1	SVM	'C': 10, 'kernel': 'rbf'
	K-Nearest Neighbors	'n_neighbors': 5
	Decision Tree	'max_depth': 10
	Gradient Boosting	'learning_rate': 0.1, 'n_estimators': 100
	Logistic Regression	'C': 10, 'solver': 'liblinear'
	Random Forest	'max_depth': 10, 'n_estimators': 100
Dataset 2	SVM	'C': 10, 'kernel': 'rbf'
	K-Nearest Neighbors	'n_neighbors': 7
	Decision Tree	'max_depth': 10
	Gradient Boosting	'learning_rate': 0.5, 'n_estimators': 50
	Logistic Regression	'C': 10, 'solver': 'liblinear'
	Random Forest	'max_depth': 10, 'n_estimators': 100
Dataset 3	SVM	'C': 10, 'kernel': 'rbf'
	K-Nearest Neighbors	'n_neighbors': 7
	Decision Tree	'max_depth': 10
	Gradient Boosting	'learning_rate': 0.5, 'n_estimators': 50
	Logistic Regression	'C': 1, 'solver': 'liblinear'
	Random Forest	'max_depth': 10, 'n_estimators': 100
Dataset 4	SVM	'C': 10, 'kernel': 'rbf'
	K-Nearest Neighbors	'n_neighbors': 7
	Decision Tree	'max_depth': 10
	Gradient Boosting	'learning_rate': 0.5, 'n_estimators': 50
	Logistic Regression	'C': 10, 'solver': 'liblinear'
	Random Forest	'max_depth': None, 'n_estimators': 100
Dataset 5	SVM	'C': 10, 'kernel': 'rbf'
	K-Nearest Neighbors	'n_neighbors': 7
	Decision Tree	'max_depth': 10
	Gradient Boosting	'learning_rate': 0.5, 'n_estimators': 50
	Logistic Regression	'C': 10, 'solver': 'liblinear'
	Random Forest	'max_depth': 10, 'n_estimators': 100

Table 4. Evaluation of Models.

		Accuracy	Precision	Recall	F1 Score
Dataset 1	Logistic Regression	0.93	0.93	0.93	0.92
	Random Forest	0.97	0.97	0.97	0.97
	SVM	0.94	0.94	0.93	0.94
	K-Nearest Neighbors	0.88	0.90	0.88	0.89
	Decision Tree	0.95	0.95	0.95	0.95
	Gradient Boosting	0.96	0.96	0.96	0.96
Dataset 2	Logistic Regression	0.86	0.87	0.86	0.85
	Random Forest	0.91	0.91	0.91	0.91
	SVM	0.87	0.89	0.87	0.88
	K-Nearest Neighbors	0.90	0.91	0.90	0.91
	Decision Tree	0.92	0.93	0.92	0.92
	Gradient Boosting	0.91	0.91	0.91	0.91
Dataset 3	Logistic Regression	0.90	0.90	0.90	0.89
	Random Forest	0.98	0.98	0.98	0.97
	SVM	0.94	0.94	0.94	0.94
	K-Nearest Neighbors	0.96	0.96	0.96	0.95
	Decision Tree	0.97	0.97	0.97	0.97
	Gradient Boosting	0.97	0.97	0.97	0.97
Dataset 4	Logistic Regression	0.90	0.89	0.90	0.89
	Random Forest	0.97	0.96	0.97	0.97
	SVM	0.93	0.93	0.93	0.93
	K-Nearest Neighbors	0.94	0.93	0.94	0.93
	Decision Tree	0.95	0.95	0.95	0.95
	Gradient Boosting	0.96	0.96	0.96	0.96
Dataset 5	Logistic Regression	0.86	0.87	0.86	0.85
	Random Forest	0.90	0.91	0.90	0.90
	SVM	0.87	0.89	0.87	0.88
	K-Nearest Neighbors	0.90	0.91	0.90	0.91
	Decision Tree	0.92	0.92	0.92	0.92
	Gradient Boosting	0.90	0.91	0.90	0.90

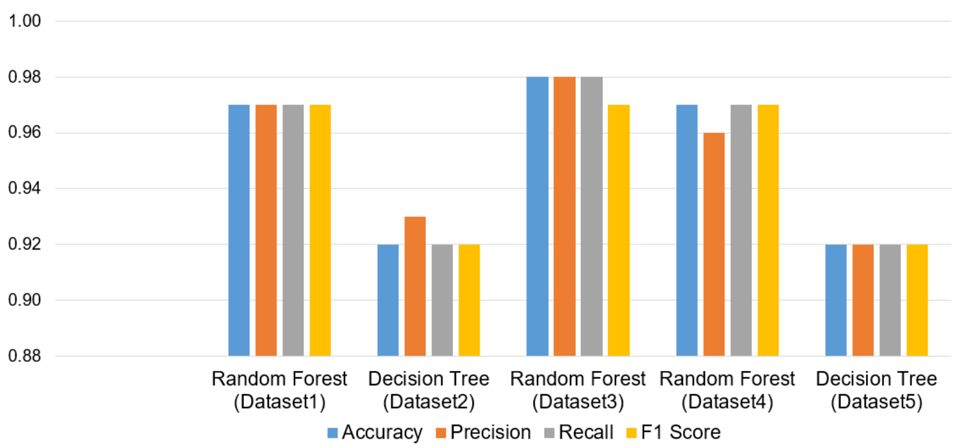

Figure 6. Best models using the tested datasets.

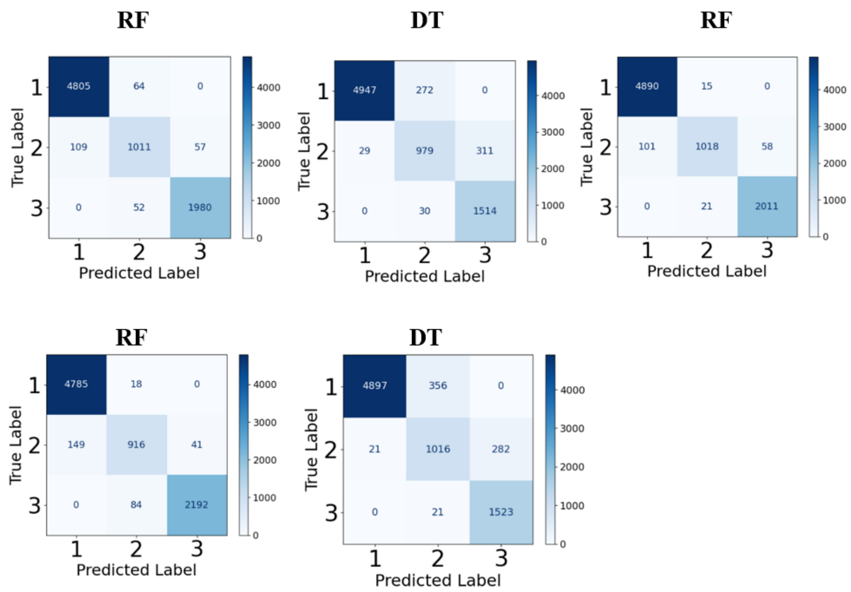

Figure 7. Confusion matrix for the five dataset splits.

When comparing the evaluated models, we found that the RF model achieved the highest overall performance. Achieving an average accuracy of 95% compared to 89% for LR, 91% for SVM, 91.6% for KNN, 94.2% for DT, and 94% for GB. Additionally, the RF model demonstrated a good balance between precision and recall, achieving an F1-score of 94.4%. These results revealed the effectiveness of the RF model in accurately predicting the correct class, reducing false positives and false negatives.

Overall, our findings of this research present significant implications for the fresh food industry. Using the remaining shelf-life and health-class classifications can be effectively leveraged and integrated into demand forecasting and inventory management, which are key applications in food supply chain decision-support systems. This integration enables the development of dynamic systems capable of adapting to changing conditions and proactively taking informed decisions to sustain food systems. For instance, by integrating up-to-date information on the shelf-life of stocks into demand forecasting, food retailers can make more precise predictions about the quantities needed. Additionally, by managing inventory and closely monitoring self-life, decision-makers can prioritize selling products approaching their expiration dates, ensuring fresh offerings and minimizing waste. This approach not only accounts for the inventory state but also significantly enhances efficiency, minimizes waste, and supports sustainable practices. In future work, we will extend the proposed work by modeling shelf-life predictions and food freshness status in more time-steps, enabling more realistic and proactive interventions, such as environmental adjustments, to further prevent waste.

6. Conclusions

In this study, we explored the potential of utilizing a sensor-based dataset collected from real-world experiments to automatically classify food freshness, using bananas as a case study. Parameters such as temperature, humidity, VOCs, and alcohol levels in ethylene gas were first collected from environmental and chemical sensors to monitor the freshness and quality of bananas over time. Several preprocessing approaches were applied to the real-world dataset to clean and prepare it for automatic classification of food freshness into three classes: fresh, ripening, and spoiled. Additionally, to address the limitation of the real-world dataset size, we developed a synthetic dataset by applying Gaussian noise to the real dataset, resulting in a larger dataset with a similar distribution to the real one. Utilizing the prepared dataset, we further assessed the performance of the LR, RF, SVM, KNN, DT, and GB models to classify the freshness of bananas into three classes: fresh, ripening, and spoiled. To prevent overfitting and to ensure the models' generalization, hyperparameter tuning was conducted using a grid search with group 10-fold cross-validation. The comparative analysis revealed that the RF model outperformed others on the first, third, and fourth dataset splits, while the DT model outperformed others on the second and fifth dataset splits. The results further revealed that the RF model outperformed the others, achieving an average accuracy of 95% and a weighted F1-score of 94.4%.

This study provides a real-world benchmark dataset that can be updated and scaled for fruit freshness classification. Using a sensor-based dataset enables stakeholders to detect fruit spoilage early and continuously monitor critical parameters over time. This proactive approach not only enhances food quality but also reduces waste, making it a crucial tool in preserving freshness. Additionally, through intensive analysis of real-world data, we provide practical, actionable insights that help professionals in the food industry make informed decisions.

Despite the importance of integrating information on food freshness and quality to predict future demand, researchers have not addressed this issue. Subsequent research linking the freshness of food items to food demand predictions is crucial for reducing waste and enhancing resilience, making it a promising research direction. In addition, future research on developing freshness classification models that combine sensor and image data is a promising direction. Moreover, future research under different temperature conditions would enhance the accuracy of context-dependent variables and provide a more generalized understanding of their role in food freshness quality.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

Jun Shen is an editorial board member for Applied Computing and Intelligence and was not involved in the editorial review and the decision to publish this article.

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