Rapid and reliable approach for detecting milk spoilage

Srushti Jamewar, Ritika Patki, Nishad Gharote, Tanika Mathur, Mridula Korde
Department of Electronics and Communication Engineering, Ramdeobaba University, Nagpur, India

Article Info

Article history:

Received Sep 1, 2025
Revised Mar 10, 2026
Accepted Apr 19, 2026

Keywords:

Carbon monoxide measurement
Machine learning
Milk quality prediction
Milk spoilage
pH measurement

ABSTRACT

Milk spoilage poses a major challenge to food safety, public health, and sustainability, often resulting in unnecessary waste across households and dairy supply chains. Traditional detection methods, such as smelling or boiling, are subjective, delay early identification, and frequently lead to misjudgment. This study proposes a machine learning (ML)–based spoilage detection framework that integrates real-time pH and carbon monoxide (CO) sensor data to classify milk as fresh, not fresh, or spoiled. multiple supervised learning models, including random forest, eXtreme gradient boosting (XGBoost), support vector machine (SVM), and decision tree, were trained and evaluated using datasets collected from raw and boiled milk samples under varying conditions. Performance was assessed using coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) metrics to identify the most reliable model for shelf-life prediction. Experimental results show that random forest and XGBoost outperform traditional threshold-based approaches, with random forest demonstrating superior consistency and operational efficiency. The findings highlight the potential of intelligent, low-cost sensor–ML systems to significantly enhance early spoilage detection, strengthen food safety, and reduce milk wastage across domestic and industrial environments.

Corresponding Author:

Mridula Korde
Department of Electronics and Communication Engineering, Ramdeobaba University
Ramdeo Tekdi, Gittikhadan, Katol Road, Nagpur, Maharashtra, India
Email: kordems@rknec.edu

1. INTRODUCTION

Milk, as a staple dietary component worldwide, is highly prone to microbial spoilage due to its nutrient-rich composition, high moisture content, and near-neutral pH. These characteristics create an optimal environment for microbial proliferation, particularly lactic acid bacteria, which metabolize lactose into lactic acid and produce volatile compounds that alter the taste, odor, and safety of milk. Spoilage progresses rapidly under inadequate storage conditions, especially in warm climates or regions with limited refrigeration, making timely detection crucial for consumer safety, economic sustainability, and food waste reduction [1], [2].

Traditional methods for assessing milk freshness, such as smelling, visual inspection, or boiling, are subjective, inconsistent, and error-prone. These manual techniques frequently result in premature disposal of safe milk or delayed recognition of spoilage, both of which carry negative consequences for public health and the dairy supply chain. This underscores the pressing need for objective, reliable, and real-time approaches to milk quality monitoring [3], [4]. With advancements in sensor technology, non-invasive tools such as pH sensors and gas sensors (e.g., MQ-7 for carbon monoxide (CO) detection) have shown potential for early spoilage detection by capturing chemical and physical indicators of microbial activity [5]. However, conventional sensor-based systems often rely on microcontrollers with fixed thresholds, limiting their adaptability to diverse spoilage patterns influenced by storage conditions, environmental variations, and milk types [6], [7].

Recent technological advances have introduced sensor-based systems and machine learning (ML) models as more objective and scalable solutions for predicting spoilage. Studies from 2020–2025 have demonstrated promising results using pH sensors, gas sensors, volatile organic compounds (VOC) detection, electronic nose (E-nose) systems, internet of things (IoT)-driven monitoring, and ML algorithms for food quality assessment. However, many works rely on simulated datasets, laboratory conditions, or single-sensor evaluations, limiting their real-world applicability. To address this challenge, the present study investigates the integration of ML with sensor-based monitoring to improve milk spoilage detection [8], [9]. The guiding research question is: can ML models applied to sensor data, pH, and CO levels enhance the accuracy and adaptability of milk spoilage classification compared to traditional threshold-based methods?

Accordingly, the objectives of this work are: i) to develop an ML framework for classifying milk samples as fresh, not fresh, or spoiled using sensor data; ii) to evaluate model performance on raw and boiled milk datasets; and iii) to explore the feasibility of deploying such models in practical dairy and food logistics systems [10], [11]. The significance of this research lies in its potential to improve food safety, minimize unnecessary waste, and support sustainable resource use in the dairy sector. By combining sensor technologies with ML algorithms, the study advances a scalable solution that could be integrated into smart dairy management systems, household devices, and IoT-enabled supply chains.

In summary, this work contributes a ML–based spoilage detection framework that demonstrates higher reliability and adaptability than conventional methods, thereby enhancing the efficiency of milk quality monitoring and strengthening sustainability in the dairy industry. The key contributions include: creation of a real-world sensor dataset for raw and boiled milk; development and comparison of multiple ML models for shelf-life prediction; integration of the best-performing model into an IoT-ready embedded system; and demonstration of accurate, low-cost, and scalable spoilage detection. Overall, the work advances food safety, reduces milk wastage, and supports sustainability by enabling reliable, automated milk-quality assessment across households and dairy supply chains.

2. LITERATURE REVIEW

This literature review synthesizes research on milk spoilage mechanisms and emerging detection technologies. Key findings include insights into microbial spoilage processes, the application of E-nose technology to identify VOCs, and sensor-based methods for real-time freshness monitoring. Additionally, ultrasonic methods for non-invasive assessment and the integration of IoT and blockchain for advanced spoilage detection are highlighted. The following sections provide an in-depth analysis of these approaches [12], [13].

Milk spoilage detection has garnered increasing academic and industrial interest due to its implications for public health, economic efficiency, and environmental sustainability. As one of the most widely consumed and perishable food products, milk presents a compelling use case for integrating intelligent systems to monitor and predict quality in real time. In this section, we review the evolution of milk quality detection methods—from manual and sensory assessments to sensor-based systems and, more recently, ML-powered intelligent frameworks [14], [15].

2.1. Understanding spoilage in milk: microbial and chemical basis

Milk spoilage primarily occurs due to the activity of microorganisms, especially lactic acid bacteria (LAB), which ferment lactose into lactic acid. This biochemical process leads to a gradual reduction in pH and the production of VOCs, including carbon dioxide (CO_2), hydrogen sulfide (H_2S), and, in some redox conditions, CO. Spoilage also changes the viscosity, color, and smell of milk—factors typically used by consumers for freshness checks [16], [17]. Scientific studies have confirmed that these chemical changes serve as reliable indicators of microbial activity and spoilage progression. The acidity level (measured via pH) and the emission of gases such as CO (detectable in low concentrations using metal oxide semiconductor sensors like MQ-7) are particularly effective in quantifying freshness. These indicators form the foundation for modern electronic spoilage detection systems [18], [19].

2.2. Traditional detection approaches and their limitations

Conventional methods used to evaluate milk freshness include: i) sensory testing: relying on smell or taste, prone to human error; ii) boiling: still widely used in countries like India, but fails to provide objective quantification; and iii) chemical kits: limited use due to cost, time consumption, and single-use nature. These techniques, while simple and accessible, are inadequate for early-stage spoilage detection. More importantly, they do not offer the precision, reproducibility, or scalability required for modern supply chain systems or smart appliances. As a result, they often lead to either premature waste or unintended consumption of spoiled milk [20], [21].

2.3. Sensor-based technologies for real-time monitoring

Sensor systems have emerged as a more precise and scalable alternative. Modern implementations typically utilize a combination of; i) pH sensors: to measure acidity changes due to microbial activity; ii) MQ-series gas sensors (e.g., MQ-7): to detect CO, a secondary spoilage by-product with strong sensitivity and selectivity; and iii) Arduino: for data acquisition and simple threshold-based decision logic. Such systems are capable of classifying milk like "fresh," "not fresh," and "spoiled" in real-time, using hard-coded thresholds for CO levels and pH. These sensor-based setups are increasingly being integrated into portable devices for use in rural areas, dairy farms, and distribution networks. Despite their utility, these systems still rely on static logic—predefined ranges that may not account for variation across milk types, storage conditions, or microbial strain behavior. Hence, they lack adaptability and predictive intelligence, which ML can provide [22], [23].

2.4. Machine learning in food spoilage detection

The recent emergence of data-driven intelligence has revolutionized spoilage detection systems, particularly through the application of supervised learning algorithms. These models can learn from historical sensor data, identify complex non-linear patterns, and generalize to new, unseen data. Key algorithms explored in this domain include: i) decision trees: simple and interpretable, well-suited for rule-based classification; ii) random forests and eXtreme gradient boosting (XGBoost): ensemble models offering high accuracy and robustness against overfitting; and iii) support vector machines (SVM): effective for high-dimensional data, especially in binary or multi-class classification. Several studies have implemented these algorithms using features such as pH, gas emissions, temperature, and even sound waves (in ultrasonic setups). These models are evaluated using precision, recall, F1-score, and accuracy—metrics that provide a deeper understanding of classifier performance across class imbalances. A study indicated that SVMs classify milk spoilage with high precision using pH and turbidity data. Another research project integrated random forests with a multi-sensor array, achieving over 95% classification accuracy [24], [25]. However, these efforts often use lab-controlled datasets or simulated values rather than real-time sensor readings from field-deployable devices, which limits their practical impact. Our work addresses this gap.

2.5. Novel techniques: E-nose, ultrasonics, and blockchain integration

In parallel to traditional sensors, E-nose systems simulate olfactory detection by using sensor arrays to detect and classify VOCs. These systems have shown exceptional sensitivity but are typically more expensive, complex, and sensitive to environmental noise. Ultrasonic sensors, on the other hand, detect spoilage by monitoring changes in acoustic impedance, velocity, and attenuation of sound waves traveling through milk. These non-invasive methods reduce contamination risk but require calibration for different sample compositions. Looking forward, researchers are exploring the integration of these methods with IoT platforms and blockchain for traceability and decentralized quality assurance across supply chains. A 2022 study proposed an IoT-enabled milk quality sensor system that updates a centralized dashboard and automatically notifies logistics operators of quality deterioration. The overall summary of the relevant references used for this work is given in Table 1.

Table 1. Key literature survey

Reference	Focus area/methodology	Key findings
NDDB [1]	Milk production in India	National statistics on milk supply
Poghossian *et al*. [2]	Rapid methods and sensors for spoilage detection	Overview of biosensors
Ziyaina *et al*. [3]	Microbial detection in dairy	Rapid testing techniques
Hashim *et al*. [6]	Review of spoilage detection approaches	Comprehensive review of technologies
S *et al*. [14]	IoT-based spoilage detector	Simple IoT-based model
Kadam and Shinde [15]	Real-time monitoring	IoT-based milk monitoring prototype
Bhavsar *et al.* [17]	ML-based milk quality prediction	ML models for freshness prediction
Su *et al.* [18]	Spoilage simulation framework	Models kinetics under different temperatures
Balivo *et al*. [21]	E-nose for pasture milk	Volatile-based detection
Frizzarin *et al*. [22]	Mid-IR spectroscopy	Data competition on milk traits
Shahzad *et al*. [23]	ML+IoT	Freshness classification
Fernández-González *et al*. [24]	Sensors for dairy safety	Review of sensor technologies
Durgun [25]	Multispectral adulteration detection	Portable logistic regression model
Dragone *et al*. [26]	AI+sensors for HACCP	Industrial quality monitoring
Martelli *et al*. [27]	Data analysis in sensor platforms	Challenges in field sensor deployment
Palanisamy *et al.* [28]	Food packaging sensors	Packaging automation and detection
Singh *et al*. [29]	ML for pasteurization review	ML-assisted pasteurization
Kapse *et al*. [30]	Non-invasive freshness detection	Novel packaged milk detection
Çetintav and Yalçın [31]	Explainable ML for grading	XAI-based quality grading

2.6. Research gap and contribution

While prior research has successfully demonstrated the viability of sensor-based spoilage detection and the potential of ML classification, a unified framework combining real-world sensor data, robust ML models, and scalable deployment, is largely missing. This study addresses that gap by: i) using actual sensor readings of pH and CO collected under varied spoilage conditions (raw and boiled milk); ii) applying and comparing multiple ML models, including decision tree, random forest, XGBoost, and SVM; iii) evaluating the models using a rich set of classification metrics to establish not just accuracy but reliability, recall behavior, and class-wise effectiveness; and iv) demonstrating the feasibility of this approach as a low-cost, real-time monitoring tool for milk freshness in domestic and industrial settings.

3. PROPOSED SYSTEM

The proposed work presents a hybrid milk quality prediction system that integrates real-time sensor-based data acquisition with supervised ML algorithms to accurately classify the spoilage status of milk into three categories: fresh, not fresh, and spoiled. The design is motivated by the limitations of conventional rule-based approaches, which often fail to capture the nonlinear and time-dependent patterns of milk spoilage. By combining embedded hardware with intelligent classification models, the system ensures both real-time responsiveness and data-driven decision-making.

The system comprises two major subsystems: i) hardware module (sensor-based embedded system): responsible for acquiring pH, gas, temperature, and humidity measurements through low-cost sensors connected to an Arduino Uno and ii) software module (ML-based classification): responsible for model training using historical sensor data, deployment of the trained model, and real-time prediction of milk spoilage status. This architecture provides a cost-effective, portable, and scalable solution for milk quality monitoring, with potential applications in households, dairy farms, cold chains, and milk transportation logistics.

3.1. Dataset preparation

The dataset was developed to capture the natural spoilage process of milk under various storage and handling conditions. The following types of datasets were generated: open raw milk at room temperature, open boiled milk at room temperature, and open raw milk at refrigerated temperature.

For each category, milk samples were allowed to spoil under natural conditions. Sensor readings for pH, gas concentration, temperature, and humidity were recorded at hourly intervals. Each observation was logged systematically into a tabular dataset. To extend the dataset's utility, a new column called remaining-lifespan was introduced. It was derived by calculating the difference between the total shelf life and the elapsed time since the milk was fresh. This enabled the system not only to classify spoilage status but also to estimate the remaining usable time of milk**.** The software module for dataset handling and model development was implemented in Python, using libraries such as Pandas, Scikit-Learn, XGBoost, and Matplotlib.

The data preparation process followed three stages:

- Preprocessing

Normalization of sensor readings to ensure uniform scaling. Encoding spoilage categories (fresh, not fresh, and spoiled) into machine-readable labels. Splitting the dataset into training (80%) and testing (20%) subsets for evaluation.

- Model training

Four supervised ML models were trained and evaluated: decision tree, random forest, XGBoost, and SVM. Separate models were trained for raw and boiled datasets to improve generalization across conditions.

- Evaluation metrics

The performance of each model was assessed using regression and classification metrics, including coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These metrics ensured that the selected model performed reliably in predicting spoilage patterns.

3.2. Real-time prediction integration

Once the optimal model, random forest was identified as superior in experiments, it was exported and integrated into a real-time prediction pipeline**.** In practical deployment: real-time sensor values (pH, gas, temperature, and humidity) from the Arduino Uno are transmitted to the classification engine. The ML model processes the inputs and outputs the predicted milk status (fresh/not fresh/spoiled). The prediction result is displayed on the LCD and simultaneously transmitted via the ESP-01 Wi-Fi module for remote monitoring. This seamless integration ensures that the system can be deployed in kitchens, dairy processing units, retail outlets, vehicles, and cold chain facilities, thereby enhancing food safety and reducing wastage.

3.3. Advantages of the proposed system

The proposed system offers several significant benefits that enhance its practical applicability and reliability. By learning from historical sensor data, the ML model enables intelligent decision-making, thereby reducing misclassification errors commonly associated with traditional threshold-based approaches. The system operates in real time, providing immediate detection of spoilage and instant feedback through its embedded hardware platform. Its design is both cost-effective and portable, utilizing affordable and easily accessible components that make the solution suitable even for resource-constrained environments. Furthermore, the integration of Wi-Fi through the IoT module enables centralized monitoring across various stages of the dairy supply chain, improving traceability and oversight. The modular architecture also ensures scalability and replicability, allowing seamless adaptation to larger deployments such as cloud-connected monitoring systems. Additionally, the system demonstrates reliable performance for both raw and boiled milk, making it versatile and practical for a wide range of real-world scenarios.

4. DISCUSSION AND RESULTS

This section presents the outcomes of a regression model applied to raw and boiled milk datasets. We also analyze the behavior of key spoilage indicators (pH and CO concentration) over time and their correlation with the estimated remaining lifespan of milk. The aim is to evaluate model performance, understand data patterns, and assess the practical viability of the proposed system. Tables 2 and 3 give the performance metric of raw and boiled milk at room temperature (34-35 °C).

Table 2. The performance of the raw milk dataset at room temperature (34-35 °C)

Models	Decision tree	Random forest	XGBOOST	SVR
MSE	0.1153	0.1083	0.1429	1.0642
R2	0.9841	0.9851	0.9803	0.8534
MAE	0.0902	0.0955	0.1318	0.5025
RMSE	0.3395	0.3291	0.3781	1.0316
MAPE	1.40%	1.60%	2.35%	9.52%

Table 3. The performance of the boiled milk dataset at room temperature (34-35 °C)

Models	Decision tree	Random forest	XGBOOST	SVR
MSE	0.9908	0.9910	0.9927	0.9923
R2	0.0991	0.0970	0.0789	0.0825
MAE	0.3148	0.3114	0.2809	0.2873
RMSE	0.0923	0.0981	0.0743	0.1661
MAPE	1.26%	1.33%	1.10%	2.26%

4.1. Trends in sensor data

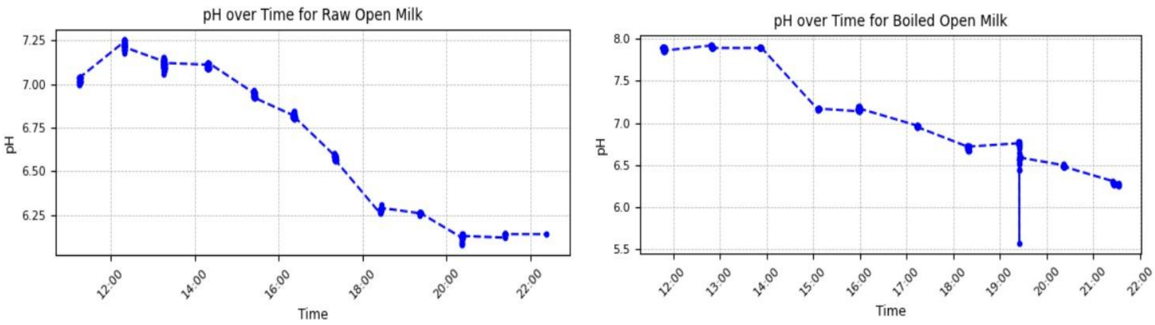
The progression of spoilage was studied using time-series visualizations of pH, CO concentration (CO_ppm), and remaining lifespan.

4.1.1. pH over time

The pH values exhibited a consistent downward trend over time. This aligns with the expected microbial activity, wherein lactic acid-producing bacteria metabolize lactose, causing acidity to rise and pH to fall. Occasional anomalies in the pH graph (e.g., sudden dips) were likely due to environmental noise or sensor calibration drift. Figure 1 shows pH performance of raw and boiled milk. As shown in Figure 1(a), the pH of raw milk decreases steadily during spoilage, whereas Figure 1(b) presents the comparatively slower decline in boiled milk. The figure illustrates the continuous decrease in pH as microbial activity intensifies, with raw milk showing a faster decline due to a higher initial microbial load.

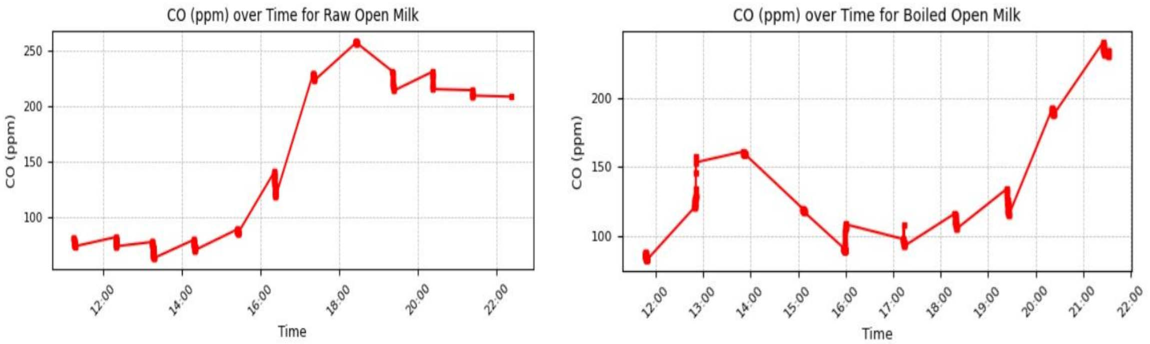
4.1.2. CO_ppm over time

CO levels initially fluctuated but showed a marked increase after a certain time point, indicating a surge in microbial respiration. The delay in CO rise, compared to pH drop, suggests that CO may serve as a secondary indicator, useful for confirming spoilage after acidic conditions remain. Figure 2 shows CO ppm over time for raw and boiled milk. As shown in Figure 2(a), the CO of raw milk decreases steadily during spoilage, whereas Figure 2(b) presents the comparatively slower decline in boiled milk. The delayed rise in CO indicates secondary spoilage stages, confirming microbial respiration patterns consistent with the literature.



(a) (b)

Figure 1. Change in pH values of; (a) raw open milk and (b) boiled open milk during spoilage detection



(a) (b)

Figure 2. Changes in CO of; (a) raw open milk and (b) boiled open milk during spoilage detection

4.1.3. Remaining lifespan over time

The linear decline in the predicted remaining lifespan suggests that spoilage is a continuous process and that sensor-derived data can reliably be used to forecast spoilage progression. This supports the viability of regression models for estimating shelf life for both the raw and boiled.

4.2. Regression results

4.2.1. Open raw milk dataset 1

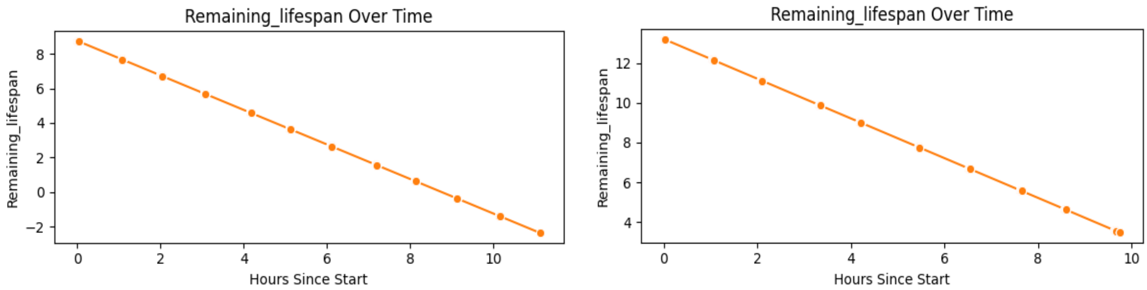
This milk sample, stored at room temperature, had an estimated shelf life of 12–15 hours. It was packed between 4:00 and 5:00 AM and showed visible spoilage by evening. Spoilage started gradually and accelerated over time

4.2.2. Open boiled milk dataset 2

Stored at room temperature, this boiled milk sample had a slower spoilage rate, with a shelf life of about 18–20 hours. Packed between 4:00 and 5:00 AM, it began to spoil around midnight.

4.2.3. Open raw milk dataset 3

Stored at 8–10 °C, this sample lasted approximately 2–3 days. Spoilage was observed after 3 days, particularly during boiling, as the temperature increased. The pH remained within the neutral range during storage. The linear decline in remaining lifespan supports the progression of continuous spoilage and the effectiveness of sensor-based regression models, with differences between raw and boiled samples highlighting the role of the initial microbial load. Figure 3 shows the overall lifespan of raw and boiled milk. As shown in Figure 3(a), the remaining lifespan of raw milk decreases steadily during spoilage, whereas Figure 3(b) presents the comparatively slower decline in boiled milk. Predicted remaining lifespan for raw milk and boiled milk, showing the linear decrease in shelf-life estimation as spoilage progresses.



(a) (b)

Figure 3. Remaining lifespan of; (a) raw open milk and (b) boiled open milk during spoilage detection

4.3. Performance evaluation on raw milk dataset

The random forest model emerged as the most effective among the models tested for the raw milk dataset, achieving an R^2 score of 0.9851 and MSE of 0.1083, indicating excellent predictive capabilities. Though decision tree and XGBoost also performed competitively with R^2 scores of 0.9841 and 0.9803, respectively, their error margins were slightly higher. Support vector regression (SVR) lagged significantly behind the other models, with an R^2 score of 0.8534 and MSE of 1.0642, indicating a lower capability in fitting the data trends. Additional metrics supported these findings, with random forest recording MAE of 0.0955, RMSE of 0.3291, and MAPE of 1.60%.

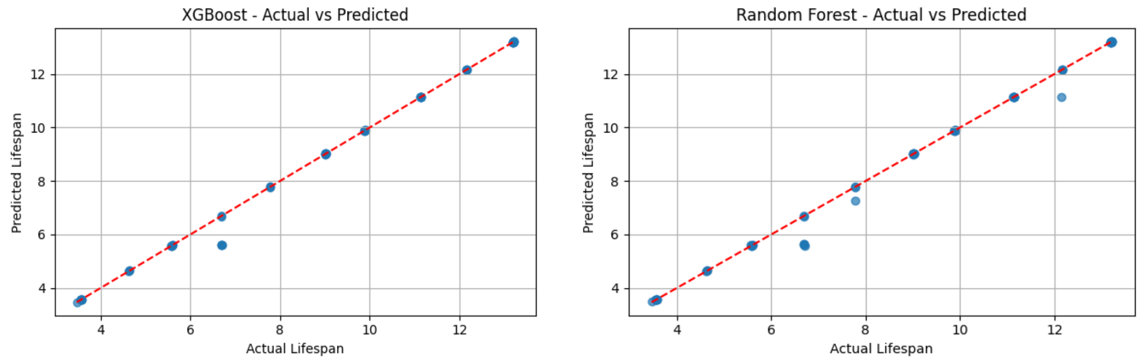
4.4. Performance evaluation on boiled milk dataset

For the boiled milk dataset, XGBoost slightly outperformed random forest in terms of R^2 score (0.9927) and MSE (0.0789). However, random forest was close behind with R^2 of 0.9910 and MSE of 0.0970, demonstrating consistent performance across both datasets. Decision tree also performed commendably with an R^2 of 0.9908, while SVR improved compared to its raw milk performance but still trailed the others slightly. SVR recorded an R^2 of 0.9923, MSE of 0.0825, and higher MAE and MAPE values than the leading models. Random forest achieved a MAE of 0.0981, RMSE of 0.3114, and MAPE of 1.33%, which are all well within acceptable error thresholds. Despite XGBoost's slight edge in metrics, random forest was selected as the final model for its overall consistency, reduced complexity, and ease of interpretation. The observed pH decline and CO emission patterns align with previously reported spoilage mechanisms, where lactic acid accumulation and microbial respiration serve as key indicators of milk deterioration. Similar trends were noted by Huang *et al*. [9] and Hashim *et al*. [6], supporting the reliability of the selected sensor features. The superior performance of random forest and XGBoost is consistent with recent studies applying ensemble models for food-quality prediction, demonstrating their robustness in handling nonlinear relationships and mixed sensor data. Compared to earlier works that relied on controlled laboratory datasets or limited sensing modalities, the present study combines real sensor measurements with supervised learning in a unified architecture, offering higher practical relevance.

4.5. Model selection justification

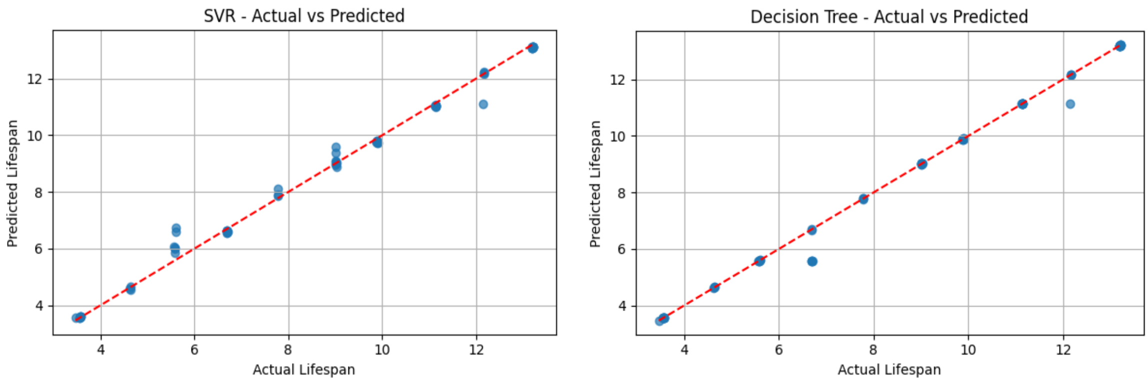
Performance comparison of lifespan prediction using different ML algorithms are shown in Figures 4 and 5. Figure 4(a) XGBoost and Figure 4(b) random forest, show strong correlation between predicted and actual values. Model evaluation using Figure 5(a) SVR and Figure 5(b) decision tree, highlight comparatively lower performance than ensemble-based models.

Based on the inferences drawn from Figure 5, it is evident that while both random forest and XGBoost exhibited high predictive accuracy, random forest was ultimately selected as the preferred algorithm due to several advantages. It demonstrated consistent and stable performance across all datasets, maintaining high accuracy and low error metrics. Additionally, random forest required significantly less computational power and training time compared to XGBoost, making it more efficient for practical implementation. Its interpretability further enhances its usefulness, as the model structure allows for clearer understanding of decision patterns, which is valuable in real-world applications. The observed decline in pH aligns with previously reported microbial spoilage behavior in milk [2], while the delayed CO rise is consistent with secondary gas formation noted in earlier studies [9]. The algorithm also showed strong robustness, performing effectively with minimal parameter tuning, thereby indicating good generalizability. Overall, these attributes validate random forest as a balanced, efficient, and scalable solution for predicting milk shelf life, with reliable performance across both raw and boiled milk datasets in various handling and storage conditions.



(a) (b)

Figure 4. Performance analysis of lifespan with; (a) XGBoost and (b) random forest algorithm during spoilage detection



(a) (b)

Figure 5. Performance analysis of lifespan with; (a) SVR and (b) decision tree algorithm during spoilage detection

5. CONCLUSION

This study presents a rapid and reliable ML–based framework for milk spoilage detection using real-time pH and MQ-7 gas sensor data. The system classifies milk as fresh, not fresh, or spoiled and estimates remaining shelf life. Among the tested models, random forest demonstrated the best balance of accuracy, stability, computational efficiency, and interpretability, making it suitable for real-time deployment. Integration with an Arduino-based embedded system confirmed the feasibility of IoT-enabled monitoring for households, dairy farms, retail outlets, and cold-chain logistics. Compared to conventional threshold methods, the proposed approach provides an intelligent, data-driven solution that enhances food safety and reduces milk wastage. Although the study is limited by a moderate dataset size and the need for broader field validation, future work will focus on expanding datasets, incorporating additional sensors (e.g., VOC and turbidity), applying deep learning models, and deploying cloud-connected IoT platforms for scalable and centralized monitoring.

FUNDING INFORMATION

No funding is involved in carrying out this work.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Srushti Jamewar	✓	✓					✓		✓		✓			
Ritika Patki		✓		✓	✓		✓		✓		✓			
Nishad Gharote			✓		✓			✓	✓					
Tanika Mathur				✓	✓			✓	✓					
Mridula Korde	✓	✓		✓		✓				✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [initials: MK], upon reasonable request.

REFERENCES

[1] National Dairy Development Board, “Milk Production in India,” National Dairy Development Board (NDDB). [Online]. Available: https://www.nddb.coop/information/stats/milkprodindia.

[2] A. Poghossian, H. Geissler, and M. J. Schöning, “Rapid methods and sensors for milk quality monitoring and spoilage detection,” *Biosensors and Bioelectronics*, vol. 140, no. 2, Sep. 2019, doi: 10.1016/j.bios.2019.04.040.

[3] M. Ziyaina, B. Rasco, and S. S. Sablani, “Rapid methods of microbial detection in dairy products,” *Food Control*, vol. 110, 2020, doi: 10.1016/j.foodcont.2019.107008.

[4] N. J. Kannampilly, K. Thangavel, D. Peter, and L. Rose, “Milk spoilage detection by impedance measurement,” *International Journal of Current Research and Review*, vol. 13, no. 5, pp. 183–187, 2021, doi: 10.31782/IJCRR.2021.13534.

[5] M. Lu *et al*., “Milk Spoilage: Methods and Practices of Detecting Milk Quality,” *Food and Nutrition Sciences*, vol. 04, no. 07, pp. 113–123, 2013, doi: 10.4236/fns.2013.47a014.

[6] N. M. Z. Hashim *et al*., “A Review: Milk Spoilage and Staleness Detection Approaches, Technique, and Technology Trends,” *International Journal of Scientific and Research Publications (IJSRP)*, vol. 12, no. 4, pp. 130–135, 2022, doi: 10.29322/ijsrp.12.04.2022.p12419.

[7] D. R. Sepulveda, M. M. Góngora-Nieto, J. A. Guerrero, and G. V. Barbosa-Cánovas, “Production of extended-shelf life milk by processing pasteurized milk with pulsed electric fields,” *Journal of Food Engineering*, vol. 67, no. 1–2, pp. 81–86, 2005, doi: 10.1016/j.jfoodeng.2004.05.056.

[8] Q. Cai, K. Zeng, C. Ruan, T. A. Desai, and C. A. Grimes, “A Wireless, Remote Query Glucose Biosensor Based on a pH-Sensitive Polymer,” *Analytical Chemistry*, vol. 76, no. 14, pp. 4038–4043, Jul. 2004, doi: 10.1021/ac0498516.

[9] S. Huang, S. Ge, L. He, Q. Cai, and C. A. Grimes, “A remote-query sensor for predictive indication of milk spoilage,” *Biosensors and Bioelectronics*, vol. 23, no. 11, pp. 1745–1748, 2008, doi: 10.1016/j.bios.2008.01.036.

[10] H. M. Al-Qadiri, M. Lin, M. A. Al-Holy, A. G. Cavinato, and B. A. Rasco, “Monitoring quality loss of pasteurized skim milk using visible and short wavelength near-infrared spectroscopy and multivariate analysis,” *Journal of Dairy Science*, vol. 91, no. 3, pp. 950–958, 2008, doi: 10.3168/jds.2007-0618.

[11] N. Nicolaou, Y. Xu, and R. Goodacre, “Fourier transform infrared spectroscopy and multivariate analysis for the detection and quantification of different milk species,” *Journal of Dairy Science*, vol. 93, no. 12, pp. 5651–5660, 2010, doi: 10.3168/jds.2010-3619.

[12] L. Quintieri, L. Caputo, M. Brasca, and F. Fanelli, “Recent Advances in the Mechanisms and Regulation of QS in Dairy Spoilage by *Pseudomonas* spp,” *Foods*, vol. 10, no. 12, p. 3088, 2021, doi: 10.3390/foods10123088.

[13] R. Dhakane, R. Gulve, A. Shinde, A. Jadhav, and S. Bhusnar, “Spoilage and preservation of milk and milk products: A review,” *Journal of Emerging Technologies and Innovative Research*, vol. 6, no. 6, pp. 173–179, 2019.

[14] H. S, M. M. H. K, and Neha B. M, “IoT Based Food Spoilage Detector,” *International Journal for Research in Applied Science and Engineering Technology*, vol. 11, no. 7, pp. 80–85, Jul. 2023, doi: 10.22214/ijraset.2023.54562.

[15] P. R. Kadam and K. P. Shinde, “Real Time Milk Monitoring System,” *in 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), IEEE*, Aug. 2018, pp. 1–5, doi: 10.1109/ICCUBEA.2018.8697373.

[16] N. D. Naik, M. K Shetty, and S. A. Bhyratae, “Smart Milk Quality Monitoring System: IoT-Driven Sensor and Data Analytics Interface,” *International Journal of Innovative Science and Research Technology*, vol. 10, no. 3, pp. 1573–1581, Mar. 2025, doi: 10.38124/ijisrt/25mar1061.

[17] D. Bhavsar, Y. Jobanputra, N. K. Swain, and D. Swain, “Milk Quality Prediction Using Machine Learning,” *EAI Endorsed Transactions on Internet of Things*, vol. 10, no. 07, pp. 1–9, Nov. 2023, doi: 10.4108/eetiot.4501.

[18] J. Su, S. I. Murphy, N. H. Martin, A. Trmcic, R. Ivanek, M. Wiedmann, and C. Qian, “A fluid milk spoilage simulation framework reveals the need for spoilage intervention strategies that account for frequency of bacterial postpasteurization contamination,” *Journal of Dairy Science*, vol. 108, no. 9, pp. 9309–9329, Sep. 2025, doi: 10.3168/jds.2025-26719.

[19] J. Xu *et al*., “Evaluation of UHT milk spoilage caused by proteases from psychrophilic bacteria based on peptidomics,” *Food Chemistry: X*, vol. 24, p. 102059, 2024, doi: 10.1016/j.fochx.2024.102059.

[20] Y. Yang and L. Wei, "Application of E-nose technology combined with artificial neural network to predict total bacterial count in milk," *Journal of Dairy Science*, vol. 104, no. 10, pp. 10558–10565, 2021, doi: 10.3168/jds.2020-19987.
[21] A. Balivo, S. Cipolletta, R. Tudisco, P. Iommelli, R. Sacchi, and A. Genovese, "Electronic Nose Analysis to Detect Milk Obtained from Pasture-Raised Goats," *Applied Sciences*, vol. 13, no. 2, p. 861, 2023, doi: 10.3390/app13020861.
[22] M. Frizzarin *et al*., "Mid infrared spectroscopy and milk quality traits: A data analysis competition at the 'International Workshop on Spectroscopy and Chemometrics 2021,'" *Chemometrics and Intelligent Laboratory Systems*, vol. 219, p. 104442, Dec. 2021, doi: 10.1016/j.chemolab.2021.104442.
[23] A. Shahzad, S. Javaid, and Z. Alamsyah, "Milk Quality Detection Using Machine Learning," *Engineering Proceedings*, vol. 107, no. 1, p. 119, 2025, doi: 10.3390/engproc2025107119.
[24] A. Fernández-González, R. B. Laíño, J. M. Costa-Fernández, and A. Soldado, "Progress and Challenge of Sensors for Dairy Food Safety Monitoring," *Sensors*, vol. 24, no. 5, 2024, doi: 10.3390/s24051383.
[25] M. Durgun, "Real-Time Detection of Milk Adulteration with a Portable Multispectral Analysis Device: A Multispectral Sensor and Optimized Logistic Regression Approach," *Journal of Advanced Research in Natural and Applied Sciences*, vol. 10, no. 4, pp. 968–980, Dec. 2024, doi: 10.28979/jarnas.1569065.
[26] R. Dragone, G. Grasso, G. Licciardi, D. D. Stefano, and C. Frazzoli, "Sensors driven system coupled with artificial intelligence for quality monitoring and HACCP in dairy production," *Sensing and Bio-Sensing Research*, vol. 45, p. 100683, Aug. 2024, doi: 10.1016/j.sbsr.2024.100683.
[27] F. Martelli, C. Giacomozzi, R. Dragone, C. Frazzoli, and G. Grasso, "Data Analysis in Newly Developed Milk Sensor Platforms: Good Practices, Common Pitfalls, and Hard-Earned Lessons from Field Application," *Foods*, vol. 14, no. 10, May 2025, doi: 10.3390/foods14101724.
[28] Y. Palanisamy, V. Kadirvel, and N. D. Ganesan, "Recent technological advances in food packaging: sensors, automation, and application," *Sustainable Food Technology*, vol. 3, no. 1, pp. 161–180, 2025, doi: 10.1039/D4FB00296B.
[29] P. Singh, S. Pandey, and S. Manik, "A comprehensive review of the dairy pasteurization process using machine learning models," *Food Control*, vol. 164, 2024, doi: 10.1016/j.foodcont.2024.110574.
[30] S. Kapse, P. Kedia, A. Kumar, S. Kausley, P. Pal, and B. Rai, "A non-invasive method for detection of freshness of packaged milk," *Journal of Food Engineering*, vol. 346, 2023, doi: 10.1016/j.jfoodeng.2023.111424.
[31] B. Çetintav and A. Yalçın, "Explainable Machine Learning Framework for Milk Quality Grading," *Kocatepe Veterinary Journal*, vol. 18, no. 3, pp. 227–235, 2025.

BIOGRAPHIES OF AUTHORS

Srushti Jamewar has completed her B.Tech. in Electronics and Communication Engineering from Ramdeobaba University, Nagpur, India. She can be contacted at email: jamewarsp@rknec.edu.

Ritika Patki has completed her B.Tech. in Electronics and Communication Engineering from Ramdeobaba University, Nagpur, India. She can be contacted at email: patkirh@rknec.edu.

Nishad Gharote has completed his B.Tech. in Electronics and Communication Engineering from Ramdeobaba University, Nagpur, India. He can be contacted at email: gharotenr1@rknec.edu.

Tanika Mathur has compleeted her B.Tech. in Electronics and Communication Engineering from Ramdeobaba University, Nagpur, India. She can be contacted at email: mathurta@rknec.edu.

Mridula Korde works as an associate professor in the Department of Electronics and Communication Engineering at Ramdeobaba University, Nagpur, India. She has received her Doctorate Degree from Visvesvaraya National Institute of Technology, Nagpur. She has a passion for teaching with 20+ years of teaching experience in the domain of Electronics/Electronics & Communication Engineering. Her research area includes advanced wireless communication and synchronization. She can be contacted at email: kordems@rknec.edu.