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Performance comparison of algorithms in the classification of fresh fruit types based on MQ array sensor data

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ABSTRACT

Accurate classification of fresh fruit types is essential in the agricultural sector for ensuring quality control, minimizing waste, and enhancing food safety across the supply chain. This study evaluates the performance of four machine learning algorithms—artificial neural network (ANN), K-nearest neighbors (KNN), logistic regression (LR), and random forest (RF)—in classifying fruit freshness based on data obtained from electronic noses equipped with MQ array sensors. Experiments were conducted using a comprehensive dataset comprising various fruit combinations, and model performance was assessed using accuracy, precision, recall, and F1 score metrics. Results indicate that the RF algorithm achieved the highest accuracy (100%) and precision (1.00), demonstrating superior performance in both classification accuracy and computational efficiency. ANN and KNN also performed well, with accuracies of 96.80% and 97.10%, respectively, while LR yielded a lower but still effective accuracy of 91.16%. Statistical analysis confirms that RF's superior performance is statistically significant when compared to the other algorithms. These findings suggest that RF is the most effective algorithm for fruit freshness classification using electronic nose data, offering fast and reliable results that are well-suited for integration into real-time monitoring systems in agricultural and food retail applications.

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1. INTRODUCTION

Fruit classification using sensor data has become a central focus in modern agricultural research, aiming to improve the accuracy and efficiency of quality assessments. A variety of machine learning algorithms—including support vector machines (SVM), regression trees, Fisher's linear discriminant analysis (LDA), K-nearest neighbors (KNN), and deep learning methods—have been used to differentiate between fresh and spoiled fruit based on sensor inputs [1].

These algorithms demonstrate strong capabilities in processing data to classify fruits and vegetables by freshness and other attributes. For instance, KNN, decision trees, artificial neural networks (ANN), and convolutional neural networks (CNN) have been applied in practical scenarios, showcasing their flexibility. One example is the classification of mango harvest age using near-infrared (NIR) spectral data, which achieved high accuracy and highlighted the adaptability of these models [2].

Sensor arrays combined with machine learning have also been used for food spoilage detection. Techniques like KNN, SVM, and ANN help identify volatile organic compounds (VOCs), contributing to food safety and quality control. ANNs have further been used to predict quality attributes of fruits, such as dates, aiding in decisions about storage and distribution [3].

Electronic noses paired with ANNs have proven effective for fast, non-destructive classification of pure and industrial fruit juices, helping to verify product quality and authenticity [4], [5]. CNNs are used to classify the type and ripeness of fruit using image data, which enhances efficiency in agricultural workflows [6]. Additionally, spectroscopic methods combined with machine learning support non-destructive estimation of shelf life and quality for fruits in modified atmosphere packaging (MAP), ensuring freshness throughout the supply chain. Advanced probabilistic neural networks also show high accuracy in classifying chemical sensor array data, reflecting the progress in sensor-based machine learning techniques [7].

Beyond agriculture, these technologies extend to fields like security and materials analysis. Algorithms for acoustic signal enhancement have improved target classification in unmanned ground sensor systems [8], [9], while decision tree-based multiclass SVMs have been successfully used for accurate material identification using microwave sensor arrays [10], [11].

This study aims to explore and compare the effectiveness of various machine learning algorithms—specifically ANN, KNN, logistic regression (LR), and random forest (RF)—for fruit classification based on sensor data. The results highlight the strengths and weaknesses of each method in terms of accuracy, precision, recall, and computational efficiency. By providing valuable insights into the performance and limitations of these algorithms, this study contributes to the development of more effective and efficient fruit classification systems and supports the selection of the most suitable approach for specific applications in fruit quality assessment. Table 1 presents a summary of recent studies applying machine learning to food product classification, detailing the commodities, technologies, models, and sensor features used [12].

Table 1. Overview of recent studies on machine learning models for food product classification

Study	Fruit/ commodity	Technology	Best model	Objective	Sensors/features	Notes
Mohammed *et al.* [7]	Dates	TinyML+ multispectral sensor	Neural net (R^2=0.951)	Predict shelf life and quality under MAP	Multispectral (410–940 nm), pH, total soluble solids (TSSs), sugar content (SC), moisture content (MC), and tannin content (TC)	Packaging under different gas mixes (MAP1 and MAP2)
Qiao *et al.* [13]	Grapes	Electronic nose (e-nose)	SVM (94.4%)	Detect CPPU-treated grapes	Volatile compounds: aldehydes, esters, alcohols	Focus on swelling agent treatment
Madhubhashini *et al.* [14]	Frigate tuna	PEN3 e-nose	RF (100%)	Predict freshness via storage day	W2S, W1S, W1W, W3S, and W6S	Total volatile base nitrogen (TVB-N) used as reference for freshness level
Anwar and Anwar [15]	Apple and banana	E-nose +machine learning (review)	–	Review of e-nose in fruit grading	General VOCs sensors	Review paper; various machine learning models discussed
Kalpana and Baghyam [16]	Mango, pineapple, and orange	E-nose (MQ-3, MQ-135)	KNN	Classify fruit type and freshness	MQ-3 (alcohol), MQ-135 (ammonia); pH probe	Low-cost and educational context
Qiao *et al.* [17]	Crab apples	E-nose	RF (98.3%)	Detect artificial ripening	Wavelet-transformed e-nose signal curves	Compared with sugar/acid ratio and soluble protein
Yang *et al.* [18]	Yellow peach	E-nose +GC-MS	93.33% accuracy (24 h)	Detect compression damage	VOCs: aldehydes, esters, lactones, and terpenes	Supported by gas chromatography-mass spectrophotometry (GC–MS) for VOC profile validation

2. METHOD

This study focuses on the classification of fruit freshness using an electronic nose (e-nose) system in combination with machine learning algorithms, including ANN, KNN, LR, and RF. The primary objective is to develop an accurate and efficient method for assessing fruit freshness by leveraging the capabilities of machine learning techniques. A labeled dataset is employed to train and validate the models, enabling a supervised learning approach that ensures reliability and repeatability in classification results. The research methodology involves multiple experimental stages, from data acquisition using e-nose sensors to model training, evaluation, and performance comparison based on standard metrics such as accuracy, precision, recall, and F1 score. The overall workflow and experimental setup are illustrated in Figure 1, providing a clear overview of the steps involved in the study.

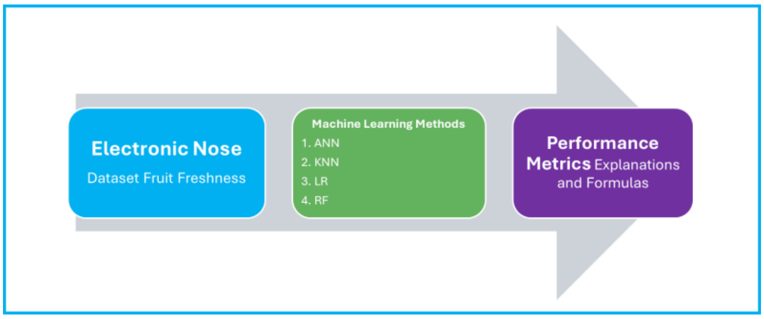

Figure 1. Experiment scenario

2.1. Research design

This study employs a quantitative experimental approach consisting of several key stages: data collection using an MQ sensor array [19]; data preprocessing and feature extraction to prepare the dataset for analysis; implementation of machine learning algorithms; performance evaluation and comparison of the models; and statistical analysis of the results to validate the findings and assess the significance of performance differences among the algorithms.

2.2. Electronic nose: dataset fruit freshness

The dataset used in this study was sourced from a public repository [19] and comprises several CSV files named according to the types of fruit measured, such as AppleBanana, AppleBananaMandarin, and AppleBananaTomato. Data collection adhered to standardized electronic nose sensing protocols [20], ensuring reliability and reproducibility. The experimental setup included a sensor array consisting of MQ2, MQ3, MQ4, MQ5, MQ6, MQ7, MQ8, MQ9, and MQ135 sensors, with data captured via an Arduino-based microcontroller. Each measurement lasted 180 seconds, with a sampling rate of one sample per second. Environmental conditions during data collection were controlled at a temperature of 25±2 °C and relative humidity of 60±5%, providing consistent conditions for accurate sensing. Content of MQ array sensors function can be seen in Table 2.

Table 2. Content about MQ array sensor function

No	Gas sensor	Information
1	MQ2	Alcohol, LPG, smoke, propane, methane, butane, and hydrogen
2	MQ3	Alcohol, carbon monoxide, methane, LPG, and hexane
3	MQ4	Methane
4	MQ5	Alcohol, carbon monoxide, hydrogen, LPG, and methane
5	MQ6	LPG, Propane, and Iso-butane
6	MQ7	Carbon monoxide
7	MQ8	Hydrogen
8	MQ9	Methane, propane, and carbon monoxide
9	MQ135	Nox, alcohol, carbon dioxide, smoke, ammonia, and benzene

The study describes an array system of sensors used to assess the freshness of the fruit in real-time. The system includes a variety of sensors such as MQ2, MQ3, MQ4, MQ5, MQ6, MQ7, MQ8, MQ9, and MQ135, each of which detects different gas emissions. These sensors are connected to a processing unit, which is an Arduino or Raspberry Pi, which collects and processes data for 3 minutes or 180 seconds. These sensors are able to detect different gas emissions, which has the potential to indicate the freshness level of each fruit. The architecture of data acquisition is shown in Figure 2. The resulting data examples show readings from sensors at different time intervals, with consistent results across multiple sensors. This indicates stable sensor performance during the testing period.

2.3. Machine learning methods

Electronic nose technology and machine learning methods have attracted attention in assessing the quality of fresh fruit. The combination of electronic nose devices with machine learning algorithms, such as LDA, RF, and SVM, enables fast and accurate identification of fruits based on their ripeness, freshness, and potential spoilage. This integration is efficient in detecting quality parameters in fruits such as apples, bananas, and strawberries [13]. This technology provides valuable insights for the agriculture and food industries, improving the decision-making process in fruit quality assessment [15].

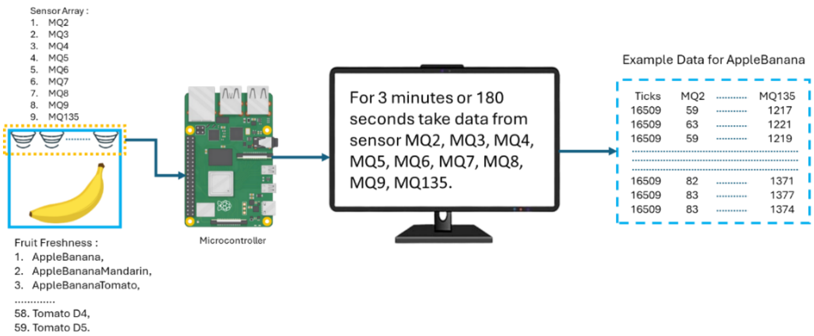

Figure 2. Data acquisition architecture

In addition, electronic noses and machine learning are also effective in predicting fruit ripeness and assessing its quality attributes, supporting fruit monitoring and management practices [21]. The use of models such as KNN for fruit classification has enabled the accurate detection of fruit odor and freshness, which is important for the food industry in product development and consumer satisfaction by utilizing machine learning, the electronic nose improves the efficiency and accuracy of fruit quality assessments, supporting better agricultural practices and higher food quality standards [22].

2.3.1. Artificial neural networks

ANNs have been successfully integrated with electronic nose (e-nose) technology to enhance the classification and quality assessment of fresh fruit. This combination has shown promising results across various fruit analysis applications. For instance, Rasekh and Karami [5] effectively detected adulteration in fruit juice using a metal oxide semiconductor (MOS)-based e-nose system paired with ANN, showcasing the efficiency and non-destructive capabilities of this approach. Similarly, Tyagi *et al.* [23] developed a cost-effective e-nose system for monitoring fruit ripeness, demonstrating its high precision in categorizing fruit samples based on their maturity stages.

Additionally, the study by Yang *et al.* [18] highlights the rapid and non-invasive detection of compression damage in yellow peaches using an e-nose combined with chemometric analysis. This work underscores the system's effectiveness in identifying subtle quality attributes in fruit. Overall, the integration of ANNs with e-nose technology offers a fast, reliable, and non-destructive method for fruit classification, quality evaluation, and fraud detection, reinforcing its significance in modern fruit analysis and post-harvest management.

2.3.2. Algorithm K-nearest neighbors

The KNN algorithm is widely utilized in electronic nose (e-nose) applications for a range of analytical purposes. A study by Raspagliesi *et al.* [24] demonstrated the effectiveness of KNN in detecting ovarian cancer through breath analysis, incorporating principal component analysis (PCA) for feature reduction. Hasan [25] applied KNN to differentiate pineapple aromas, showcasing the capability of the e-nose combined with KNN to classify fruit characteristics based on volatile compounds. Similarly, Malikhah *et al.* [26] employed ensemble learning on e-nose datasets, using KNN as a base classifier to detect wine properties, identify diabetes, and recognize substances like ginseng.

Further highlighting KNN's versatility, Okur *et al.* [27] used the algorithm to identify mint aromas with quartz crystal microbalance sensors, integrating PCA and LDA for improved performance. Nasution *et al.* [28] developed a low-cost e-nose system to classify coffee roasting levels using KNN in combination with Stepwise LDA. These studies collectively demonstrate KNN's adaptability and effectiveness in analyzing and classifying a variety of aroma-based characteristics, reinforcing its value in electronic nose applications across multiple domains.

2.3.3. Logistic regression

LR is frequently employed in analyzing data from electronic nose (e-nose) technology to assess the quality of fresh fruit. This technology works by detecting VOCs emitted by the fruit, allowing for the non-destructive evaluation of ripeness, freshness, and spoilage. In a study by Yang *et al.* [18], an e-nose system was used to identify damage in yellow peaches by analyzing VOCs. They combined chemometrics and machine learning algorithms to predict the extent of damage and effectively distinguish between spoiled and non-spoiled samples, demonstrating the significant potential of this approach.

Similarly, Qiao *et al.* [17] utilized an e-nose to detect artificially ripened crab apples, developing a prediction model based on partial least squares regression (PLSR) that showed a strong correlation between the sensor data and fruit quality indices. Cozzolino *et al.* [29] also applied e-nose technology to differentiate between fresh and stored fruits under various conditions, using the projection to latent structures (PLS) method. These studies underscore the value of integrating e-nose technology with machine learning algorithms, including LR, chemometric techniques, and statistical modeling. Together, these tools enable accurate, non-invasive prediction of fruit quality attributes, enhancing the effectiveness of quality control processes in the fruit industry.

2.3.4. Random forest

RF is a widely used machine learning algorithm that has gained traction in combination with electronic nose (e-nose) technology for various applications related to fruit quality assessment. The integration of RF with e-nose systems has yielded promising results in multiple studies. For instance, Qiao *et al.* [17] applied RF alongside other algorithms, such as LDA and SVM, to analyze electrical signals from an e-nose in detecting artificially ripened crab apples. Similarly, Madhubhashini [14] developed a classification model to evaluate the freshness of tuna using an e-nose, achieving remarkably high accuracy rates of 100% with RF and 99.8% with SVM.

Additionally, a 2024 review highlights the practical implementation of e-nose systems combined with machine learning algorithms, including RF, for assessing the quality of various fruits such as apples, bananas, and peaches. This underscores the broad applicability of RF in fruit quality monitoring. Sekula *et al.* [30] also emphasize the versatility of RF, noting its effectiveness in both regression and classification tasks beyond fruit analysis. Overall, RF proves to be a highly effective tool in e-nose applications, offering robust performance in handling complex datasets and delivering accurate classifications of fruit freshness, ripeness, and overall quality.

2.4. Performance metrics

Performance measurement methods, or performance metrics, are essential tools used across various sectors to assess and enhance performance. One widely recognized set of indicators is key performance indicators (KPIs), which are critical measurable metrics used to monitor and compare progress toward strategic and operational goals [20]. KPIs serve as meaningful quality metrics that facilitate benchmarking, performance evaluation, and the identification of areas requiring improvement [31]. In clinical pharmacy, for example, KPIs have been shown to significantly enhance performance by aligning measured outcomes with strategic objectives [32]. Similarly, in machine learning, performance metrics are vital for evaluating and optimizing models, particularly in classification tasks.

Overall, the application of KPIs and performance metrics is fundamental in diverse fields such as the public sector, medicine, clinical pharmacy, and computer science. These tools not only enable the assessment of current performance but also provide a structured framework for benchmarking and continuous improvement, ensuring consistent advancement across various disciplines. Evaluation metric formulas can be seen in Table 3.

Table 3. Evaluation metric formulas

No	Metrics	Formula
1	Accuracy (AC)	$\frac{TP+TN}{TP+TN+FP+FN} \ x \ 100$
2	F1 score (F1)	$2 \ x \ \frac{PR \ x \ RE}{PR+RE}$
3	Precision (PR)	$\frac{TP}{TP+FP}$
4	Recall (RE)	$\frac{FP}{FP+TN}$

3. RESULTS AND DISCUSSION

This study addresses the need for accurate and efficient classification of fresh fruit types using sensor array data. While previous research has investigated various machine learning approaches for fruit quality assessment, few have conducted a comprehensive comparison of multiple algorithms specifically utilizing MQ sensor array data for fruit freshness classification. The experimental implementation in this study was conducted using Google Colab, with a T4 GPU hardware accelerator, to run all the selected algorithms. The results of data acquisition for all types of fresh fruit are presented in Figure 2. Figure 3 displays the visualization of sensor data from four different fruit combinations: i) AppleBanana, ii) AppleBananaMandarin, iii) AppleBananaTomato, and iv) TomatoMandarin. Each graph represents the sensor responses over time (180 seconds) for the nine MQ sensors in the array.

As shown in Figure 3(a), the AppleBanana sample exhibits a steady increase in sensor responses over time, indicating a consistent emission of volatile compounds. In Figure 3(b), the AppleBananaMandarin sample shows more complex behavior, with some sensor responses plateauing after initial growth, suggesting stabilization in VOC emissions after a certain period. Figure 3(c) illustrates that the AppleBananaTomato sample follows a similar trend to AppleBanana, with gradual increases across all sensors. In contrast, Figure 3(d) shows that the TomatoMandarin sample demonstrates higher variability between sensor responses, with some sensors showing sharp peaks and troughs, indicating significant differences in VOC profiles.

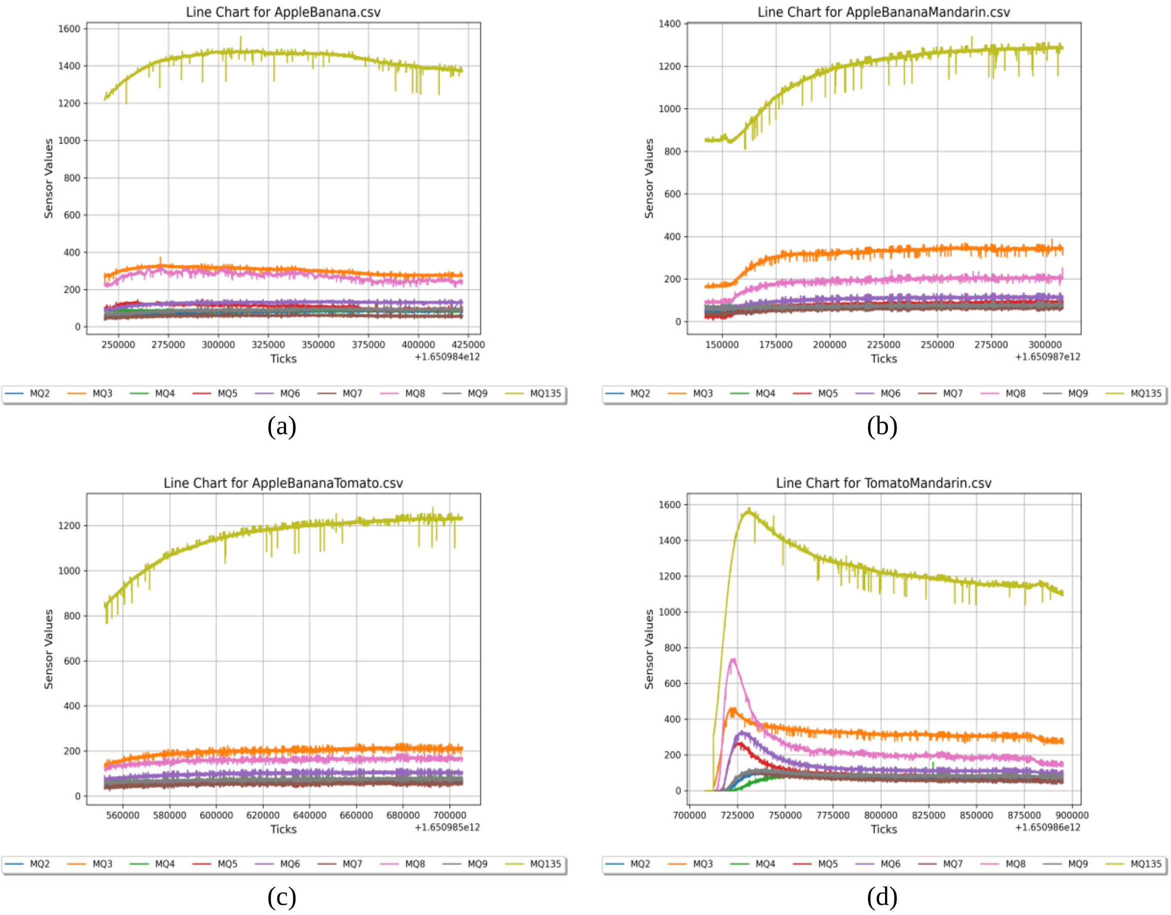

Figure 3. Data visulaization; (a) AppleBanana, (b) AppleBananaMandarin, (c) AppleBananaTomato, and (d) TomatoMandarin

These visualizations highlight that different fruit combinations produce distinct VOC emission patterns, which can be leveraged by machine learning algorithms for classification. The variations observed in sensor responses across different fruit combinations underscore the importance of using multiple sensors to capture the complex chemical signatures of fresh fruits. Overall, these results indicate that variations in fruit combinations and experimental conditions affect the metrics measured. Further studies are needed to understand the factors underlying this variability and to optimize the fruit freshness monitoring system in real time. These findings have the potential to provide important insights for the agriculture and retail industries in an effort to ensure better product quality.

Figure 4 illustrates the workflow of the machine learning model evaluation process designed to improve accuracy and reliability in predictions. The process begins with collecting data from various sources which is then combined into a unified data set. The combined datasets are then processed through random sampling techniques to ensure a balanced distribution of data between the training data and the test data. After that, the data is classified using several machine learning algorithms, such as ANN, KNN, LR, and RF. Each algorithm is tasked with evaluating the predictive power of the processed dataset. The classification results of each model are then analyzed at the performance evaluation stage, to measure the effectiveness of the model in making predictions. This evaluation is an important step in determining which algorithms are the most optimal and reliable in the context of complex and heterogeneous data. The performance of the four machine learning algorithms was evaluated using the metrics described in Table 3. Figure 4 illustrates the workflow of the machine learning model evaluation process, which begins with data collection and combination, followed by algorithm processing and performance evaluation.

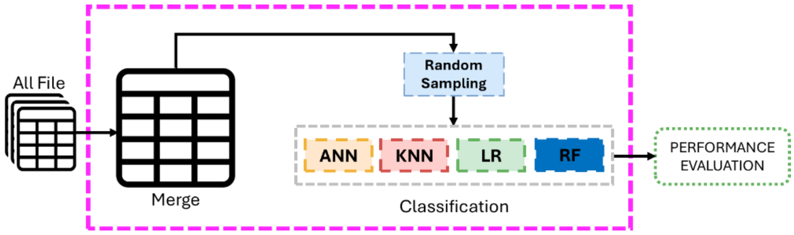

Figure 4. Machine learning model evaluation process

Table 4 presents the results of this study, offering a clear comparison of the performance of four machine learning algorithms ANN, KNN, LR, and RF for classifying fresh fruit types using MQ sensor data. The RF algorithm performed the best, achieving perfect accuracy (100%) along with F1 score, precision, and recall all at 1.00. It also had a fast training time of 88.62 seconds, although the testing time was slightly longer at 6.88 seconds. This indicates excellent overall performance and consistency.

Table 4. Results from performance metrics

No	Method	AC (%)	F1	PR	RE	Train test (s)	Test time (s)
1	ANN	96.80	0.97	0.97	0.97	1,605.83	0.61
2	KNN	97.10	0.97	0.97	0.97	2.10	12.88
3	LR	91.16	0.91	0.91	0.91	1,133.97	0.09
4	RF	100.00	1.00	1.00	1.00	88.62	6.88

KNN also showed strong results, with 97.10% accuracy and F1 score, precision, and recall values of 0.97 each. It had a very short training time of 2.10 seconds, making it ideal for quick model updates. However, its testing time was longer at 12.88 seconds, which may be a drawback in some applications. The ANN achieved 96.80% accuracy, with F1 score, precision, and recall also at 0.97. While the training time was relatively long (1,605.83 seconds), the testing time was very fast at 0.61 seconds, showing it is efficient for deployment once trained.

LR had the lowest performance among the four, with 91.16% accuracy and F1 score, precision, and recall all at 0.91. It had a training time of 1,133.97 seconds but an extremely short testing time of just 0.09 seconds. Despite lower accuracy, it may be useful when rapid prediction is a priority. Compared with recent studies in fruit freshness classification (see Table 1), the use of RF in this study stands out. For example, Madhubhashini *et al.* [14] also achieved 100% accuracy in fish freshness evaluation using RF, aligning with the results here. Most other studies report accuracy levels between 92% and 97%, depending on the fruit type and sensor setup. This study contributes significantly by offering a side-by-side evaluation of multiple algorithms on the same dataset, providing a fair and consistent performance comparison. Overall, this analysis highlights the strengths and weaknesses of each algorithm. RF excels in accuracy and consistency, KNN offers the fastest training, ANN is efficient during testing, and LR delivers the fastest predictions. Selecting the right algorithm depends on the specific requirements of the application, whether focused on accuracy, speed, or a balance of both.

4. CONCLUSION

This study systematically evaluated four machine learning algorithms RF, KNN, ANN, and LR for fruit freshness classification using electronic nose data collected from MQ-series gas sensors. All models were trained and tested using default hyperparameters to ensure a fair comparison and to simulate realistic deployment scenarios without extensive model tuning.

The results show that RF is the most effective model, achieving perfect accuracy (100%) along with strong computational efficiency, significantly outperforming the other algorithms. KNN and ANN also demonstrated high accuracy (97.10% and 96.80%, respectively), making them strong alternatives depending on specific application needs. LR, although less accurate (91.16%), offered the fastest inference time, making it a practical option in resource-limited environments. Overall, the integration of electronic nose technology with machine learning provides a robust, non-destructive, and scalable approach to fruit quality assessment, with promising applications in postharvest quality control and real-time supply chain monitoring.

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AUTHOR CONTRIBUTIONS STATEMENT

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

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Ridwan Raafi'udin		✓		✓		✓	✓	✓	✓	✓	✓	✓		

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available on Kaggle at the following URL: https://www.kaggle.com/datasets/mehrabmahdian/food-freshness-electronic-nose-data/data. The dataset was created and uploaded by Mehrab Mahdian. and is used in this study in accordance with its open access license.

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