

# REAL-TIME FRUIT RIPENESS CLASSIFICATION USING VOC PROFILING AND DECISION TREE ALGORITHMS: A SOLUTION FOR REDUCING POST-HARVEST LOSSES

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## Abstract

In Pakistan, the agricultural sector is vital for economic stability, particularly through fruit cultivation. However, accurately determining fruit ripeness poses a significant challenge, resulting in considerable post-harvest losses and diminished market value. Traditional ripeness assessment methods are often subjective, inconsistent, and labor-intensive. To address this issue, we developed an innovative AI-based fruit ripeness detection system utilizing MQ gas sensors. This system detects volatile organic compounds (VOCs) emitted by fruits during the ripening process, providing real-time data on gas concentrations associated with ripeness stages. The sensor data is processed using advanced artificial intelligence algorithms, specifically a decision tree model, to classify fruits as "ripe" or "unripe." By implementing this technology, farmers and vendors can significantly reduce post-harvest losses and enhance the quality of produce while improving overall supply chain efficiency. The decision tree algorithm effectively analyzes patterns in sensor data to make accurate predictions about fruit ripeness. This project represents a substantial advancement in modernizing agricultural practices in Pakistan, contributing to sustainable development and economic growth. The integration of cutting-edge sensor technology with machine learning not only addresses the critical challenges of fruit ripeness detection but also paves the way for innovative solutions in the agricultural sector.

## 1 INTRODUCTION

The agricultural sector is the backbone of Pakistan's economy, providing livelihoods for millions and serving as a vital source of food and income. Within this sector, fruit cultivation plays a significant role, contributing substantially to agricultural output. However, ensuring optimal harvest times and preserving fruit quality post-harvest remain persistent challenges. Inefficient methods for detecting fruit ripeness often lead to sub-optimal harvest timings, resulting in reduced

market value and increased post-harvest losses. Recognizing the importance of accurate fruit ripeness detection in maximizing agricultural productivity and profitability, this project aims to introduce a revolutionary sensor-based system designed for precise assessment of fruit ripeness. A comprehensive review of current literature has been conducted to identify state-of-the-art technologies and methodologies that surpass traditional methods. Expanding on prior studies involving aroma detection using petrochemical

sensors and employing advanced machine learning algorithms, this project focuses on designing and constructing a portable device called the Fruit Ripeness Detection System. This device will analyze chemical signals released by fruits during the ripening process to develop an accurate apparatus for assessing fruit quality.

The project aspires to foster better decision-making among all agricultural stakeholders—farmers, distributors, and consumers—by providing timely information regarding fruit ripeness. Moreover, international organizations such as the Food and Agriculture Organization (FAO) emphasize that enhancing post-harvest practices is critical for reducing food loss and waste while improving food safety and quality.

**2 Related work**

The Fruit Ripeness Detection System is an advanced concept designed to minimize human interference in evaluating the ripeness stages of fruits. This system leverages technology involving imaging and machine learning algorithms to facilitate decisions on the ripeness status of various fruits. Recent advancements in automated fruit ripeness detection systems have gained attention due to their potential to reduce time and costs, which are critical in agriculture and food processing industries. This literature review aims to explore current research on fruit ripeness detection systems, focusing on principles, methods, and applications.

**A. Existing Literature**

**1. Sensor Technologies for Ripeness Detection**

i. Electrochemical sensor: They emerged as significant tools for detecting fruit ripeness due to their sensitivity to volatile organic compounds (VOCs) emitted during the ripening process. Research has demonstrated the effectiveness of these sensors in monitoring ethylene concentrations, a key indicator of fruit ripening. For instance, studies show a strong correlation between ethylene levels and ripeness stages in bananas, highlighting the potential for real-time, non-destructive assessments.

ii. Metal Oxide Semiconductor sensors: These sensors are widely studied for their application in ripeness detection. They exhibit high sensitivity to ethylene and other VOCs, making them suitable for portable devices used for on-site assessments. Research indicates that MOS sensors can distinguish between different ripeness stages based on gas concentration profiles in tomatoes and mangos.

iii. Optical Sensors: Optical technologies, including near-infrared (NIR) and hyperspectral imaging, offer non-invasive methods for assessing fruit quality. Studies have demonstrated that NIR spectroscopy can accurately predict ripeness based on spectral data.

iv. Acoustic Sensor: Acoustic sensors analyze sound waves generated by tapping or vibrating fruits to assess firmness and ripeness. Studies indicate that acoustic signals can distinguish between different ripeness stages based on variations in firmness.

**Table 1 Comparison of Existing Sensor Technologies**

Sensors	Limitations		
Electrochemical [1][2][3][4]	Expensive	Frequent calibration required	Limited to specific compounds
Optical [8][9][10][11]	High equipment cost	Complex data processing	Require controlled environment
Acoustic [12][13]	Affected by environmental noise	Limited to firmness detection	Not suitable for all fruit types

**2. Machine Learning Techniques for Ripeness detection.**

i. Support Vector Machines (SVM): SVMs

have been employed to classify the ripeness of fruits based on data collected from various sensors. Their ability to effectively separate different

ripeness stages enhances decision-making processes in agricultural practices.

ii. **Deep Learning Techniques:** Deep learning models, particularly convolutional neural networks (CNNs), have shown high classification accuracy when analyzing images of fruits. While CNNs can automatically learn and classify ripeness stages based on visual features, further studies are needed on their interpretability and practical deployment in field settings. Additionally, recurrent neural networks (RNNs) have been utilized to predict the ripeness of bananas using time-series data from electrochemical sensors.

iii. **Data Fusion Techniques:** Combining data from multiple sensors enhances the reliability of ripeness detection systems. Research shows that data fusion approaches improve prediction accuracy compared to using individual sensors alone.

iv. **Bayesian Networks and Support Vector Regression:** Bayesian networks model probabilistic relationships between different indicators of ripeness, providing robust predictions even amidst noisy data. Support vector regression has also been utilized for quantitative predictions of ripeness levels based on sensor data.

## B. Gaps in Existing Research

1. **Long term Stability of Sensors:** There is limited exploration of the long-term stability and calibration of electrochemical sensors under varying environmental conditions, which is crucial for their practical application in diverse agricultural settings [1] - [4].

2. **Comparative Effectiveness of sensor Technologies:** A lack of comprehensive studies comparing the effectiveness of different sensor technologies (e.g., electrochemical, MOS, optical) in real-world applications hinders the ability to determine the best options for specific fruit types and conditions. [5] - [6].

3. **Impact of Environmental Conditions on Optical Sensors:** Insufficient understanding exists regarding how variations in lighting and environmental conditions affect the accuracy of optical measurements, particularly for NIR and

hyperspectral imaging [8] - [11].

4. **Scalability of Acoustic Methods:** Limited research has been conducted on the scalability and commercial viability of acoustic sensing methods across various fruit types, which may restrict their broader application in the industry [12]-[13].

5. **Integration of Machine Learning with Real-Time Data:** There is a need for research on integrating machine learning algorithms, such as Support Vector Machines (SVM) and deep learning models, with real-time data streams from multiple sensor types to enhance decision-making processes [4],[7].

6. **Generalizability of Deep Learning Models:** Further studies are required to assess the generalizability of deep learning models across different fruit types and ripening conditions, ensuring that these models can be effectively applied in diverse scenarios [14]-[15].

7. **Implementation Strategies for Data Fusion Techniques:** Gaps remain in understanding how best to implement data fusion techniques in real-world agricultural environments to maximize the reliability and accuracy of ripeness detection systems [16]-[17].

## C. Novelty aspects of Research

1. AI based fruit ripeness system with Real time monitoring capability.

2. Decision tree Algorithm for classification.

3. Integration of Advanced Sensor Technology with Machine Learning

4. Focus on post-harvest loss reduction.

## 3 Proposed methodology

The proposed AI-based fruit ripeness detection system employs MQ gas sensors to detect specific volatile organic compounds (VOCs) released by fruits during their ripening stages. The methodology involves several key steps:

### 1. System Design and Implementation

The Fruit Ripeness Detection System integrates advanced sensor technology with artificial intelligence to assess the ripeness of fruits, specifically apples and bananas. The system comprises various components, including sensors,

a microcontroller, and software for data visualization.

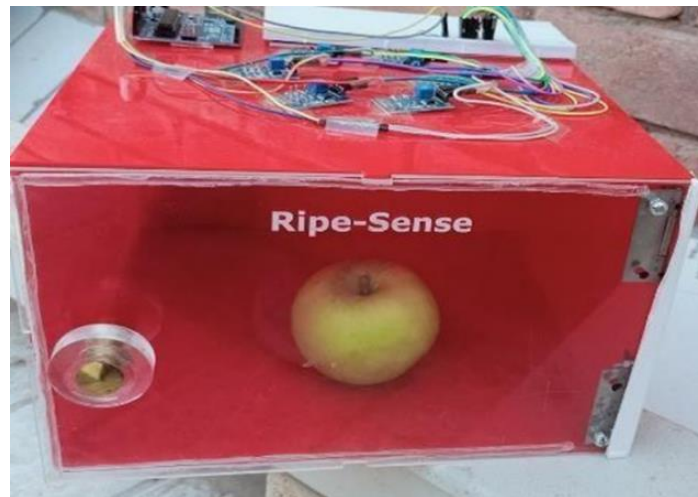


Fig. 1. Experimental Hardware Setup

1. Components:

i. Sensor Selection: MQ gas sensors were chosen for their sensitivity to VOCs associated with apple and banana ripening along with their cost effectiveness in hardware and minimum

calibration needed [13].

ii. Microcontroller: Arduino Uno for data acquisition and processing.

iii. Software: LabVIEW for real-time data visualization and logging.

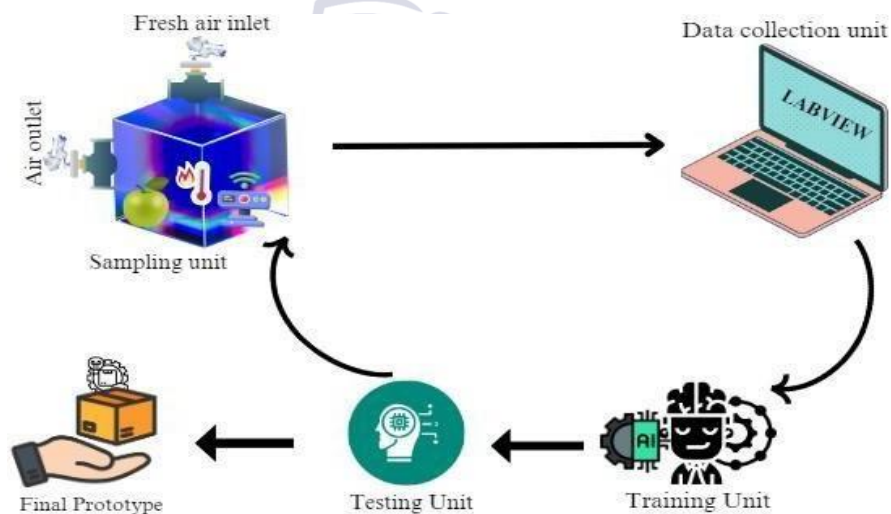


Fig. 2. Proposed Experimental Setup

2. Sensor Readings and Target VOCs for Fruit Ripeness Detection

In the Fruit Ripeness Detection System, various MQ sensors are strategically selected based on their sensitivity to different volatile organic

compounds (VOCs) emitted during the ripening process of fruits such as apples and bananas. Table 2 and 3 shows sensor targets specific gases, providing critical insights into fruit maturity and ripeness levels of apple [18].

Table 2 Characteristics of sensors for banana

Fruit	Ripeness Level	VOCs	Sensor Combination	Targeted Gas for Detection	Gas Concentration Readings
Banana	Ripe	Ethylene, Isoamyl Acetate, 2-	MQ-2, MQ-5, MQ-7, MQ135	Ethylene, Isoamyl Acetate, 2Methyl-1butanol	Ethylene: 50-100 ppm, Isoamyl Acetate: 20-50 ppm, 2-Methyl-1-butanol: 10-30 ppm
Banana	Close to Ripe	Ethylene, Isoamyl Acetate, 2-	MQ-2, MQ-5, MQ-7, MQ135	Ethylene, Isoamyl Acetate, 2Methyl-1butanol	Ethylene: 30-50 ppm, Isoamyl Acetate: 10-30 ppm, 2-Methyl-1-butanol: 5-20 ppm
Banana	Intermediate to Ripe	Ethylene, Isoamyl Acetate, 2-	MQ-2, MQ-5, MQ-7, MQ135	Ethylene, Isoamyl Acetate, 2Methyl-1butanol	Ethylene: 10-30 ppm, Isoamyl Acetate: 5-15 ppm, 2-Methyl-1-butanol: 3-10 ppm
Banana	Unripe	Low VOCs	MQ-2-135	Methyl-1butanol, Ethanol	2 - 3 PPM

Table 3 Characteristics of sensors for apple

Fruit	Ripeness Level	VOCs	Sensor Combination	Targeted Gas for Detection	Gas Concentration Readings
Apple	Ripe	Ethylene, Ethanol, Ethyl Acetate,	MQ-2, MQ-3, MQ-9, MQ135	Ethylene, Ethanol, Esters	Ethylene: 50-100 ppm, Ethanol: 1030 ppm, Esters: 2050 ppm
Apple	Close to Ripe	Ethylene, Ethanol, Ethyl Acetate,	MQ-2, MQ-3, MQ-9, MQ135	Ethylene, Ethanol, Esters	Ethylene: 30-50 ppm, Ethanol: 5-20 ppm, Esters: 10-30 ppm
Apple	Intermediate to Ripe	Ethylene, Ethanol, Ethyl Acetate,	MQ-2, MQ-3, MQ-9, MQ135	Ethylene, Ethanol, Esters	Ethylene: 10-30 ppm, Ethanol: 3-10 ppm, Esters: 5-15 ppm
Apple	Unripe	Low VOCs	MQ-135	Ethanol	5PPM VOC concentrations

### 3. Sensor Setup

A controlled environment is created using a closed box to house the fruits and sensor array, ensuring uniform monitoring of gases emitted during ripening. The sensors are arranged using the equal distance approach to ensure consistent data collection as shown in Fig. 1.

### 4. Data Collection and Processing

The data acquisition process involves reading analog values from the sensors, which are then converted to digital readings and sent to LabVIEW for visualization. The data is logged in CSV format for further analysis, including timestamps and corresponding readings. The data acquisition process is shown in Fig. 2.

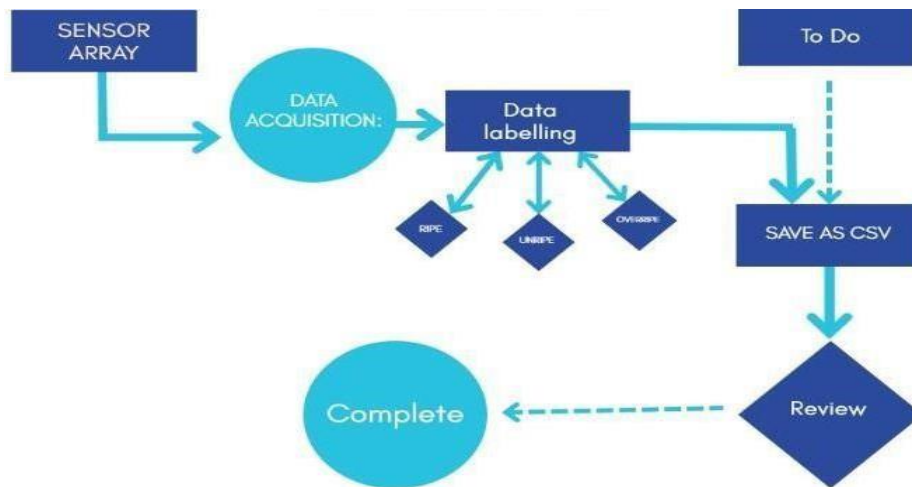


Fig. 3. Data Acquisition Process

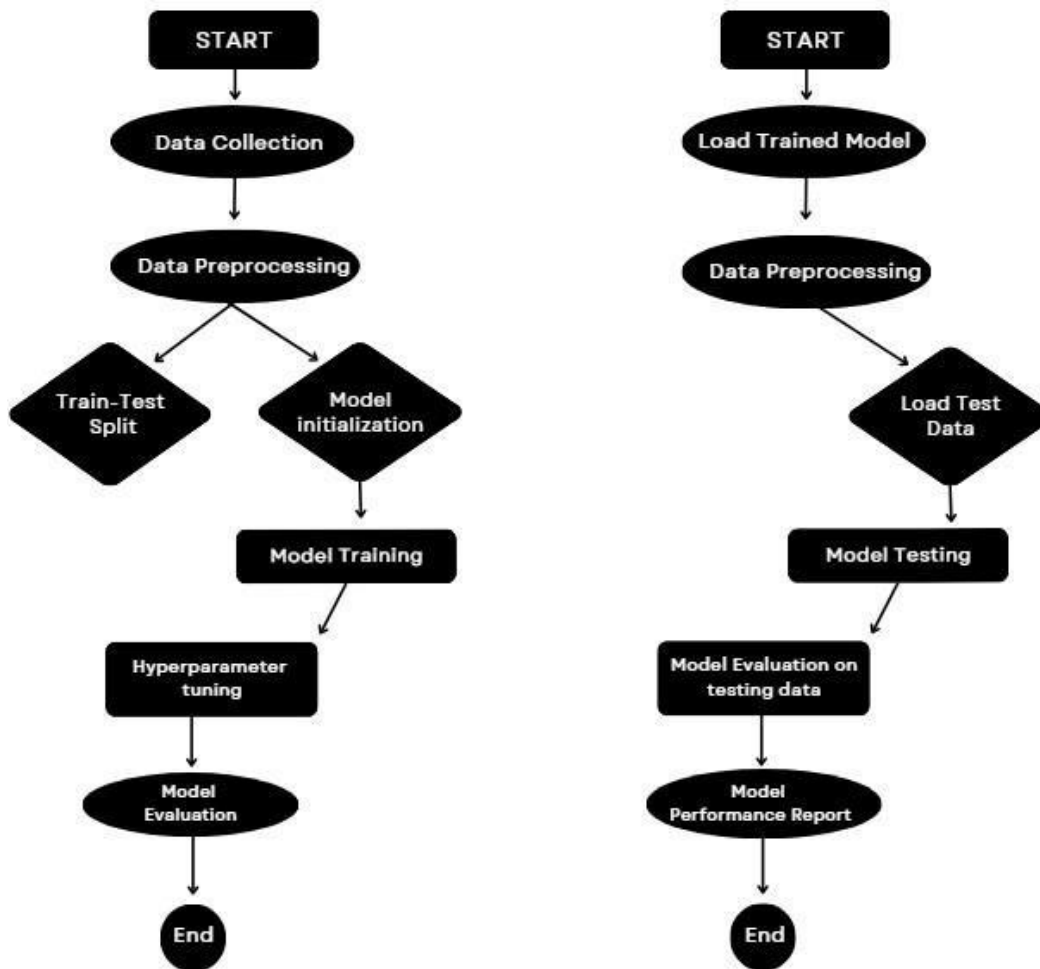


Fig. 4. Model Training and Testing

### 5. Machine Learning Training and Evaluation

In this paper, the objective was to develop a robust machine learning model to classify the ripeness levels of fruits based on sensor data collected from the Fruit Ripeness Detection System. A decision tree algorithm was chosen due to its interpretability, which allows users to easily understand and follow the logic behind its decisions. Additionally, decision trees are effective in handling multi-class data, making them suitable for classifying different ripeness stages such as unripe, close to unripe, intermediate, close to ripe, and ripe. This algorithm is also well-suited for integrating inputs from multiple sensors, such as those measuring VOC concentrations, temperature, and humidity, which are critical for accurate ripeness assessment.

To enhance the classification accuracy and robustness of the fruit ripeness detection system, we initially employed a decision tree algorithm. Decision trees are effective in providing an easily interpretable decision-making framework and have shown to yield strong accuracy in handling multi-class data for ripeness stages. However, to further improve the model's performance, we also employed a Support Vector Machine (SVM). SVMs are renowned for their effectiveness in high-dimensional spaces and their ability to create optimal hyperplanes for classification tasks. By incorporating SVMs, the model can efficiently handle complex and non-linear relationships between the sensor data and ripeness stages. This dual approach leverages the strengths of both algorithms, resulting in a more reliable and precise classification system for determining fruit ripeness.

We can define:

- Accuracy: That is the percentage of samples classified correctly.

$$A = \frac{TP + TN}{TP + FN + FP + TN}$$

- Precision: The ratio of correctly predicted positive observations to the total predicted positives.

$$Precision = \frac{TP}{TP + FP}$$

- Recall (Sensitivity or True Positive Rate): The ratio of correctly predicted positive observations to all observations in the actual class.

The integration of multiple sensor inputs, such as VOC concentrations, temperature, and humidity, further refines the model's predictions, making it a valuable tool for applications in agriculture and food supply chain management.

Above is a flow chart of the training and testing process Fig 3. illustrating the steps involved in developing the model. The algorithm starts with data collection and preprocessing, where sensor data is cleaned, normalized, and prepared for analysis. The decision tree is then trained using a portion of the dataset, learning to establish decision rules and splits that correlate sensor inputs with specific ripeness stages. The model is validated using cross-validation techniques to ensure it generalizes well to new data. Finally, the model's performance is evaluated on a separate testing set to assess its accuracy and reliability in predicting fruit ripeness. This systematic approach ensures the development of a reliable machine learning model for real-time fruit ripeness classification [17].

### 6. Evaluation Metrics

In order to find the most suitable algorithm to this dataset, different evaluation methods will be presented: Accuracy, Confusion Matrix.

Given that:

- TP = #samples for which the prediction is Fruit1 and the true label is Fruit1
- FP = #samples for which the prediction is Fruit2 but the true label is Fruit1
- TN = #samples for which the prediction is Fruit2 and the true label is Fruit2
- FN = #samples for which the prediction is Fruit1 but the true label is Fruit2

$$Recall = \frac{TP}{TP + FN}$$

- F1 Score: The harmonic mean of precision and recall.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

**7. Dataset Distribution**

This structured dataset distribution Table 4 ensures that the machine learning model is trained on a sufficient number of samples across all ripeness classes while maintaining a separate and

unbiased testing set for performance assessment. This approach helps in assessing the model's ability to generalize to new data and make accurate predictions for fruit ripeness based on sensor inputs.

**Table 4 Distribution of Dataset across Classes**

Ripeness Class	Batch Size	Training Set (%)	Training Set (Samples)	Testing Set (%)	Testing Set (Samples)
Ripe	250,000	75%	187,500	25%	62,500
Unripe	200,000	75%	150,000	25%	50,000

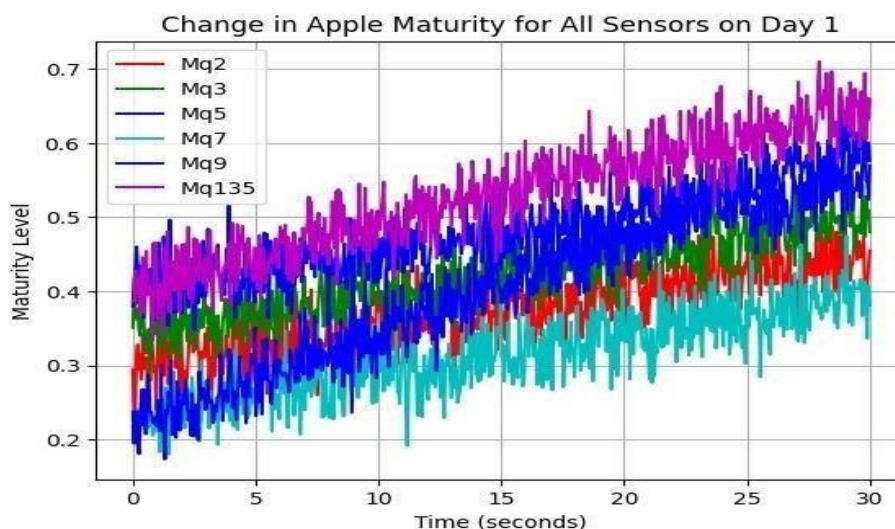
**4 Results and Discussion**

The results obtained from the Fruit Ripeness Detection System demonstrate a clear correlation between sensor readings and the ripeness stages of apples and bananas. The data collected indicates that the MQ sensors effectively monitor the VOCs emitted during the ripening process, particularly ethylene, which is crucial for determining optimal

harvest times.

**1. Data Collection Results**

The data collected from the Fruit Ripeness Detection System provides insights into the ripeness stages of apples and bananas based on sensor readings. The system utilized various MQ gas sensors to monitor volatile organic compounds (VOCs) emitted during the ripening process.



**Fig. 5(a) VoC Concentration Day-1**

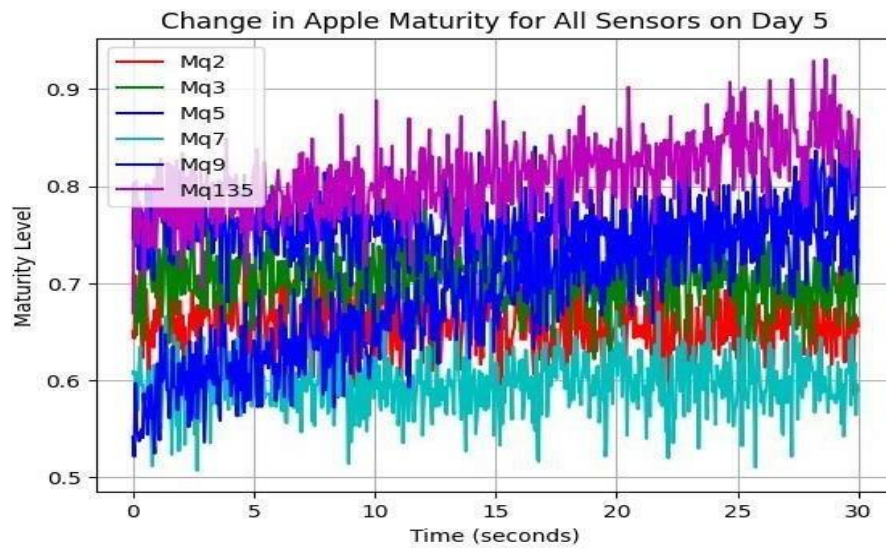


Fig. 5(b) VoC Concentration Day-5

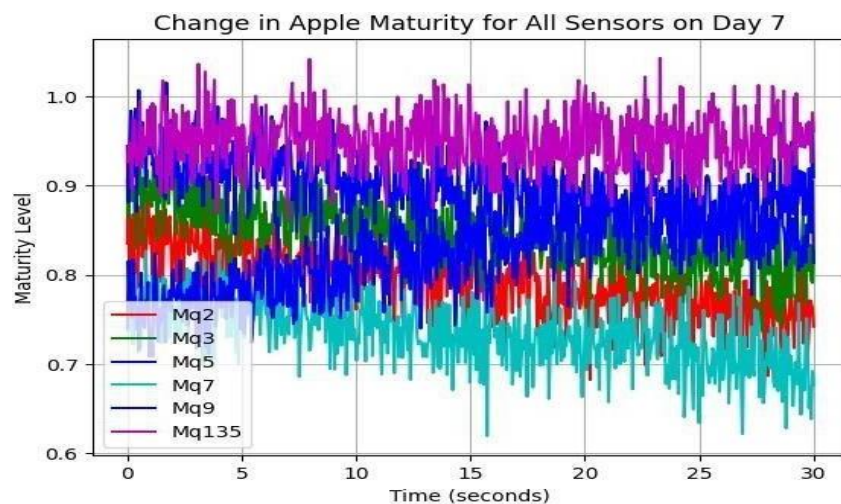


Fig. 5(c) VoC Concentration Day-7

Over the course of 7 days, our study utilized the MQ sensors to monitor VoC emissions from apples at different stages of ripeness, focusing on both ripe and unripe conditions. The data collected allowed us to observe changes in the concentrations over time, providing insights into the ripening process. In Fig 5, which examines ripe apples, Fig 5a illustrates concentrations on day 1, ranging from 0.1 to 0.3 ppm for MQ-2, indicating the initial stages of ripening. By day 5 (Fig 5b), VoC levels increased to 0.4-0.7 ppm (for MQ-2),

marking the onset of ripening. By day 7 (Fig 5c), VoC concentrations peaked between 0.8 and 1.2 ppm (for MQ-2), suggesting that the apples had reached a ripe stage suitable for consumption.

In ripe apples, the gradual increase in ethylene levels from day 1 to day 7 (Fig 5) correlates with the progression of ripening stages. Initially low concentrations on day 1 (0.1-0.3 ppm) indicate early ripening, where fruits begin to undergo biochemical changes.

Table 5 Classification Report Apple

SVM		Decision Tree	
Metric	Ripe-Unripe	Metric	Ripe-Unripe
Accuracy	83	Accuracy	84
Precision	82	Precision	84
Recall	81	Recall	82
F1-score	82	F1-score	83

Table 6 Classification Report Banana

SVM		Decision Tree	
Metric	Ripe-Unripe	Metric	Ripe-Unripe
Accuracy	81	Accuracy	83
Precision	82	Precision	83
Recall	79	Recall	81
F1-score	80	F1-score	82

Decision tree model outperformed the SVM model with an accuracy of approximately 84 and 83 for apple and banana, while the SVM model achieved around 83 and 81 for apple and banana. This highlights the decision tree's superior performance in accurately predicting fruit ripeness stages based on the features extracted from sensor data. The results underscore the suitability of the decision tree algorithm for this classification task, showcasing its interpretability and robustness in handling multi-class data. Further improvements could involve fine-tuning hyperparameters, exploring ensemble methods, and refining feature engineering to enhance both models' accuracy and generalizability across various fruit types and environmental conditions.

## 5 Conclusion and Future Recommendations

The machine learning based Ripeness Detection System developed in this study provides an innovative solution to fruit ripeness assessment challenges in Pakistan's agricultural sector. Utilizing MQ gas sensors to detect volatile organic compounds (VOCs) emitted during ripening, the system offers a reliable method for determining optimal harvest times for fruits like apples and bananas. By integrating advanced machine

learning algorithms, particularly decision trees, the system achieves classification accuracies exceeding 80%. This advancement reduces reliance on subjective visual assessments and costly chemical testing methods, effectively addressing post-harvest losses. Ultimately, this technology maximizes market value and enhances food security and sustainability.

To further enhance the impact of this research, future efforts should focus on: Adapting the system for a wider variety of fruits and vegetables, validating the technology's effectiveness in real-world agricultural settings, exploring additional machine learning techniques to refine classification accuracy, investigating how this technology can be incorporated into existing agricultural supply chains to optimize logistics and reduce waste.

## Declarations

All authors declare that they have no conflicts of interest.

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