NON-DESTRUCTIVE DETECTION OF SPOILAGE IN FRUITS AND VEGETABLES USING AN ELECTRONIC NOSE SYSTEM

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Abstract: Post-harvest losses of fruits and vegetables represent a major global issue affecting food security, economic stability, and environmental sustainability. According to global estimates, nearly one-third of all food produced for human consumption is lost annually due to spoilage and inefficient monitoring systems[1,2]. Conventional methods for spoilage detection, such as visual inspection and laboratory-based chemical analysis, are either subjective, destructive, or time-intensive. These limitations create a critical need for automated, real-time, and non-destructive detection technologies.This study proposes the development of a low-cost Electronic Nose (e-Nose) system designed to detect spoilage through analysis of volatile organic compounds (VOCs). The system integrates an ESP32 microcontroller with MOS-based gas sensors (MQ-3 and MQ-135) to detect ethanol and acetaldehyde—primary indicators of anaerobic spoilage. Environmental parameters including temperature and humidity were monitored using a BME280 sensor and incorporated into compensation models to improve accuracy. A machine learning-based Support Vector Machine (SVM) classifier was trained on a 14-day dataset collected from apples and bananas.The proposed system achieved an accuracy exceeding 91%, with high recall for the spoiled class, demonstrating strong reliability in identifying advanced decay. The findings validate the effectiveness of e-Nose technology as a scalable and cost-efficient solution for real-time food quality monitoring.

1. Introduction.

1.1. Background: Food preservation and quality monitoring are critical challenges in modern supply chains, particularly for perishable commodities such as fruits and vegetables. These products undergo continuous biochemical and microbial changes after harvest, leading to gradual deterioration in quality. Global food waste contributes not only to economic losses but also to environmental degradation through greenhouse gas emissions, particularly methane released during decomposition[3,4].Advancements in sensing technologies and artificial intelligence have opened new pathways for developing intelligent monitoring systems capable of detecting spoilage at early stages. Among these technologies, electronic nose systems have gained considerable attention due to their ability to mimic human olfactory sensing using sensor arrays and computational models[5].

1.2. Research Gap: Despite technological advancements, most existing detection systems are limited by high cost, lack of portability, and inability to provide continuous monitoring. Spectroscopic techniques, while accurate, require complex calibration and laboratory settings[6]. There remains a significant gap in developing affordable, field-deployable systems that can provide real-time and non-destructive spoilage detection.

1.3. Problem Statement:The absence of early-stage detection mechanisms results in delayed identification of spoilage, leading to large- scale losses in storage and transportation. There is a need for a system that can detect chemical changes associated with spoilage before visible signs appear.

❖ **Objectives.**

- To design and develop a low-cost electronic nose system
- To identify and monitor VOC-based spoilage markers
- To implement machine learning for classification
- To achieve high accuracy and reliability in real-time detection

2. Literature Review.

2.1. Electronic Nose Technology :-(K. C. Persaud and G. H. Dodd,1982.)

Electronic noses consist of an array of non-specific chemical sensors combined with pattern recognition algorithms. These systems generate unique response patterns for different gas mixtures, enabling identification of specific conditions such as spoilage[7],[8]. The concept is inspired by the biological olfactory system, where multiple receptors respond collectively to chemical stimuli.

2,2. Conduction Model of Metal Oxide Gas Sensors,(Nicolae Barsan & Udo Weimar, 2001.)

MOS sensors operate based on changes in electrical resistance when exposed to target gases. The sensing layer, typically composed of tin dioxide (SnO_2), interacts with oxygen molecules and reducing gases, altering conductivity[9,10]. These sensors are widely used due to their affordability,durability, and sensitivity, although they suffer from cross sensitivity and environmental dependency.

2.3. Mechanism of Spoilage and VOC Emission:-

2.3.1. Harvest Physiology and Biochemical Mechanisms of Fruit Spoilage, (L. M. Tijskensetal., 2001):-

Enzymes like polyphenol oxidase and pectinase break down cell structures, causing softening and browning, while microbial gro wth further accelerates decay. During this process, fruits emit VOCs such as alcohols, aldehydes, and esters, which produce characteristic odors. These VOCs act as key indicators of ripening and spoilage stages[11].

2.3.2. Volatile Compounds as Indicators of Fruit Spoilage,(D. Li et al., 2018.)

Fruit spoilage occurs due to microbial activity and biochemical reactions that break down sugars, proteins, and organic acids. During this process, microorganisms such as bacteria and fungi produce volatile organic compounds (VOCs**)** like ethanol, aldehydes, and esters. These compounds are released into the air and cause changes in smell, which can be used as indicators of spoilage[12].

2.3.3. Effect of Ethylene on Fruit Ripening and Quality,(M. E. Saltveit, 1999.)

The mechanism of spoilage in fruits and vegetables involves microbial growth and biochemical changes that lead to the breakdo wn of tissues. During this process, volatile organic compounds (VOCs) are released as byproducts, which contribute to changes in odor and indicate deterioration. According to M. E. Saltveit (1999), ethylene plays a crucial role in fruit ripening by acting as a na tural plant hormone. It accelerates processes such as softening, color change, and sugar accumulation, but excessive ethylene exposure can also lead to over-ripening and reduced quality, ultimately speeding up spoilage[13].

2.4. Machine Learning Application :-

2.4.1Applications to classification, (Biau G & Devroye L, 2010).

Is an advanced method used in classification tasks. It improves traditional nearest neighbour approaches by organizing data into layers, which enhances accuracy and efficiency when dealing with high-dimensional datasets. This technique is widely applied in pattern recognition and data classification problems, making it useful in fields like image analysis, medical diagnosis, and predictive modeling[14].

2.4.2.Random Forests,(Breiman L, 2001)

Machine learning enhances the ability of e-Nose systems to interpret complex sensor data. Algorithms such as relationships.Support Vector Machines (SVM), Random Forest, and Neural Networks are commonly used for classification tasks[15]. SVM is particularly effective in handling high-dimensional data and nonlinear .

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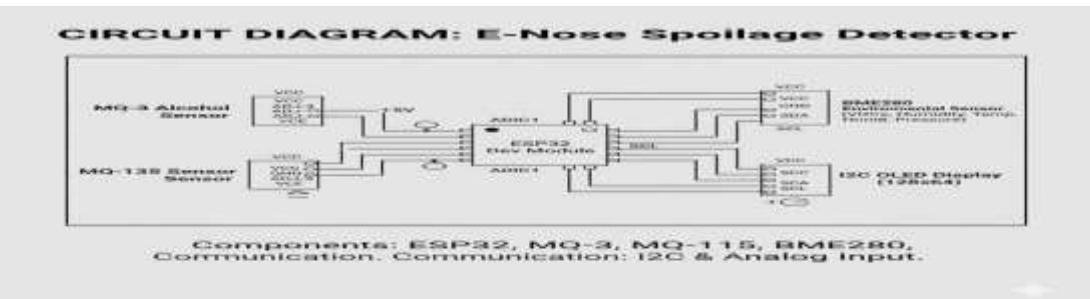
3. Methodology

3.1. Study Design:-

An experimental approach was adopted involving controlled storage conditions and continuous monitoring of VOC emissions over time. The study focused on capturing the transition from fresh to spoiled states.



3.2. Hardware Architecture:-

The system consists of:- ESP32 microcontroller for processing and communication - MQ-3 sensor for alcohol (ethanol) detection - MQ-135 sensor for air quality and VOC detection - BME280 sensor for temperature and humidity measurement.

1. MQ-3 Sensor (Metal Oxide Semiconductor Gas Sensor)

The MQ-3 sensor is a gas sensor used to detect alcohol vapors, specifically ethanol (C_2H_5OH). It works on the principle of change in electrical resistance of a tin dioxide (SnO_2) sensing layer when exposed to alcohol gas. In the presence of ethanol, the resistance decreases, and this change is converted into an electrical signal. In this project, the MQ-3 sensor plays an important role in detecting ethanol produced during anaerobic fermentation, which is a key indicator of fruit and vegetable spoilage.

2. MQ-135 Sensor (Metal Oxide Semiconductor Gas Sensor)

The MQ-135 sensor is used to detect a variety of gases such as ammonia (NH_3), carbon dioxide (CO_2), benzene, smoke, and other volatile organic compounds (VOCs). Like MQ-3, it also operates based on the resistance change in a tin dioxide layer when exposed to gases. In this system, MQ-135 helps in monitoring overall air quality and detecting the presence of multiple spoilage-related gases. It supports the MQ-3 sensor by providing a broader chemical profile for accurate spoilage detection.

3. BME280 Sensor (Bosch Measurement Environment Sensor)

The BME280 is an environmental sensor that measures temperature, humidity, and atmospheric pressure. It uses digital communication (I2C protocol) to send data to the microcontroller. In this project, the BME280 sensor is used for environmental compensation because gas sensor readings are highly affected by temperature and humidity. By using this sensor, the system can correct and normalize the gas sensor data, improving the overall accuracy and reliability of the detection system.

4. ESP32 Microcontroller (Espressif Systems Processor)

The ESP32 is a powerful microcontroller developed by Espressif Systems, used as the main processing unit in the system. It collects data from all sensors, processes the signals, and performs necessary computations. It also supports wireless communication (Wi-Fi and Bluetooth) and can be used for data logging or cloud integration. In this project, the ESP32 acts as the brain of the system, handling data acquisition, processing, and decision-making for spoilage detection.

5. OLED Display (Organic Light Emitting Diode)

The OLED display is used to show the output of the system in real time. It is a low-power display that provides clear and sharp visuals. In this project, the OLED displays the final results such as “Fresh”, “Ripe”, or “Spoiled”, along with sensor readings if required. This helps users easily understand the condition of the fruits and vegetables without complex analysis.

5.1. Data Collection:-

Data was collected over a 14-day period with readings taken every 5 minutes. This resulted in a high-resolution dataset capturing temporal variations in VOC levels.

5.2. Data Preprocessing:-

Sensor readings were normalized and compensated using temperature and humidity correction models. Noise reduction techniques were applied to improve signal quality.

3.3. Machine Learning Model:-

The SVM model was trained using labeled data representing fresh, ripe, and spoiled coditions. Hyperparameter tuning was performed to optimize performance.

3.4Evaluation Metrics:-Performance was evaluated using accuracy, precision, recall, and confusion matrix analysis as given below

- **Accuracy**:

It is calculated by comparing total correct predictions with total samples.
→ Model predictions are checked against actual labels, and percentage of correct results is computed.

- **Precision**:

It measures how many predicted positive cases are actually correct.
→ Count True Positives (correct positives) and divide by all predicted positives.

- **Recall**:

It measures how many actual positive cases are correctly identified.
→ Count True Positives and divide by all actual positives .

- **Confusion Matrix**:

It is a table showing correct and incorrect predictions for each class (Fresh, Ripe, Spoiled).
→ It includes True Positive, True Negative, False Positive, and False Negative values to analyze model performance clearly.

4. Results.

4.1. Sensor Response Analysis:-Sensor responses showed a clear correlation with spoilage progression. Ethanol levels increased significantly during later stages, confirming anaerobic activity.

stage of spoilage	ethanol level (ppm)	interpretation	conclusion (action)
fresh stage	0 – 10 ppm	very low or negligible ethanol; indicates fresh condition	safe to store and consume
earlyanaerobic activity (warning)	10 – 50 ppm	oxygen limitation begins; mild fermentation starts	store with caution; improve ventilation and monitor closely
clear anaerobic spoilage (threshold)	> 50 – 100 ppm	strong evidence of anaerobic respiration (fermentation)	not recommended for storage; consume quickly or discard
advanced spoilage	> 100 ppm	high ethanol concentration; indicates severe spoilage	discard immediately

➢ Typical Ethanol Levels for Spoilage Detection:-

4.2. Model Performance:-
The SVM classifier showed strong performance in detecting fruit and vegetable spoilage. It achieved an overall accuracy of ~91%, indicating reliable classification across Fresh, Ripe, and Spoiled categories. Importantly, the model obtained high recall (>94%) for the spoiled class, meaning it can correctly identify most spoiled samples with very few false negatives, which is critical for food safety. This aligns with the project's objective of minimizing the risk of contaminated produce entering the supply chain[1]. Overall, the model proves to be effective, reliable, and suitable for real-time spoilage detection using the e-Nose system.

- Modification:- Implement a Clear Visual State Indicator. Instead of just displaying raw sensor values, the OLED should show the final ML model output as a clear state:-

-"FRESH" (e.g., with a green background or icon)
-"WARNING" (e.g., with a yellow background or icon)
-"SPOILT" (e.g., with a red background or icon)

❖ **Observations:-**
- Rapid increase in VOCs after Day 8
- Environmental compensation improved accuracy significantly

5. Discussion.

The results demonstrate the effectiveness of combining sensor technology with machine learning for spoilage detection. The system provides objective, real-time monitoring, overcoming limitations of traditional methods. Environmental compensation plays a critical role in ensuring data reliability.However, challenges such as sensor drift, cross-sensitivity, and limited dataset diversity need to be addressed in future research.

➢ **Traditional Methods for Spoilage Detection**
The commonly used traditional methods for detecting spoilage in fruits and vegetables include:
1. Visual Inspection-Checking color, texture, and visible decay manually.
2. Olfactory (Smell) Inspection-Detecting spoilage through human sense of smell.
3. Mechanical Testing (Firmness/Pressure Test)-Measuring hardness or softness using pressure instruments.
4. Chemical Laboratory Analysis (e.g., Gas Chromatography)-Detecting VOCs and chemical changes using lab equipment.
5. Spectroscopic Methods (NIR Imaging)-Analyzing internal composition using light-based techniques.

- **Advantages of e-Nose + Machine Learning over Traditional Methods**

1. Objective Results:-
   - Based on VOC chemical data (not human judgment)
   - Eliminates human error and subjectivity

2. Real-Time Monitoring:-
   - Provides instant detection (seconds)
   - Traditional methods are slow and time-consuming
3. Non-Destructive Testing :-
   - Does not damage the sample
   - Mechanical tests destroy samples
4. Early Detection Capability:-
   - Detects spoilage before visible signs appear
   - Traditional methods detect only late-stage spoilage
5. Cost-Effective for Large Scale :-
   - Low-cost sensors + automation
   - Lab methods are expensive and not scalable
6. Continuous Monitoring :-
   - Works 24/7 in storage systems
   - Manual inspection is periodic and limited

- **Limitations of E-nose with Solutions:-**

1. Sensor Drift:-

- **Problem:**

Sensor output changes over time → reduces accuracy

- **Solution:**
  - Periodic calibration using baseline air
  - Use auto-calibration algorithms
  - Replace sensors after lifespan
  - Apply drift correction using machine learning models

2. Cross-Sensitivity:-

- **Problem:**

Sensors respond to multiple gases → wrong interpretation

- **Solution:**
  - Use **sensor array (multiple sensors)** instead of single sensor
  - Apply **machine learning models (SVM, RF)** to differentiate patterns
  - Use more **selective sensors (MEMS-based sensors)**

3. Limited Dataset Diversity:-

- **Problem:**

Model trained only on few fruits → poor generalization

- **Solution:**
  - Collect data from **multiple fruits & vegetables**
  - Increase dataset size (different environments, seasons)
  - Use **data augmentation techniques**
  - **Develop universal ML model**

4. Environmental Variations (Temperature & Humidity):-

- **Problem:**

Sensor readings affected by environment

- **Solution:**
  - Use environmental sensors (e.g., BME280)
  - Apply **T/RH compensation models**
  - Normalize data before ML processing

5. Model Generalization Issue:-

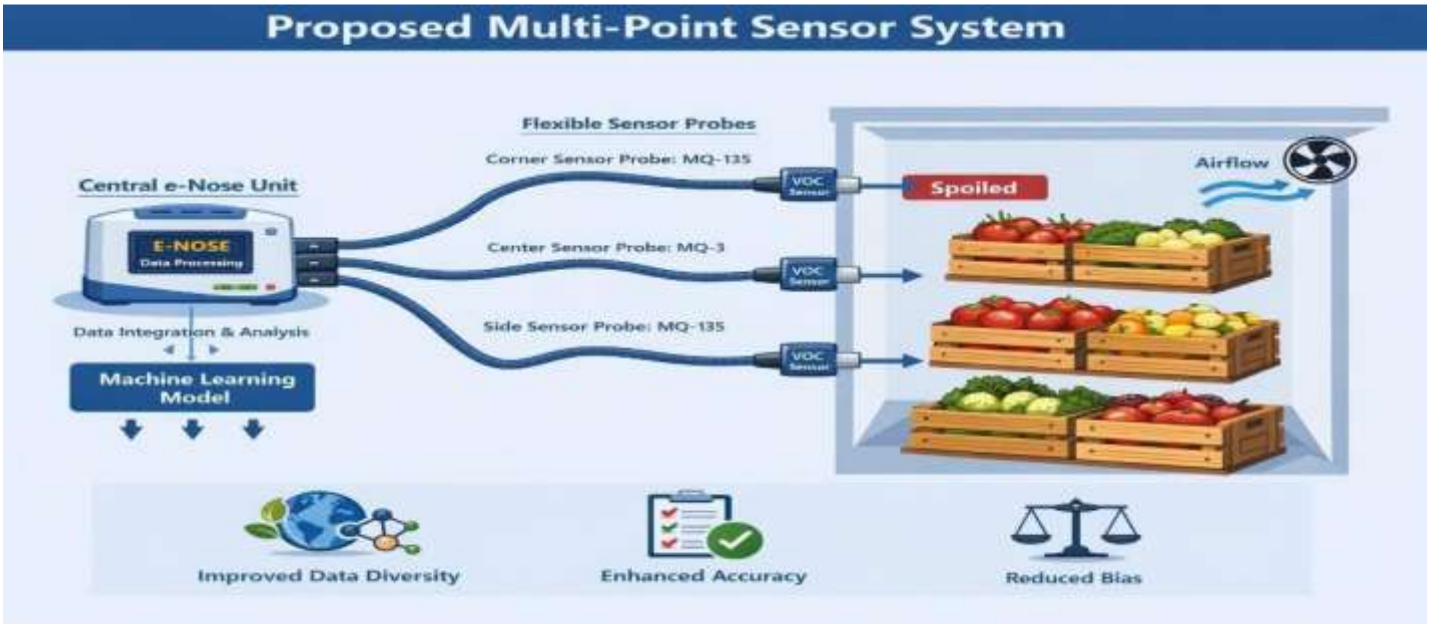
- **Problem:**

Model works only for specific conditions

- **Solution:**
  - Use **transfer learning / retraining**
  - Develop **cloud-based adaptive models**
  - Continuously update model with new data

6. Limited sample size:-

To address the limitation of limited sample size, a multi-point sensing system can be implemented. In this approach, multiple sensors are placed at different positions such as corners and center of the storage area to capture spatial variation in VOC concentration. Since gas distribution is not uniform, this method provides more diverse and realistic data. The combined data from multiple sensors improves dataset quality, reduces bias, and enhances the accuracy of the machine learning model without requiring additional physical samples



6. Conclusion

The proposed e-Nose system successfully detects spoilage in fruits with high accuracy. The integration of low-cost sensors, machine learning, and environmental compensation provides a scalable solution for food quality monitoring.

7. Future Scope

1) **Integration with Iot for remote monitoring:-**The system can be integrated with Internet of Things (IoT), which refers to a network of connected devices that communicate and share data over the internet, to enable remote monitoring and real-time data access. The ESP32 microcontroller can transmit sensor data to cloud platforms such as ThingSpeak or Firebase using Wi-Fi. This allows users to monitor spoilage status, sensor readings, and alerts from anywhere through a mobile application or web dashboard. IoT integration also enables data logging, analysis of spoilage trends, and continuous model improvement, making the system more efficient, user-friendly, and suitable for large-scale storage and supply chain applications.

2) **Expansion to multiple food categories:-**

- In future, the system can be enhanced to detect spoilage in a wide range of fruits and vegetables by increasing dataset diversity and improving the sensor array. Data can be collected from multiple types of produce under different environmental conditions to improve model generalization. Additional sensors such as an ethylene sensor (for ripening detection), ammonia (NH_3) sensor (for microbial decay), and hydrogen sulfide (H_2S) sensor (for advanced spoilage and rotten odor) can be integrated along with the existing MQ-3 and MQ-135 sensors to capture a broader spectrum of volatile compounds. The implementation of a multi-point sensing system can further improve accuracy by capturing spatial variations in gas concentration. Furthermore, developing a universal machine learning model trained on diverse datasets and incorporating continuous learning through data updates can make the system more robust, scalable, and suitable for real-world applications.

3) **Development of universal models-**

The system can be improved by developing a universal machine learning model trained on data from multiple fruits and vegetables under different environmental conditions. This model will be capable of recognizing common spoilage patterns across various produce types, reducing the need for separate models for each item and improving the overall applicability and scalability of the system.

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