

A scalable low-cost internet of things-based electronic nose for identifying chemical ripening in fruits

Amit R. Welekar¹, Gaurav Vishnu Londhe², Amit Pimpalkar³, Abhrendu Bhattacharya⁴, Nilesh Shelke², R. Jeberson Retna Raj⁵

¹Department of Computer Science and Engineering, J. D. College of Engineering and Management, Nagpur, India

²Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University), Pune, India

³School of Computer Science and Engineering, Ramdeobaba University, Nagpur, India

⁴Department of Computer Science and Engineering, Faculty of Engineering and Technology, JIS University, Kolkata, India

⁵School of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, India

Article Info

Article history:

Received May 14, 2025

Revised Feb 13, 2026

Accepted Apr 21, 2026

Keywords:

Artificial intelligence
Artificial ripening
Electronic nose
Ethylene sensing
Internet of things in agriculture
Machine learning
Volatile organic compounds
detection

ABSTRACT

Indiscriminate use of chemical agents like calcium carbide and ethephon for the ripening of fruits poses grave health hazards, emitting carcinogenic and neurotoxic compounds. Here we present a new, scalable, inexpensive, internet of things (IoT)-enabled electronic nose (e-nose) AI-Bot system for the detection of chemically ripened fruits. This would involve the development of a system that uses an MQ-3 gas sensor to quantify the ethanol content, as well as an MQ-135 gas sensor with an ESP32 microcontroller to quantify even further the amount of volatile organic compounds (VOCs) suggestive of artificial ripening. Flutter-based mobile application allows real-time monitoring, ripening classification using machine learning (ML) algorithms, and logging the historical data. A small sample was taken for inter-document feature literature mining, modelling sensor behaviors according to voltage dividers and gas concentration-resistance laws for robust calibration and classification performance. Validation studies were performed on mango, banana, and papaya fruit in the laboratory environment. Total 75 samples (25 each of banana, mango, papaya across 3 trials) of fruit were tested. The implemented system achieved 95% for banana, 92% for mango, and 90% classification accuracy for papaya when cross validated.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Nilesh Shelke

Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University)

Pune 440008, India

Email: nilesh.shelke@sitnagpur.siu.edu.in

1. INTRODUCTION

This section provides the background, motivation, and problem statement surrounding chemical fruit ripening adulteration in India. Its summaries limitations of existing electronic nose (e-nose) solutions and establishes the need for a low cost, portable, and internet of things (IoT) enabled alternatives. The section also introduces the core sensing strategy and mobile integrated workflow adopted in this work. India is the second-largest producer of fruits in the world, yet it has a rising concern about fruit adulteration. Ripening in an artificial process using chemicals like calcium carbide is illegal and a serious risk, as it gives off acetylene gas, which is carcinogenic when it reacts. Traditional laboratory testing methods are time-consuming, expensive, and not feasible in rural areas. The Food Safety and Standards Authority of India (FSSAI) has recently alerted to the increasing cases of the application of chemical ripening agents on fruits and stressed

the need for fast detection tools. Indeed, FSSAI has already been issuing recognition and guidance on the use of calcium carbide and promoting ethylene ripening in controlled conditions [1]. It also emphasizes safe food practices and considers artificial ripening as an important food safety issue in the FSSAI, as well as the eat right India campaign [2]. An e-nose is an AI-Bot that can rapidly, non-destructively, and in a portable way identify artificial ripening by checking the volatile organic compounds (VOCs) emitted by fruits. Various e-nose systems are available on the international market, including the PEN3 e-nose, alpha metal oxide semiconductor (MOS) FOX series [3], [4], and airsense compact e-nose [5]. These systems commonly use MOS sensor arrays or conductive polymer sensors combined with machine learning (ML) algorithms for the classification of odors. But they are mostly built for expensive lab use and with multiple caveats. Commercial models cost between INR 5-10 lakhs, which small-scale Indian farmers and vendors can't afford. Most systems are not portable and can only be used inside an environment. Requires calibration and operation by highly educated personnel, thus limiting field application, and has limited customization.

The recent studies in the field of intelligent agriculture tend to utilize the concept of IoT, sensors, and deep learning to enhance the ability to monitor the quality of fruits and predict their ripeness. The intelligent fruit quality monitoring system [6] integrates sensor network and deep learning to monitor the freshness and quality of fruits in real-time, with a focus on the use of temperature and gaseous sensors and CNN-based classification in structure of the quality control of different fruits. According to Thakur and Khan [7], the prototype has gas sensors (MQ3, MQ7) and ML to identify fresh and rotten fruit with a high accuracy, and the emphasis is placed on low-cost spoilage monitoring. According to Hassan *et al.* [8], sustainable date fruit quality analysis is achieved through attention-enhanced deep learning models, which promote image-based date fruit ripeness models. Also, CNN-based artificially ripened mango fruit prediction systems exhibit good performance in the classification of ripeness levels of fruit based on visual or volatile signal and therefore support the usefulness of deep learning models in predicting fruit ripeness and fruit safety without the need to be destructive [9], [10]. Table 1 gives a comparative summary of the recent IoT, sensors, and ML-based solutions to the assessment of fruit quality, precise agriculture, and biosensing. It compares domains of application, sensor modalities, algorithms, datasets and results of different studies. The comparison shows the performance improvement gained with the help of data-driven approaches and demonstrates the typical drawbacks associated with the size of the dataset, crop specificity, scalability and the application to real-world tasks.

Table 1. Comparative study of sensor and ML based approaches

Reference (Year)	Application domain	Crop / fruit used	Sensors / data sources	Algorithm	Dataset / experimental setup	Key outcomes	Limitations
Grzywacz <i>et al.</i> [11], 2025	Fruit spoilage monitoring	Strawberry, Raspberry	Metal oxide gas sensors (e-nose)	Basic chemometrics	Controlled lab setup, periodic spoilage sampling	Effective detection of spoilage-related gas patterns	No validated ML classifier; small dataset; lab-scale
Cosme <i>et al.</i> [12], 2025	Digital sensory analysis	General food products	E-nose, e-tongue, computer vision, VR/AR	SVM, ANN, DL	Secondary literature analysis	Highlights shift from human panels to digital sensing	No experimental validation; broad scope
Rajini and Voola [13], 2025	Fruit ripeness and spoilage	Banana	Temperature, humidity, gas sensors (ESP32)	CatBoost, RF, SVM	Sensor data across ripeness stages	High accuracy ripeness prediction	Single fruit focus; limited generalization
Thongnim and Srinil [14], 2025	Precision irrigation	Durian (9–10 yr trees)	Soil moisture, environment sensors, weather data	Rule-based + data-driven logic	Field study at Chanthaburi center	21.65% water saving with equal fruit quality	Crop- and site-specific validation
Gammanpila <i>et al.</i> [15], 2024	Smart sensing systems	General agriculture	IoT sensor networks	ML classifiers	Controlled sensor deployments	Improved monitoring accuracy	Limited real-world scaling
Wasilewski <i>et al.</i> [16], 2024	Biosensors & diagnostics	General agriculture	Biosensors, wearable sensors	ML, AI fusion models	Review of clinical and PoC systems	Shows AI-driven sensing potential	Data privacy, model transparency
Ferreira <i>et al.</i> [17], 2023	Chemical sensing	Fruits / agriculture	Spectroscopy-based sensors	Statistical and ML analysis	Lab-scale spectral datasets	High sensitivity chemical detection	Equipment cost; lab dependency
Shelke <i>et al.</i> [18], 2023	Smart sensing & classification	Fruits / agriculture	Multi-sensor data	SVM, ANN	Conference-scale experiments	Accurate classification	Limited dataset; prototype level
Qiao <i>et al.</i> [19], 2018	Ripening analysis	Crab apple	E-nose, physicochemical tests	PCA, LDA	Artificial vs natural ripening	Clear ripening discrimination	No real-time deployment
Sreeraj <i>et al.</i> [20], 2020	Fruit classification	Multiple fruits	RGB image datasets	CNN, ML classifiers	Benchmark image datasets	High classification accuracy	Lighting and background sensitivity

The strategy seeks to overcome these limitations by designing an e-nose system that's optimized for field use in Indian environments. The optimization procedure will entail the selection of gas sensors able to identify pertinent chemical indicators such as VOCs and ethylene which are readily available in the market [21], [22]. Moreover, the sensor housing and airflow system were designed by 3D modelling to make them portable and achieve precise gas sampling. With embedded thresholds and straightforward rule-based classification, the data processing becomes more effective and thus, there is no requirement to have complex ML algorithms in the early deployment [23], [24]. The use of the ESP32 microcontroller is based on the ability to perform wireless communication and energy efficiency which makes it easy to integrate the microcontroller with mobile applications and cloud system [25]. Among the features of a custom mobile application are real time results, improved usability and user history [26]. Optimization of the e-nose system has resulted in the creation of a combination of accuracy, cost, and mobile capability and usability in multiple applications can provide multi-application to agricultural markets, cold storage and transportation chains.

2. METHOD

This section describes the end-to-end technical methodology followed to design, prototype, calibrate, and validate the IoT based electronic-nose AI-Bot. It outlines the hardware design PCB development, sensor calibration principles, mobile-app integration, system work flow, and experimental evolution process. The section further details the controlled gas-sensing and classification logic implemented at each stage. Circuit design, PCB prototyping, sensor calibration, mobile app development, and workflow automation are all included in this. It is important to develop an affordable, high-capacity e-nose system that can be shipped and used in other markets. Measuring artificial ripening by measuring ethylene, acetylene, and VOCs. The objective is to design a mobile app interface that is user-friendly and responsive, with immediate feedback.

2.1. Circuit diagram

This subsection elaborates electrical connection and control design employed on the preliminary prototyping of the e-nose AI-Bot. It detects sensing units, power management, actuator units, and feedback units combined with the ESP32 and MQ-series sensors. Analog signal acquisition based on the mathematical foundations of voltage-divider modelling is also mentioned. The hardware architecture has the following significant parts such as ESP32 DevKit V1, MQ-135, MQ-3 (alcohol/ethylene), smartphone display, IRFZ44N MOSFet to control fans, exhaust fan, buzzer, status LED, and TP4056 charger and Li-ion battery. A circuit, represented in Figure 1, that uses Arduino uno is an example of the required elements in order to differentiate between ripe and artificial fruits.

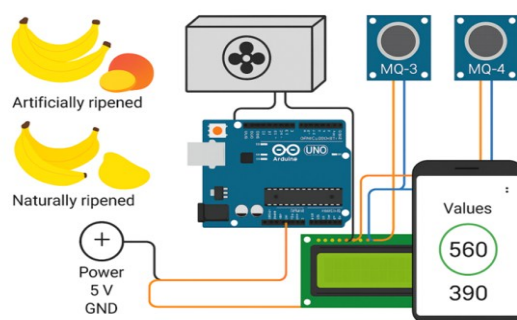


Figure 1. Simplified hardware circuit diagram used for prototyping

The fruit's chemical signature is detected using gas sensors such as MQ-3 and MQ-4. The gas sensing mechanism of MQ-series sensors follows resistive variation principles widely used in e-nose systems [3], [4], where sensor resistance varies with gas concentration. Similar low-cost MOS sensor -based designs for fruit ripening identification have been reported in recent studies [17], [19]. The output of the Arduino is displayed on a smartphone display, and then automatically starts up after processing the data. A fan circulates air well to allow sensors to be read accurately. To design and operate the circuit, the mathematical principles of the voltage divider are used. A standard MQ sensor's output voltage V_{out} is measured and sensor resistance R_s changes as (1) and (2), respectively.

$$V_{\text{out}} = V_{\text{cc}} \times \frac{R_L}{R_L + R_s} \quad (1)$$

$$R_s = R_0 \times \left(\frac{P_{\text{gas}}}{P_0}\right)^{-\alpha} \quad (2)$$

Where in (1), V_{cc} is supply voltage, R_L is load resistance, and R_s is sensor resistance, which varies with gas concentration. In (2), R_0 is resistance to clean air, P_{gas} is gas concentration, P_0 is reference concentration, and α is gas specific sensitivity factor. To calculate the average sensor reading over 'n' intervals (e.g., over 3 minutes with readings every 10 s) as (3).

$$\text{Average}_{\text{sensor}} = \frac{1}{n} \sum_{i=1}^n \text{Sensor}_i \quad (3)$$

2.2. PCB layout and prototyping

This subsection describes the PCB design strategy, fabrication workflow, and structural integration of sensors and microcontroller into a compact double-sided board. After validating the circuit on a breadboard, we designed a compact double-sided PCB. The design optimized trace lengths and minimized noise interference. Gerber files were generated for professional fabrication, and the layout was visualized in 3D to ensure compatibility with the enclosure. This 3D view of the final e-nose hardware design. It features MQ-3 and MQ-135 gas sensors for detecting ethylene and other gases related to fruit ripening. An ESP32-WROOM-32 microcontroller that processes sensor data and connects to the mobile app. A smartphone display or OLED display for showing real-time readings and results directly on the AI-Bot. A buzzer and mini cooling fan for alert feedback and airflow control. This compact PCB-based design integrates all components necessary for ripeness detection in a portable unit.

2.3. Mobile application integration

This subsection explains the software design and communication logic implemented in the mobile application to interface with the ESP32 based e-nose AI-Bot. The mobile app was developed using Flutter for cross-platform deployment. It connects to the e-nose AI-Bot over Bluetooth or Wi-Fi (via ESP32) and performs functions like receiving sensor readings in real-time, displaying live data from MQ-135 and MQ-3 gas sensors, classifying the fruit as naturally ripened or artificially ripened using preset threshold logic, log history of tests with time, date, and sensor values and visual alerts and buzzers for abnormal readings.

Figure 2 shows a mobile application interface for the e-nose system that detects artificially ripened fruits. The user starts the scan by pressing "Start scan", which connects the app to the e-nose AI-Bot. Real-time gas sensor readings (MQ-3, MQ-4, MQ-135) are displayed alongside a graph showing gas trends using a live data screen. The app processes the data and classifies the fruit as "Artificially ripened" with a confidence level. The history screen shows the log of past test results with time, ripeness classification, and status for user reference. The app interface is built with a user-friendly light theme and icon-driven menus for easy navigation, suitable for farmers and field operators.

The ML model into the mobile application was used to increase the exactness of fruit ripeness classification based on the historical data from sensors equipped in the mobile application with timestamp. Sensor readouts of MQ-3 and MQ-135 concentrations of alcohol and VOC, respectively, were logged and labeled throughout different stages of ripeness levels (unripe, ripe, over ripe, and artificially ripened). Each log entry had sensor values and their corresponding timestamps. Noise reduction by moving average filter was processed to straighten the fluctuations due to environmental interference during preprocessing of data. From the above-cleaned signals, a set of statistical and temporal features was extracted. They were, for instance, mean concentration levels, peak values, variance, and signal slope (rate of change), as well as the time of peak emission. Also, the temporal data were analyzed on a very short time window, i.e. 30 seconds, for dynamic trends so that the model could differentiate between naturally ripening and artificially ripened fruits based upon the emission trends over time. Supervised learning with the use of the decision tree classifier was chosen to be implemented because of its readability and efficiency on the embedded systems. The respective entry of each dataset was provided with ripeness stages as ground truth by visual inspection and testing for firmness. Feature selection was done through correlation to remove irrelevant inputs and generalize the model. This dataset was first preprocessed to extract useful features such as magnitude, rate of change and temporal patterns.

The model was trained offline and then integrated into the Flutter-based mobile application for on-device inference to be performed in real-time on the device without other external cloud connectivity or intervention. On getting a sensor reading from the Arduino-ESP32 configuration, the app takes in the input, utilizes the trained model and shows the predicted ripeness level in addition to its timestamp. A decision tree

classifier was trained on this cleansed dataset with 80 percent and 20 percent used for training and for testing respectively. The model gave high classification accuracy and was later optimized and deployed on the Flutter mobile application for real-time, on-device inference. This ML integration enables the system to conform to subtle changes in chemical fingerprints for increased reliability of detection compared to thresholding techniques. Additionally, the app keeps log of old classifications, which allows the users to have access to ripening trends and patterns in time.

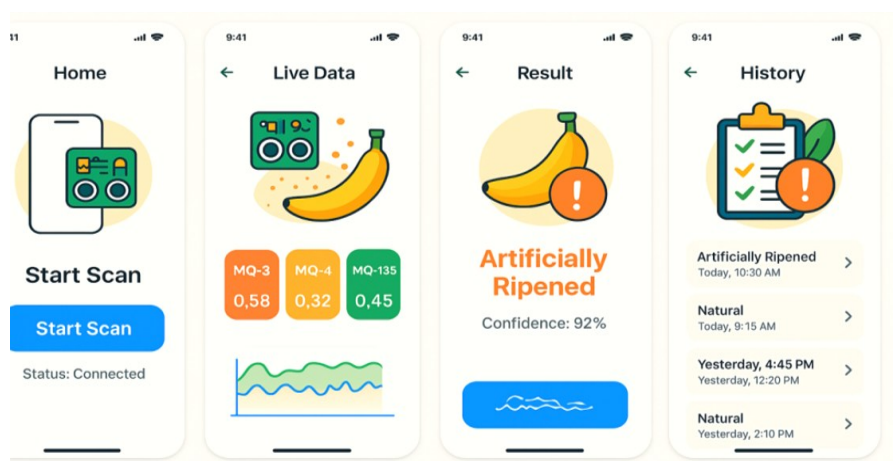


Figure 2. Mobile App: built with flutter, connected via Bluetooth/Wi-Fi, displaying real-time gas levels, ripeness classification, history log with timestamps

2.4. System workflow

This subsection presents the operational pipeline governing sensor initialization, air sampling, signal acquisition, app-level processing, classification display, alert feedback, and data traceability. The captured gas data is analyzed by the ESP 32 controller, using and print classification model, which assigns the result as artificially ripened or naturally ripened, displayed wisely to the user and shown in Figure 3. Mobile application interface as shown in Figure 3(a) and system workflow as shown in Figure 3(b).

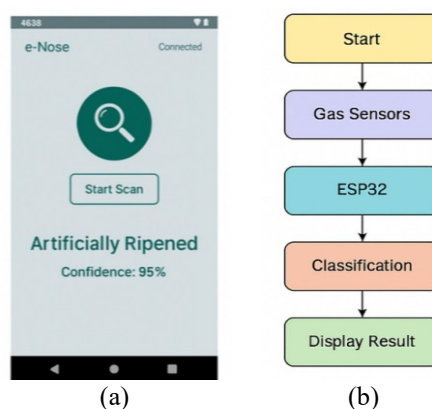


Figure 3. Implemented system: (a) mobile application and (b) system workflow

The e-nose AI-Bot is powered on and initializes the gas sensors. The internal fan draws air over the sensors to ensure a consistent VOC sample. The ESP32 reads analog signals from the gas sensors and sends data to the mobile app. The app processes the data using pre-calibrated thresholds and shows the result. Alerts are displayed with color-coded feedback (green for safety and red for artificial ripening). Historical data can be viewed in tabular or graphical format from the app. This end-to-end workflow ensures accurate, real-time fruit testing that is fast, affordable, and scalable for agricultural use across India.

2.5. Experimental setup

According to Figure 4, the setup of the experiment includes a closed test chamber that was made to be able to accommodate some fruit sample and concentrate any gas that is emitted so that it can be detected. Controlled chamber-based gas sensing experiments are commonly used to evaluate fruit ripening behaviour under standardize environmental conditions [22], [23]. The system consists of the fully assembled e-nose AI-Bot in the chamber, a small exhaust fan to achieve uniform circulation of air, test fruit samples fixed at a minimum distance of sensors, temperature and humidity kept at ambient lab conditions ($25 \text{ }^\circ\text{C} \pm 2 \text{ }^\circ\text{C}$) and data recorded through the mobile application in intervals of 2 minutes scanning. Several experiments were done on bananas, mangoes, and papayas both naturally ripened and artificially ripened (using calcium carbide). Each fruit was tested in isolation to avoid gas mixing effects. The AI-Bot was recalibrated before each test was run. Sensor readings were recorded and averaged to form detection profiles. Based on threshold values and VOC patterns, the app determined the ripening status. Cross-validation with laboratory chromatography confirmed the reliability of the results.

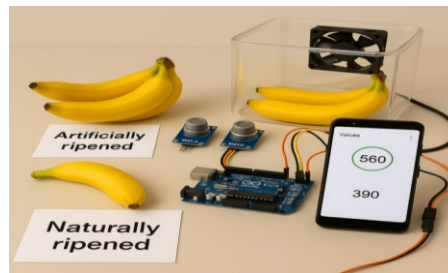


Figure 4. Experimental setup: chamber at $25 \pm 2 \text{ }^\circ\text{C}$, 2-min scans; fruits validated with chromatography

2.6. Mobile app pseudocode steps

This subsection presents the logical sequence implemented in the mobile application to interface with the ESP-32 based e-nose AI-Bot. The steps outline module initialization sensing session control, real time data capture, threshold comparison, result logging, and history visualization. Threshold-based classification combined with statistical averaging is a commonly adopted approach in embedded e-nose systems due to its computational efficiency [5], [7]. The pseudocode also summarizes optional user-configurable features exposed in the app setting. The mobile application that interfaces with the e-nose AI-Bot follows a clear step-by-step log for identifying artificially ripened fruits.

Step 1: Start application

- 1.1. Launch the mobile app
- 1.2. Initialize Bluetooth/Wi-Fi module
- 1.3. Scan and connect to the ESP32-based e-nose AI-Bot

Step 2: Trigger test session

- 2.1. Wait for the user to press "Start Test."
- 2.2. Send the "start" command to ESP32
- 2.3. Display message: "Collecting Data... Please wait 2 minutes."

Step 3: Collect sensor data

- 3.1. Start 3-minute timer
- 3.2. Repeat every 10 seconds until the timer expires:
 - a. Receive data from MQ-3 and MQ-135
 - b. Store readings in dataLog[]
 - c. Update UI with live graph

Step 4: Analyze data

- 4.1. Compute average values:
 - $\text{avg_MQ3} = \text{mean}(\text{dataLog.MQ3})$
 - $\text{avg_MQ135} = \text{mean}(\text{dataLog.MQ135})$
- 4.2. Retrieve threshold values:
 - T_MQ3 , T_MQ135

Step 5: Classify ripeness

- 5.1. If $(\text{avg_MQ3} > T_MQ3)$ OR $(\text{avg_MQ135} > T_MQ135)$:
 - Display: "Artificially Ripened" (Red alert + sound)
 - Else
 - Display: "Naturally Ripened" (Green checkmark)

Step 6: Log and store result

- 6.1. Save the result to the local database
 - Timestamp
 - Sensor averages
 - Classification

Step 7: Visualize history

- 7.1. Allow the user to view the login History tab
- 7.2. Display time-stamped result + graph for each entry

Step 8: Optional features

- 8.1. If cloud sync is enabled, → Upload the result to the cloud
- 8.2. Allow users to update thresholds, themes, or language in settings

Figure 5 shows the mobile app interface shows the complete fruit analysis process from starting the scan, visualizing live gas sensor readings, and displaying the ripeness classification with confidence (e.g., “Naturally ripened: 93.5%”). It also maintains a history log of past tests with timestamps and ripening status. This user-friendly interface ensures accurate detection and traceability of fruit ripening.

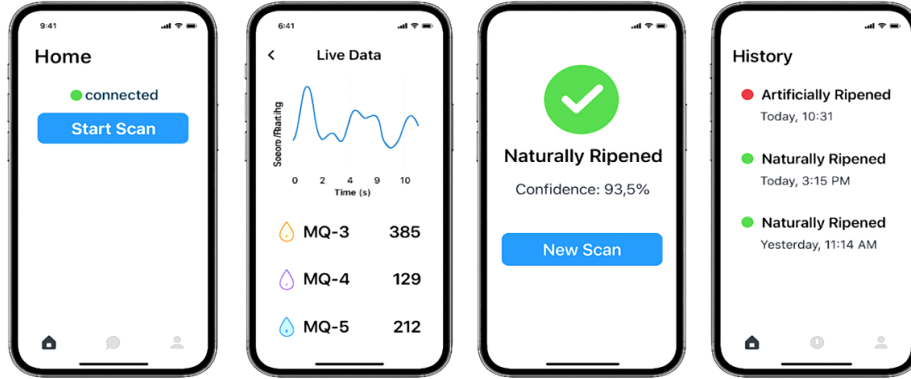


Figure 5. Results screen of the App for the fruit ripeness classification system using an e-nose

3. RESULTS AND DISCUSSION

This chapter reports the analyzed sensor response patterns, visualized emission trends, and classification outcomes obtained during laboratory and field evaluations. The results include statistical averaging of gas readings, temporal line-graph visualizations, and threshold based ripening labels. System constraints and user acceptance insights are consolidated in the final discussion subsection.

3.1. Sensor data analysis: average calculation

This section describes the statistical competition applied to RAW and Alok readings from MQ-3 and MQ-135 during each sensing session. Statistical averaging of gas sensor readings is a standard preprocessing technique used to reduce noise and improve classification reliability in electronic nose systems [5], [17]. Individual time index samples are aggregated and averaged across uniform intervals to form representative gas emission profiles. The computed mean values are letter used for threshold comparison and classification. The formulas are used to compute average gas concentration readings over the sensing session. Table 2 outlines the sensor data over time.

$$\text{avg}_{MQ-3} = \frac{1}{n} \sum_{i=1}^n (MQ-3)_i \text{ and } \text{avg}_{MQ-135} = \frac{1}{n} \sum_{i=1}^n (MQ-135)_i$$

Where $n = 18n$ readings (1 every 10 seconds over 3 minutes). $MQ-3_i$ and $MQ-135_i$ are individual gas readings at each interval.

Table 2. Sensor data over time

Time (sec)	MQ-3 (ppm)	MQ-135 (ppm)
0	180	250
10	200	260
20	210	275
----	----	----
170	190	280

After collecting all values:

$$\text{avg}_{MQ-3} = \frac{180+200+210+\dots+190}{18} \text{ and } \text{avg}_{MQ-135} = \frac{250+260+275+\dots+280}{18}$$

These average values are then compared with the predefined thresholds. Tables 3 and 4 present the predefined gas thresholds for ripeness classification and classification logic based on gas levels respectively.

Table 3. Predefined gas thresholds for ripeness classification

Sensor	Gas detected	Threshold value (ppm)	Description
MQ-3	Ethanol / alcohol	≥200 ppm	High ethanol may indicate artificial ripening (e.g., using ethanol-based agents like carbide)
MQ-135	Ammonia, CO ₂ , Benzene	≥300 ppm	Elevated volatile gases suggest chemical ripening

Table 4. Classification logic based on gas levels

Avg MQ-3 (ppm)	Avg MQ-135 (ppm)	Classification	Indicator
>200	>300	Artificially ripened	Red alert + sound
≤200	≤300	Naturally ripened	Green checkmark

3.2. Experimental results and visualization

This section the classification results generated across multiple controlled test trials on mango, banana, and papaya. It introduces the visual analysis of sensor behavior over time and the confidence values produced from heuristic threshold scoring. Tabulated summarizes and comparative graphs are used to support result interpretation. To validate the system's ability to distinguish between artificial and naturally ripened fruits, multiple test sessions were conducted. The sample sensor readings and classification outcomes are as follows. The classification confidence shown in the app is derived from a heuristic scoring model based on distance from predefined gas thresholds. Specifically, confidence score as in (4) is computed as a normalized value.

$$\text{Confidence} = 100 \times \left(1 - \frac{X_{\text{avg}} - T}{\Delta}\right) \quad (4)$$

Where X_{avg} is the average sensor reading, T is the threshold, and Δ is the margin considered safe/unambiguous. This approach yields a confidence value (0–100%) and is calibrated via cross-validation with chromatography results. Table 5 detail the sensor data.

Table 5. Tabulated sensor data

Sample ID	Ripening type	Avg MQ-3 (ppm)	Avg MQ-135 (ppm)	Classification	Confidence (%)
S01	Artificially ripened	0.58	0.45	Artificially ripened	92
S02	Naturally ripened	0.32	0.28	Naturally ripened	87
S03	Artificially ripened	0.61	0.49	Artificially ripened	95
S04	Naturally ripened	0.29	0.25	Naturally ripened	90
S05	Artificially ripened	0.55	0.43	Artificially ripened	91

3.2.1. Line graph of sensor readings over time

This subsection visualization of MQ-3 and MQ-135 measured in a 3-minute scan window. The graph shows the trends of the ethanol and VOC voltage to PPM when a single fruit was being tested. The graphic presentation indicates variation in time before and after signal pre-processing. Figure 6 shows the simulated sensor readings over time. Graph: Y-axis = PPM level, X-axis = time (sec), legend: MQ-3 (orange), MQ-135 (green). Figure 7 shows threshold comparison between naturally and artificially ripened samples. Y-axis = gas concentration (ppm), X-axis = sample type, MQ-3 levels, MQ-135 levels, threshold lines (e.g., MQ-3>0.50, MQ-135>0.40 triggers artificial classification).

To further confirm sensor response stability, temporal gas emission patterns were examined prior to signal processing and after signal processing. The previous research indicates that ethanol spikes and VOC increase is a dependable chemical ripening index particularly on climacteric fruits like mango and banana. The observed gas emission patterns align with previously reported studies indicating that ethanol and VOC concentrations are key indicators of fruit ripening stages [19], [22]. Moving average preprocessing of the environment decreases noise in the environment and enhances the reliability of classification on embedded e-nose systems.

3.3. Discussion

The following section brings together classification mistakes that have been observed, aging effects of the sensors, calibration drift, field deployment feedback, power limitations, and relative accuracy positioning. It is a summary of user experience reception of the mobile interface, expectations of accessibility, and recommendations of operational reliability. Lastly, system performance is put into perspective of previous reports of MOS sensor array accuracy. The heuristic classification method does not

avoid false positive as is true in over ripe fruits were natural fermentation releases ethanol. On the other hand, false negatives can be caused by rapid dissipation of chemical agents or in tightly closed fruit samples. Such errors could be reduced by adding more sensors to cross-verify (e.g. CO₂, temperature). Excessive use and calibration drift of the sensor by exposure to water, ageing of sensing elements or contamination. This may compromise accuracy unless periodical re-calibration is done. We suggest the use of auto-baselining algorithms or sensor re-baselining reminders. Pilot work with vendors and farmers in Nagpur suggests that the mobile interface is doing well, particularly the color coding of ripening using a so-called traffic light. Immediate categorization assists in bargaining prices and quality. Li-ion battery (power backup) is essential when using power in rural deployments which are not stable. End-users suggest the inclusion of voice prompts in local languages to enhance end-user access. Research on MOS sensor array described a ripening classification accuracy of 88-94% in controlled chambers [17], [19] which demonstrates that our low-cost two sensor model is competitive even with a smaller sensor count.

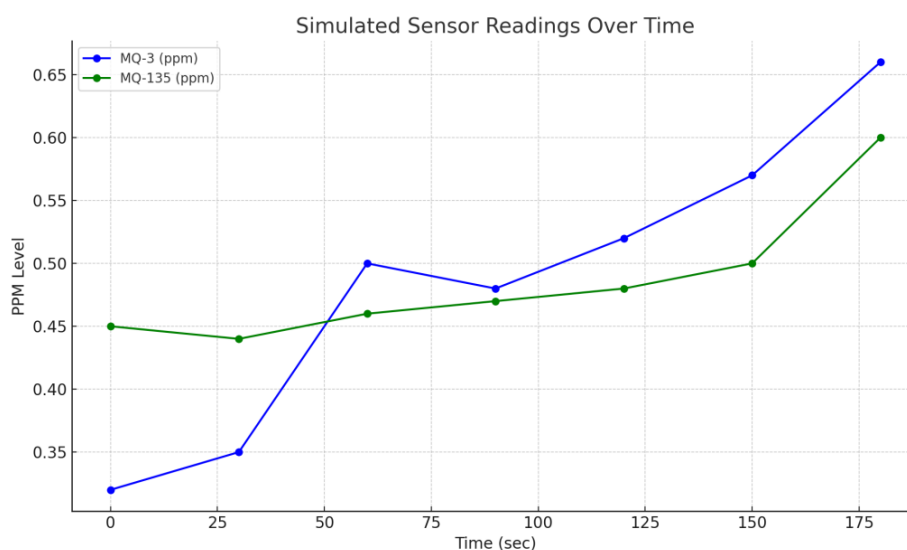


Figure 6. Sensor readings over time

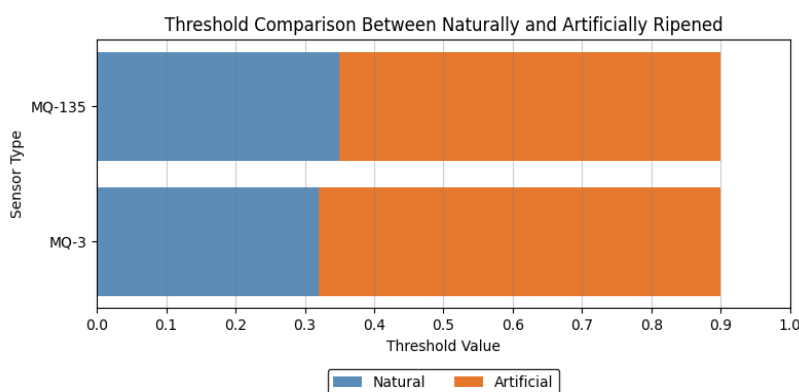


Figure 7. Threshold comparison between naturally and artificially ripened samples

4. CONCLUSION

This paper presents a robust and user-friendly e-nose system of rapid identification of artificially-ripened fruits. The system is composed of MQ-series gas sensors, ESP32-based control, as well as lightweight mobile application, which classifies fruit ripeness based on VOC profile and threshold-based decision-making. More confirmations using chromatography-based operations reveal that the detection rate of this system can be up to 90%. The sensitivity of the mathematical modeling of sensor response and average concentration calculation enhances the stability and repeatability of the process, thereby helping to

minimize the chances of error that may occur because of variation and variability of the environment. This dedicated system performed better than the current, highly accurate e-nose technologies in price and power usage without compromising end-user accessibility and therefore allowed quality evaluation on a small scale. The future uses will contain ML-based intelligent calibrations, multi-parameter sensor profiling to identify more adulterants, and the voice-assisted mobile user interface to be used easily. The proposed solution here is a possible technological intervention that can be used to enhance quality assurance in the agricultural value chain of fruits in India.

FUNDING INFORMATION

The authors state no funding is involved.

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
Amit R. Welekar	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓			
Gaurav Vishnu Londhe		✓			✓	✓			✓	✓	✓	✓	✓	
Amit Pimpalkar		✓	✓	✓	✓		✓			✓	✓	✓	✓	
Abhrendu Bhattacharya	✓	✓	✓	✓	✓			✓		✓		✓	✓	
Nilesh Shelke	✓	✓				✓				✓	✓	✓	✓	
R. Jeberson Retna Raj			✓			✓	✓	✓	✓	✓	✓	✓	✓	✓

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state there is no conflict of interest.

DATA AVAILABILITY

The full Gerber files and layout files are available upon request for research collaboration or fabrication purposes.





REFERENCES

- [1] FSSAI, "FSSAI asks states to intensify inspections and carry out drives to curb use of illegal ripening agents and synthetic coatings on fruits," *Food Safety and Standards Authority of India*. 2025. Accessed: Jan. 06, 2026. [Online]. Available: https://www.fssai.gov.in/upload/uploadfiles/files/artificial_fruit_ripening_english.pdf
- [2] FSSAI, "Eat right India," *Food Safety and Standards Authority of India*. 2025. Accessed: Jan. 06, 2026. [Online]. Available: <https://eatrightindia.gov.in/>
- [3] D. Karakaya, O. Ulucan, and M. Turkan, "Electronic nose and its applications: a survey," *International Journal of Automation and Computing*, vol. 17, no. 2, pp. 179–209, Apr. 2020, doi: 10.1007/s11633-019-1212-9.
- [4] A. D. Wilson and M. Baietto, "Applications and advances in electronic-nose technologies," *Sensors*, vol. 9, no. 7, pp. 5099–5148, Jun. 2009, doi: 10.3390/s90705099.
- [5] N. Aghilinategh, M. J. Dalvand, and A. Anvar, "Detection of ripeness grades of berries using an electronic nose," *Food Science & Nutrition*, vol. 8, no. 9, pp. 4919–4928, Sep. 2020, doi: 10.1002/fsn3.1788.
- [6] A. Kumar *et al.*, "Intelligent fruit quality monitoring system using sensor networks and deep learning," in *2024 International Conference on Smart Electronics and Communication Systems (ISENSE)*, Dec. 2024, pp. 1–6, doi: 10.1109/ISENSE63713.2024.10872000.
- [7] U. N. Thakur and A. Khan, "A prototype to prevent fruits from spoilage: an approach using sensors with machine learning," in *The 10th International Electronic Conference on Sensors and Applications*, Nov. 2023, doi: 10.3390/ecsa-10-16005.
- [8] E. Hassan, S. A. Ghazalah, N. El-Rashidy, T. A. El-Hafeez, and M. Y. Shams, "Sustainable deep vision systems for date fruit quality assessment using attention-enhanced deep learning models," *Frontiers in Plant Science*, vol. 16, Jun. 2025, doi: 10.3389/fpls.2025.1521508.
- [9] M. M. Soliman, E. Ahmed, A. Darwish, and A. E. Hassanien, "Automatic detection of mango ripening using deep learning," in *Innovative AI Technologies Driving Sustainable Farming: Strategies for Improving Food Security*, Cham, Switzerland: Springer, 2026, pp. 217–244, doi: 10.1007/978-3-032-05701-3_10.





- [10] V. Laxmi and R. Roopalakshmi, "Artificially ripened mango fruit prediction system using convolutional neural network," in *Intelligent Systems and Sustainable Computing*, Singapore: Springer, 2022, pp. 345–356, doi: 10.1007/978-981-19-0011-2_32.
- [11] T. Grzywacz, K. Brzeziński, P. Sochacki, R. Tarakowski, M. Tkaczyk, and P. Borowik, "Application of a low-cost electronic nose to monitoring of soft fruits spoilage," in *The 12th International Electronic Conference on Sensors and Applications*, Nov. 2025, doi: 10.3390/ECSA-12-26600.
- [12] F. Cosme, T. Rocha, C. Marques, J. Barroso, and A. Vilela, "Innovative approaches in sensory food science: from digital tools to virtual reality," *Applied Sciences*, vol. 15, no. 8, Apr. 2025, doi: 10.3390/app15084538.
- [13] M. Rajini and P. Voola, "Developing an IoT and ML-driven platform for fruit ripeness evaluation and spoilage detection: a case study on bananas," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 11, 2025, doi: 10.1016/j.prime.2025.100896.
- [14] P. Thongnim and P. Srinil, "Smart farming solutions for durian cultivation using IoT and chatbot integration for precision agriculture," *Discover Internet of Things*, vol. 5, no. 1, Oct. 2025, doi: 10.1007/s43926-025-00227-0.
- [15] H. W. Gammanpila, M. A. N. Sashika, and S. V. G. N. Priyadarshani, "Advancing horticultural crop loss reduction through robotic and AI technologies: innovations, applications, and practical implications," *Advances in Agriculture*, vol. 2024, no. 1, Jan. 2024, doi: 10.1155/2024/2472111.
- [16] T. Wasilewski, W. Kamysz, and J. Gębicki, "AI-assisted detection of biomarkers by sensors and biosensors for early diagnosis and monitoring," *Biosensors*, vol. 14, no. 7, Jul. 2024, doi: 10.3390/bios14070356.
- [17] M. V. D. S. Ferreira, J. L. Barbosa, M. Kamruzzaman, and D. F. Barbin, "Low-cost electronic-nose (LC-e-nose) systems for the evaluation of plantation and fruit crops: recent advances and future trends," *Analytical Methods*, vol. 15, no. 45, pp. 6120–6138, 2023, doi: 10.1039/D3AY01192E.
- [18] M. P. Shelke, N. M. Ranjan, P. Jha, A. B. Chavan, K. Thakare, and S. Pandey, "Detection of artificially ripened fruits using machine learning," in *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, Jun. 2023, pp. 401–406, doi: 10.1109/ICSCSS57650.2023.10169631.
- [19] J. Qiao *et al.*, "Study on the application of electronic nose technology in the detection for the artificial ripening of crab apples," *Horticulturae*, vol. 8, no. 5, Apr. 2022, doi: 10.3390/horticulturae8050386.
- [20] M. Sreeraj, J. Joy, A. Kuriakose, M. R. Sujith, P. K. Vishnu, and H. Unni, "CLadron*: AI assisted device for identifying artificially ripened climacteric fruits," *Procedia Computer Science*, vol. 171, pp. 635–643, 2020, doi: 10.1016/j.procs.2020.04.069.
- [21] A. R. Welekar and M. E. Patif, "Experimental investigation of segmentation methods for segmenting fruit images in the natural environment," in *Recent Advances in Science, Engineering & Technology*, London, United Kingdom: CRC Press, 2024, pp. 355–362, doi: 10.1201/9781003527442-39.
- [22] A. A. Khan, Y. Siddiqui, T. G. Heng, and A. Ali, "Application of electronic nose to monitor the quality and ripening stages of papaya during postharvest storage," *ACS Food Science & Technology*, vol. 4, no. 11, pp. 2550–2561, 2024, doi: 10.1021/acscfoodscitech.4c00140.
- [23] X. Zhang *et al.*, "Response characteristics study of ethylene sensor for fruit ripening under temperature control," *Sensors*, vol. 23, no. 11, 2023, doi: 10.3390/s23115203.
- [24] A. R. Al-Ali, A. Al Nabulsi, S. Mukhopadhyay, M. S. Awal, S. Fernandes, and K. Ailabouni, "IoT-solar energy powered smart farm irrigation system," *Journal of Electronic Science and Technology*, vol. 17, no. 4, Dec. 2019, doi: 10.1016/j.jnlest.2020.100017.
- [25] V. Mykhailyk and N. Lebovka, "Specific heat of apple at different moisture contents and temperatures," *Journal of Food Engineering*, vol. 123, pp. 32–35, Feb. 2014, doi: 10.1016/j.jfoodeng.2013.09.015.
- [26] M. Bhaiyya *et al.*, "Deep learning-assisted smartphone-based electrochemiluminescence visual monitoring biosensor: a fully integrated portable platform," *Micromachines*, vol. 15, no. 8, Aug. 2024, doi: 10.3390/mi15081059.

BIOGRAPHIES OF AUTHORS






Dr. Amit R. Welekar     is currently working as an associate professor in the Department of Computer Science and Engineering at J. D. College of Engineering and Management, Nagpur, India. He has 17+ years of academic and industrial experience. He has published over 50+ research articles in the international journal and conference proceedings. He had four national and international patents in his name. He is the author of international and national books. He is a life member of ISTE, IE(I), and ACM. He is an active reviewer for many national and international conferences and journals, including IEEE access. His research interests include artificial intelligence, data mining, machine learning, and image processing. He can be contacted at email: welekar.amit@gmail.com.






Dr. Gaurav Vishnu Londhe     has completed the Bachelor of Engineering in Information Technology and Master of Engineering in Computer Engineering from University of Mumbai, and doctorate in 2020, with research domain of wireless sensor networks. Working on cloud using IoT based devices and analysis of data received through it. A IoT and industrial robotics design is the research area for upcoming development. He has around 20 years of teaching, administration in technology and management courses and industry experience as well. He has wide experience as director in industry and academia for digital transformation, robotics, IoT. Even worked as director of Center of Excellence of Digital Transformation. His research publications are in versatile areas of IT and computer science and engineering. Currently associated with Symbiosis International University at Nagpur Campus. He can be contacted at email: gaurav.londhe@sitnagpur.siu.edu.in.






Dr. Amit Pimpalkar    is currently working as an assistant professor in the School of Computer Science and Engineering at Ramdeobaba University, formally Shri Ramdeobaba College of Engineering and Management, Nagpur, India. He earned his Ph.D. in Computer Science and Engineering from Sathyabama Institute of Science and Technology, Chennai. He received his Master of Technology from Shri Ram Institute of Technology, Jabalpur, a Bachelor of Engineering from Nagpur University, Nagpur, and a diploma in Computer Technology from Maharashtra State Board of Technical Education, Mumbai. He has 20+ years of academic and industrial experience. He has published over 100+ research articles in the international journal and conference proceedings. He had ten national and international patents in his name. He is a life member of ISTE, IAENG, ICSES, CSTA, and IEEE. He is an active reviewer for many national and international conferences and journals. His research interests include data mining, machine learning, and natural language processing. He is serving as editorial board member of Scientific Reports and Nature Portfolio. He can be contacted at email: amit.pimpalkar@gmail.com.






Dr. Abhrendu Bhattacharya    is currently working as an academician and researcher in the field of computer science and engineering under JIS University, Kolkata. He has 20+ years of teaching and research experience and has contributed to a number of research articles published in reputed national and international journals and conference proceedings. He is actively involved in academic research, scholarly writing, and technical review activities. His research interests include image processing, information security, steganography, artificial intelligence, and related emerging technologies. He has also served as a reviewer for various national and international journals and conferences. He is associated with professional academic activities and continues to contribute to research, teaching, and innovation in computer science and engineering. He can be contacted at email: abhrendu.bhattacharya@jisuniversity.ac.in.



Dr. Nilesh Shelke    is an associate professor in the Department of Computer Science and Engineering at Symbiosis Institute of Technology, Nagpur. He is an M.Tech. in Computer Science and Engineering from RTM Nagpur University. He is M.Phil. in Computer Science and acquired a Ph.D. in Computer Science and Engineering from S.G.B. Amravati University, Amravati. He is a Microsoft Certified Solution Developer and has more than 25 years of experience in imparting IT training, which includes learners from different streams, faculties, and Microsoft Certifications to corporate employees. His research areas include natural language processing, image processing, machine learning, and deep learning. He has published patents, copyrights, and technical articles in renowned journals. He has also authored books introduction to machine learning, an introduction to artificial intelligence and machine learning, knowledge representation and artificial intelligence: ML, DL. He can be contacted at email: Nilesh.shelke@sitnagpur.siu.edu.in.



Dr. R. Jeberson Retna Raj    is currently working as a professor in the School of Computer Science and Engineering at Sathyabama Institute of Science and Technology, Chennai. He completed his master's degree and then completed his doctorate research in Computer Science and Engineering. His specialization areas include big data analytics, image processing, internet of things, and cloud computing. He published various research papers on these topics in international journals and international conferences. He conducted many workshops and conferences at Sathyabama Institute of Science and Technology. He can be contacted at email: jebersonretnaraj@gmail.com.