Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 26 May 2026
Revised 26 June 2026
Accepted 10 July 2026

Natural Resources for Human Health 2026, Vol. 6 (10s): 1531–1542

KEYWORDS:
Electronic Nose, ESP32, MQ135, MQ2, MQ3, MQ4, DHT22, Machine Learning, Odour Classification, IoT.

AI-Based Electronic Nose System for Real-Time Decomposition Stage Classification Using Multi-Gas Sensors

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ABSTRACT: Odour identification using conventional single gas sensors can be challenging because different odour conditions may produce overlapping sensor responses. This work presents a low-cost AI-based electronic nose using an ESP32 microcontroller and an array of MQ135, MQ2, MQ3, and MQ4 gas sensors, along with a DHT22 sensor for temperature and humidity measurement. The collected multi-sensor data are used to train a machine-learning classification model for identifying four odour conditions: FRESH, EARLY, ACTIVE, and ADVANCED. The developed model achieved 100% classification accuracy on the test dataset of 80 samples, with precision, recall, and F1-score of 1.00 for all four classes. The proposed system demonstrates that low-cost gas sensors combined with machine learning can provide an affordable and practical approach for real-time odour-condition classification using an ESP32-based platform.

1. INTRODUCTION

Angelini et al. studied the concept of the Internet of Tangible Things (IoTT) and its role in improving interaction with IoT objects. They analyzed challenges in Human–Computer Interaction and reviewed existing tangible interaction approaches for IoT. A systematic review was conducted to identify important tangible interaction properties, followed by the development of a design card set[1].Patel et al. developed SWoTSuite, a toolkit for fast and easy prototyping of end-to-end Semantic Web of Things (SWoT) applications. The toolkit supports automation of the application development life cycle and simplifies the integration of semantic web technologies with IoT applications. Their approach reduces the time and effort required for developing and testing IoT prototypes. The study demonstrates how integrated prototyping tools can simplify the development of sensor-based IoT systems [2]. Raskin et al. proposed a rapid prototyping approach for distributed embedded systems as part of the Internet of Things. Their technique uses ready-made components that can be configured and integrated through high-level APIs. The approach supports different system components, including control programs, communication nodes, and web applications. The study demonstrates that component-based development can simplify and accelerate IoT prototype development, particularly for students and beginners [3].

Hodges and Chen studied the challenges involved in converting hardware concepts into viable low-volume products. They discussed the hardware development process, including ideation, prototyping, design iteration, and transition from prototype to product. Their work highlighted the importance of rapid prototyping and design iteration for developing innovative embedded and IoT devices. The study emphasizes the need for effective methods to move from an initial hardware concept to a functional and practical product [4]. Nguyen-Duc et al. studied Minimum Viable Products (MVPs) for Internet of Things applications and identified common challenges in IoT hardware development. They conducted a qualitative study using 12 semi-structured interviews with early-stage hardware start-ups. The study analyzed prototyping techniques, production practices, and challenges related to management, requirements, design, implementation, and testing. Their findings showed that hardware development follows an incremental prototyping process, moving from speed-focused development toward quality-focused production [5]. Dhawale et al. presented a structured approach for the rapid prototyping and testing of IoT-enabled sensor devices using open-source tools. Their methodology covered hardware and software development, sensor integration, 3D printing, cloud connectivity, dashboards, and data analytics. The study provided step-by-step guidelines to simplify the design, implementation, and testing of IoT sensor prototypes. Their work demonstrates the importance of structured open-source methods for developing practical sensor-based IoT systems [6].

Hodges et al. introduced "Circuit Stickers," a low-cost technique for rapidly constructing interactive electronic prototypes. Their method uses peel-and-stick physical components such as LEDs, buttons, sounders, and sensors on an electrically conductive substrate. The prototypes can operate independently or be connected to a microcontroller or computer. The study demonstrated that this approach enables quick, flexible, and low-cost prototyping for research, education, and hardware design [7]. Greenberg and Fitchett introduced "Phidgets," a toolkit for developing physical interfaces using reusable physical widgets. Their technique abstracts input and output devices through a well-defined API and includes device management, software–hardware linking, and simulation support. The study showed that programmers could rapidly develop, debug, and test physical interfaces. Their work demonstrates how modular hardware components can simplify and accelerate physical prototype development [8]. Lambrichts et al. presented a comprehensive survey and taxonomy of electronics toolkits for prototyping interactive and ubiquitous devices. They systematically analyzed different toolkits based on characteristics such as ease of construction, target users, and transition from prototype to product. An online user survey was also conducted to understand the priorities and practices of developers during prototyping. Their study identified existing gaps and opportunities for improving electronics prototyping tools for interactive and IoT devices [9]. Martinez et al. introduced I3Mote, an open-hardware development platform for intelligent industrial IoT applications. The platform integrates low-power sensing, on-board computing, and wired/wireless connectivity in a compact and low-cost design. They described the hardware architecture, firmware, software ecosystem, and evaluated its energy consumption performance. The study demonstrates the suitability of compact and flexible platforms for developing practical IoT sensing prototypes [10].

2. LITERATURE SURVEY

Fisher et al. [11] investigated the role of open-hardware platforms in wireless sensor networks. Their study highlighted the advantages of low-cost and flexible hardware platforms for developing and testing sensor-based applications. The work demonstrates that open-hardware systems can reduce development complexity and provide flexibility for experimenting with different sensing configurations. These characteristics are relevant to the development of low-cost multi-sensor systems such as the proposed electronic nose.Vilajosana et al. [12] introduced OpenMote, an open-source prototyping platform designed for Industrial Internet of Things (IIoT) applications. The platform uses a modular architecture in which additional boards can be connected to provide different functionalities. The study demonstrated that modular hardware can simplify the development and testing of IoT applications. This concept is relevant to the proposed system, where multiple gas sensors and an environmental sensor are integrated with an ESP32 controller.Soukaras et al. [13] proposed IoTSuite, a toolkit for prototyping Internet of Things applications. The toolkit supports several stages of IoT development, including design, development, deployment, and evolution. The study focused on reducing the effort required to integrate different IoT devices and components. This work highlights the importance of simple development frameworks for building sensor-based prototypes efficiently.

Pramudianto et al. [14] developed IoTLink, an IoT prototyping toolkit intended to support users with limited programming experience. The proposed model-driven approach allows different devices and services to be combined to create IoT applications. The study demonstrates how simplified development approaches can reduce the time and complexity involved in building IoT prototypes. Such approaches are useful for developing low-cost sensor-based systems for practical applications.Gianni and Divitini [15] extended the Tiles ideation toolkit for designing IoT applications for smart-city problems. Their work used physical cards and tangible materials to support idea generation and interaction during IoT design activities. The participation of students in workshops demonstrated that structured physical tools can help users develop and communicate IoT concepts. This study emphasizes the importance of combining physical hardware concepts with systematic idea generation during prototype development.El-Khozondar et al. [16] developed a smart energy monitoring system based on the ESP32 microcontroller. The system demonstrated the use of ESP32 as a low-cost platform for collecting and processing sensor information. The study indicates that ESP32 can provide a suitable combination of processing capability, sensing interfacing, and communication for practical IoT applications. This supports the selection of ESP32 as the central controller in the proposed electronic nose system.

Pereira et al. [17] developed an IoT-enabled smart drip irrigation system using ESP32. Multiple parameters, including soil moisture, temperature, humidity, and water flow, were monitored using sensors connected to the controller. The collected data were also made available through an IoT platform. The study demonstrates the ability of ESP32 to integrate multiple sensors and support real-time monitoring, which is an important requirement for the proposed multi-sensor odour monitoring system.Bakare and Abubaker [18] developed an indoor environmental monitoring system using ESP32-WROOM and multiple sensing parameters. Their work demonstrated the integration of several sensors with an ESP32-based controller for collecting environmental information and transferring the data for monitoring. The study supports the use of ESP32 for compact multi-parameter sensing systems and provides a relevant foundation for integrating several gas sensors with temperature and humidity measurements.Perera et al. [19] presented a survey of context-aware computing for the Internet of Things. The study explained how information obtained from sensors and connected devices can be used to understand environmental conditions and determine the current context. The authors discussed context acquisition, modelling, reasoning, and distribution. This concept is relevant to electronic nose systems because odour-related sensor responses can be interpreted together with environmental parameters to identify different conditions.

Elhanashi et al. [20] reviewed the development and applications of TinyML for IoT devices. Their work discussed the limitations of embedded devices in terms of processing capability, memory, and energy consumption. TinyML enables machine-learning models to operate closer to the sensing device, reducing the need for continuous cloud processing. This approach is relevant to the proposed system because machine-learning-based odour classification can potentially be performed using resource-constrained embedded hardware.Salman and Jain [21] reviewed communication protocols and standards used in IoT systems. Their study covered communication, routing, network management, and security aspects of connected devices. The work emphasizes the importance of selecting appropriate communication technologies when designing IoT systems. Although communication is not the primary objective of the proposed electronic nose, reliable connectivity can support future remote monitoring and data transmission.Shi et al. [22] introduced the concept of edge computing and discussed its importance for IoT applications. Edge computing performs data processing closer to the source rather than transferring all sensor data to a remote cloud. This approach can reduce latency, communication requirements, and response time. The concept is relevant to intelligent electronic nose systems, where sensor measurements can be processed locally to provide rapid odour classification.

Di Nisio et al. [23] developed a low-cost multipurpose wireless sensor network using Arduino-based hardware. The system was designed to support different sensing requirements by allowing components to be modified according to the application. The study highlights the importance of flexible and low-cost hardware architectures for sensor-network development. This supports the design philosophy of the proposed electronic nose, which uses commercially available low-cost gas sensors and an ESP32 controller.Babić et al. [24] developed an IoT-based environmental monitoring system using ESP32 and the Blynk platform. The system monitored parameters such as temperature, humidity, air pressure, and particulate matter. The study demonstrated that inexpensive sensors and an ESP32 controller can be combined to develop a practical real-time environmental monitoring system. The work is relevant to the proposed system because environmental parameters such as temperature and humidity can influence gas-sensor responses and therefore need to be considered during odour classification.Hercog et al. [25] investigated the design and implementation of IoT devices using the ESP32 platform. Their work discussed the use of ESP32 for different applications, including automation, agriculture, environmental monitoring, and other embedded applications. The study also highlighted the suitability of ESP32 for learning, experimentation, and rapid IoT development. These characteristics make ESP32 appropriate for the proposed low-cost electronic nose prototype.

Choudhary [26] presented a comprehensive review of IoT architectures, applications, enabling technologies, simulation tools, challenges, and future directions. The study described the major layers and technologies involved in IoT systems and discussed challenges associated with their implementation. This provides a broader foundation for understanding the hardware, communication, processing, and software requirements involved in developing an intelligent sensor-based system.Whitmore et al. [27] reviewed major topics and research trends in the Internet of Things. The study discussed the integration of sensing, identification, communication, and processing capabilities into ordinary physical objects. The authors also discussed context awareness and communication between connected devices. This work provides a general foundation for understanding how sensing and processing can be integrated into connected intelligent hardware.Al-Fuqaha et al. [28] presented a comprehensive survey of IoT enabling technologies, protocols, and applications. The study discussed technologies such as RFID, smart sensors, communication systems, and Internet protocols. It demonstrated how physical objects can collect information and exchange data with limited human intervention. The survey provides a technological background for selecting suitable sensing, processing, and communication components in IoT-based systems.

Atzori et al. [29] provided one of the foundational surveys of the Internet of Things. The study discussed smart objects, RFID, wireless sensor networks, and communication technologies and explained how physical objects can be connected to provide intelligent services. This work establishes the broader technological foundation for sensor-based connected systems and supports the development of intelligent embedded sensing applications.Angelini and Couture [30] proposed a card-based approach for designing interactions with tangible Internet of Things objects. Their work focused on the interaction between users and physical IoT objects and encouraged designers to explore different forms of tangible interaction during the early design stage. The study is particularly relevant to hardware ideation because it connects idea generation, physical objects, interaction design, and IoT development.

3. MATERIALS AND METHODS

3.1 System Architecture

The proposed AI-based electronic nose system is designed to identify and classify the decomposition stages of organic samples using a combination of low-cost gas sensors, environmental sensing, an ESP32 microcontroller, and a machine-learning model. The overall architecture consists of five major stages: **gas sensing, data acquisition, data processing, machine-learning classification, and real-time status prediction**.

The sensing unit consists of **MQ135, MQ2, MQ3, and MQ4 gas sensors**, which respond to different volatile gases released during the decomposition process. A **DHT22 sensor** is incorporated to measure temperature and relative humidity, as these environmental parameters can influence gas-sensor responses. The outputs from all sensors are acquired by the **ESP32 microcontroller** through its analog and digital interfaces.

The ESP32 performs the initial data acquisition and continuously transmits the sensor measurements to a computer through a USB serial interface. Each observation consists of the four gas-sensor readings along with temperature and humidity values. The collected measurements are organized as feature vectors and supplied to the machine-learning module for classification.

For model development, a dataset containing **400 samples** was prepared and categorized into four decomposition stages: **FRESH, EARLY, ACTIVE, and ADVANCED**, with 100 samples assigned to each class. The dataset was divided into training and testing subsets using an 80:20 split, resulting in 320 training samples and 80 testing samples. The trained model is stored and subsequently used for real-time classification of newly acquired sensor measurements.

During real-time operation, the sensor readings received from the ESP32 are provided to the trained machine-learning model. The model analyzes the combined gas and environmental features and predicts the corresponding decomposition stage. The predicted status is displayed continuously along with the sensor measurements and model performance information. Thus, the proposed architecture provides a **low-cost, real-time, non-destructive approach for monitoring decomposition stages using an electronic nose and machine learning**.

Natural Resources for Human Health
eISSN: 2583-1194

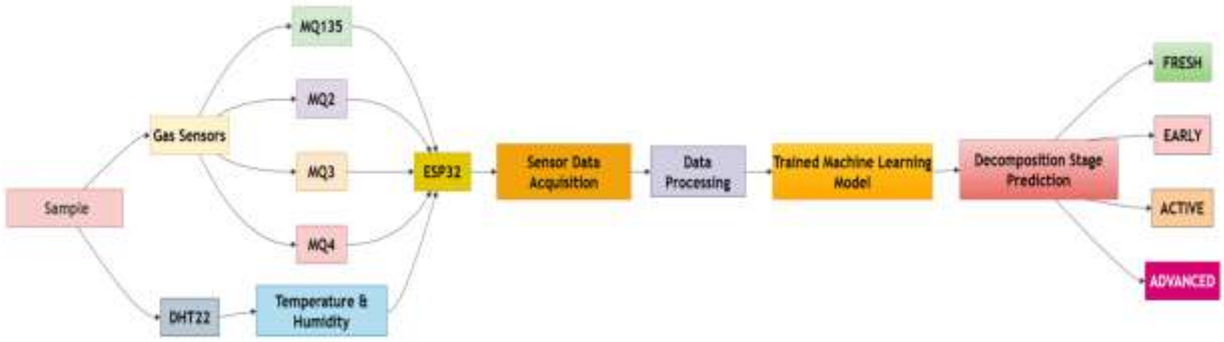

Figure 1 – System Architecture

3.2 Hardware Components

The proposed system uses an **ESP32 microcontroller, MQ135, MQ2, MQ3, and MQ4 gas sensors, and a DHT22 temperature-humidity sensor**. The MQ sensors capture the volatile-gas response generated during decomposition, while the DHT22 records temperature and humidity. The sensors are interfaced with the ESP32 for continuous data acquisition and transmitted to a computer through USB serial communication for machine-learning-based classification. The selected components provide a **low-cost and compact platform for real-time decomposition-stage monitoring**.

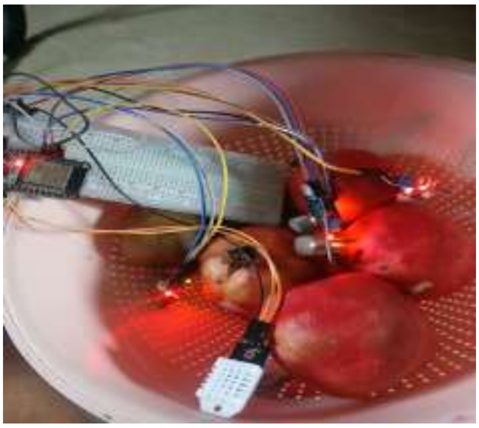

Figure 2 – Hardware Prototype

3.3 Sensor Configuration

Four MQ-series gas sensors (**MQ135, MQ2, MQ3, and MQ4**) and a **DHT22** sensor were interfaced with the ESP32 for data acquisition. The gas sensors provide analog sensor-response values, while the DHT22 measures temperature and humidity. The six sensor parameters are continuously collected and used as input features for the machine-learning model to classify the decomposition stage.

3.4 Data Acquisition

sensor data were continuously acquired using the ESP32 from MQ135, MQ2, MQ3, MQ4, and DHT22 sensors. The gas sensor responses, temperature, and humidity were recorded and transmitted through serial communication. A total of 400 samples were collected and categorized into four decomposition stages: FRESH, EARLY, ACTIVE, and ADVANCED, with 100 samples per class.

3.5 Dataset Preparation

A dataset containing 400 sensor samples was prepared using six features: MQ135, MQ2, MQ3, MQ4, temperature, and humidity. The samples were equally distributed among four classes: FRESH, EARLY, ACTIVE, and ADVANCED (100 samples per class). The dataset was divided into 80% training (320 samples) and 20% testing (80 samples) for model development and evaluation.

3.6 Feature Selection

Six sensor parameters, namely MQ135, MQ2, MQ3, MQ4, temperature, and humidity, were selected as input features. These features represent the gas-response pattern and environmental conditions associated with decomposition. The decomposition status (FRESH, EARLY, ACTIVE, or ADVANCED) was used as the target class for machine-learning classification.

3.7 Machine Learning Model

A machine-learning classification model was trained using the six selected sensor features: MQ135, MQ2, MQ3, MQ4, temperature, and humidity. The model was trained on 320 samples and evaluated using 80 test samples to classify the decomposition stages as FRESH, EARLY, ACTIVE, and ADVANCED. The trained model was saved for real-time prediction using ESP32 sensor data.

3.8 Model Training

The prepared dataset was divided into 80% training and 20% testing data. The machine-learning model was trained using the six selected sensor features to classify four decomposition stages. The trained model achieved an accuracy of 100% on the test dataset, with a precision, recall, and F1-score of 1.00 for all four classes.

3.9 Real-Time Prediction

The trained machine-learning model was integrated with the ESP32 for real-time classification. The sensor readings from MQ135, MQ2, MQ3, MQ4, temperature, and humidity are continuously transmitted to the computer through serial communication. The trained model processes the incoming data and predicts the decomposition stage as FRESH, EARLY, ACTIVE, or ADVANCED. The predicted status is displayed continuously along with the sensor readings and model accuracy.

4. RESULTS AND DISCUSSION

4.1 Dataset Distribution

A total of 400 sensor samples were used for model development. The dataset was equally distributed among four decomposition stages: FRESH, EARLY, ACTIVE, and ADVANCED, with 100 samples per class. The balanced distribution ensured equal representation of each class during model training and evaluation.

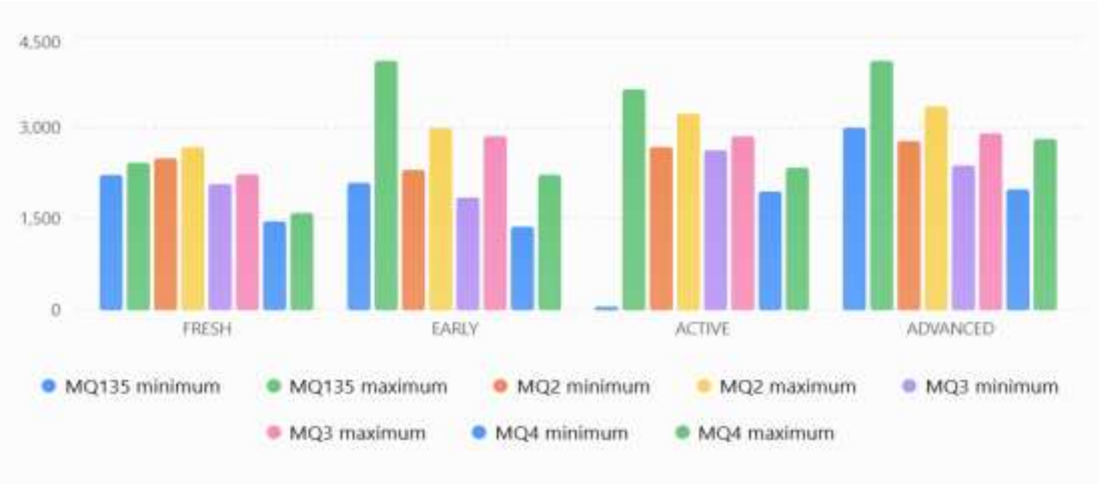

Figure 3 – Sensor response ranges across different decomposition stages.

4.2 Model Accuracy

The trained machine-learning model was evaluated using 80 test samples. The model achieved an overall accuracy of 100%, with precision, recall, and F1-score of 1.00 for all four decomposition classes: FRESH, EARLY, ACTIVE, and ADVANCED. The result demonstrates accurate classification of the decomposition stages for the prepared dataset.

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Figure 4. Machine-learning model training and classification results.

4.3 Classification Report

The classification performance of the proposed model was evaluated using **precision, recall, and F1-score**. As shown in Table 2, all four classes—**FRESH, EARLY, ACTIVE, and ADVANCED**—achieved a precision, recall, and F1-score of **1.00**, with 20 test samples for each class.

Table 1. Classification report of the proposed model

Class	Precision	Recall	F1-Score	Support
FRESH	1.00	1.00	1.00	20
EARLY	1.00	1.00	1.00	20
ACTIVE	1.00	1.00	1.00	20
ADVANCED	1.00	1.00	1.00	20
Accuracy			**1.00**	**80**

4.4 Confusion Matrix

The confusion matrix is used to evaluate the performance of the proposed AI-based electronic nose classification model. It compares the **actual odor status** with the **predicted odor status** for the test dataset. The four classes considered are **FRESH, EARLY, ACTIVE, and ADVANCED**.

Since the trained model achieved **100% accuracy**, all 80 test samples were correctly classified. Therefore, there were no false-positive or false-negative predictions.

Table 2. Confusion Matrix of the Proposed AI Model

Actual / Predicted	FRESH	EARLY	ACTIVE	ADVANCED
FRESH	20	0	0	0
EARLY	0	20	0	0
ACTIVE	0	0	20	0
ADVANCED	0	0	0	20

The diagonal values indicate that all samples belonging to each class were correctly predicted. The model correctly classified **20 FRESH, 20 EARLY, 20 ACTIVE, and 20 ADVANCED** samples, resulting in a total of **80 correct predictions out of 80 test samples**. No misclassification was observed between the four odor-status classes. This confirms the excellent classification

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eISSN: 2583-1194

performance of the proposed model on the test dataset.

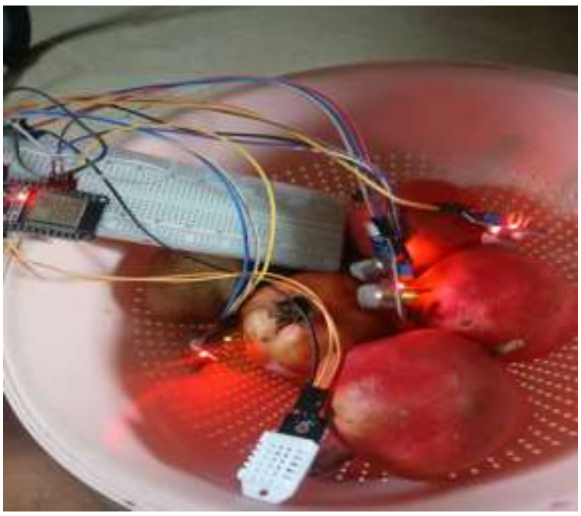
4.5 Real-Time ESP32 Validation

The developed AI electronic nose system was validated in real time using an ESP32 microcontroller, four MQ gas sensors (MQ135, MQ2, MQ3, and MQ4), and a DHT22 sensor for temperature and humidity measurement. The ESP32 continuously acquires the sensor readings and sends them to the trained machine learning model for odor-status prediction.

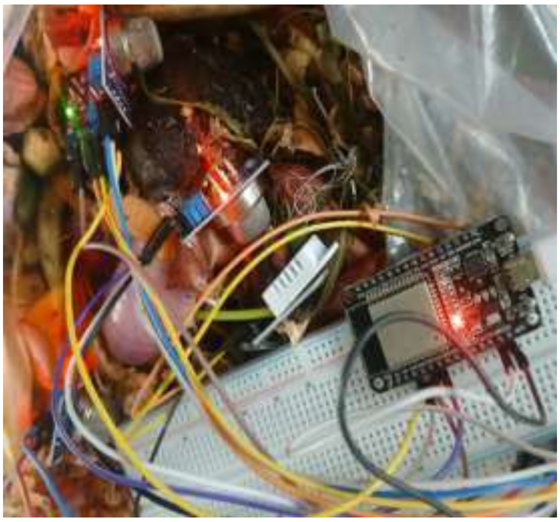
During validation, the sensor values were captured from the target sample and processed by the trained model. Based on the combined gas-sensor pattern and environmental conditions, the system classified the sample into one of four stages: FRESH, EARLY, ACTIVE, or ADVANCED.

The real-time validation demonstrates that the proposed system can continuously monitor changes in odor-related gas patterns and provide an automatic odor-status prediction. The predicted status is displayed through the ESP32 serial monitor, making the system suitable for low-cost and real-time decomposition-stage monitoring.

(a) Trained ML model/output in VS Code



(b)Physical ESP32–MQ sensor prototype during testing



(c) Real-time sensor readings and predicted status in Serial Monitor

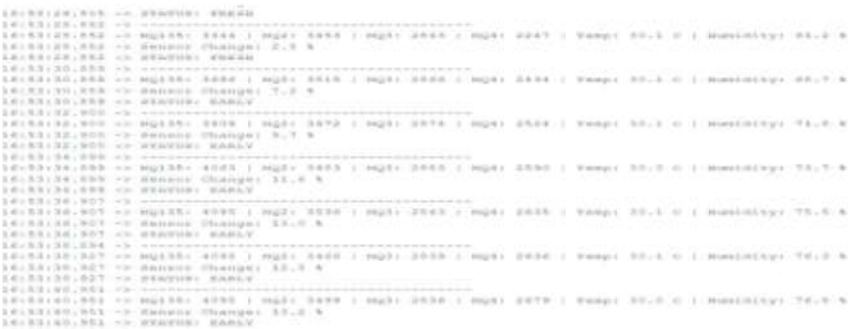


Figure 5. Real-Time ESP32 Validation of the Proposed AI Electronic Nose

Figure 4.5 presents the real-time validation of the proposed AI electronic nose system. The experimental setup consists of an ESP32 connected to MQ135, MQ2, MQ3, MQ4, and DHT22 sensors. The sensor readings are continuously acquired and processed to determine the corresponding decomposition stage. The real-time Serial Monitor displays the sensor values along with the predicted status, demonstrating the successful integration of the hardware sensing unit and the trained machine learning model.

The experimental results demonstrate that the proposed AI-based electronic nose can effectively classify decomposition stages using a combination of **MQ135, MQ2, MQ3, MQ4, temperature, and humidity measurements**. The machine learning model achieved an overall **accuracy of 100% on the test dataset**, with precision, recall, and F1-score of **1.00 for all four classes: FRESH, EARLY, ACTIVE, and ADVANCED**.

The confusion matrix further confirms that all 80 test samples were correctly classified, with no misclassification between the four decomposition stages. This indicates that the selected sensor features provided distinguishable patterns for the different stages in the experimental dataset.

The real-time ESP32 validation also demonstrated the practical operation of the proposed system. The ESP32 continuously collected gas-sensor and environmental readings and provided the corresponding decomposition-status prediction through the Serial Monitor. The physical prototype and real-time output confirm the successful integration of the **sensor array, ESP32, and machine learning model**.

However, the 100% accuracy should be interpreted with caution because the dataset used in this prototype was relatively controlled and contained an equal number of samples for each class. Further validation using **larger datasets, different sample conditions, different environmental conditions, and independent real-world samples** would be required to establish the generalization capability of the model.

Overall, the results indicate that the proposed low-cost electronic nose provides a promising approach for **real-time, non-invasive, and automated monitoring of decomposition stages**. The combination of multiple gas sensors with machine learning improves the ability of the system to recognize changes in odor-related gas patterns and can serve as a foundation for developing a more robust portable decomposition-monitoring system.

5. CONCLUSION

This study presented a **low-cost AI-based electronic nose system** for identifying different stages of decomposition. The system combines an ESP32 with MQ135, MQ2, MQ3, MQ4, and DHT22 sensors to acquire gas and environmental parameters and classify samples into **FRESH, EARLY, ACTIVE, and ADVANCED** stages.

The developed machine learning model achieved **100% accuracy** on the test dataset, demonstrating its ability to distinguish the four defined decomposition stages under the experimental conditions. Real-time ESP32 testing further demonstrated the feasibility of obtaining sensor readings and generating decomposition-status predictions continuously.

The proposed system provides a **simple, low-cost, and automated approach for decomposition-stage monitoring**. Future work will focus on increasing the dataset size, testing different environmental conditions, and validating the system with more diverse real-world samples to improve its reliability and generalization.

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