Grenze International Journal of Engineering and Technology, June Issue

A Machine Learning Enhanced Portable Electronic Nose for Seafood Freshness Evaluation

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***Abstract*— In this paper, we have proposed a small model to determine the freshness of seafood. The seafood, when spoilt, releases certain gases. So, we have used MQ series gas sensors like MQ2, MQ4, MQ8 and MQ135 to detect the gases. We also used a DHT11 sensor because the temperature and humidity change the spoiling rate. All the readings are sent to an Arduino Uno, and whenever the gas values cross the predefined limit, the system sends a message to the user through the GSM module and also alerts the user through a buzzer. A random forest machine learning algorithm is used to classify the seafood fresh and spoiled conditions. We trained the algorithm using the data collected from sensors while testing. From the tests conducted, the system response was found to be quick and steady. Since the components are simple and low cost, this model can be used in homes and small food storage places.**

***Index Terms*— random forest, gas sensors, real time monitoring, seafood freshness, Arduino uno, GSM alert system.**

I. INTRODUCTION

Currently, most people rely on transported and stored food. So, the safety and freshness of the food consumed have become a major concern. Many types of food, especially those with higher moisture contents, deteriorate rapidly due to the growth of microorganisms that form various gases. Food organizations across the globe always report that a significant proportion of food goes to waste due to spoilage before consumption, and also this spoiled food causes several diseases [1].

Established methods for freshness assessment such as chemical analyses, microbial testing, and sensory inspection all require laboratory facilities, trained personnel, and considerable time for processing, and so these are generally unsuitable for continuous real-time monitoring. Due to this, electronic nose(e-nose) systems have become popular. Basically, an e-nose uses several gas sensors to sense the gases coming out of food. These are sensors responding to methane, alcohols, hydrogen, ammonia, etc. [2]. Since their readings change in a rapid fashion once food begins to spoil, many previous studies have demonstrated that e-noses are useful for checking items like meat and seafood [3]. Also, many studies say that if we use machine learning (ML) along with these sensor readings, the predictions turn out to be much better because ML can observe patterns which are difficult for us to see manually [4].

Grenze ID: 01.GIJET.12.2.553
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In this work, we have developed a small seafood freshness checking system using a simple and inexpensive e-nose setup [11]. Four sensors, namely MQ2, MQ4, MQ8, and MQ135, are used to identify key gases produced during spoilage of seafood, while one more sensor, the DHT11, was added since temperature and humidity play an important role in seafood spoilage rate [5]. The readings are collected by Arduino Uno, and a GSM module is used so as to provide a message to the user in case the gas values cross the prefixed threshold during testing. Then a Random Forest model was used to classify the collected data into "fresh" or "spoiled" based on the features from the collected sensor data.

This approach aims to ensure a portable, energy-efficient, and affordable monitoring system that can function across domestic, commercial, and storage environments.

The main contributions of this work are as follows:

- Develop a low-cost sensor-based e-nose system capable of real-time freshness detection.
- Application of the Random Forest algorithm to classify spoilage with high accuracy based on multi-sensor data.
- Integration of Arduino and GSM modules to automate data processing and generate alerts.

II. Literature Survey

E-nose systems are widely used for food spoilage detection due to their capability for identification of volatile gases emitted during decomposition. MQ-series metal-oxide gas sensors are popular in low-cost e-nose implementations because of their sensitivity to a wide range of compounds commonly associated with spoilage, including alcohols, methane, hydrogen, and ammonia.

MQ2, MQ4, MQ8, and MQ135 sensors have been identified in various literature as capable of monitoring changes in the gas concentration that occurs due to microbial activity and thus suitable for freshness estimation in perishable food items [6].

Grassi et al. [7] demonstrated an important advancement in using e-noses to evaluate seafood freshness. They built a portable e-nose equipped with metal oxide semiconductor sensors, a photoionization detector, and electrochemical cells, and tested it on sole, red mullet, and cuttlefish from arrival to post-expiration. They were able to classify samples into three freshness levels using microbial validation and K-means clustering.

Srinivasan et al. [8] presented the "Shrimp-Nose," a non-invasive e-nose system with six metal oxide gas sensors, with the purpose of monitoring Pacific white shrimp kept in both ambient and iced conditions. PCA, Decision Tree, Random Forest, KNN, and Softmax Regression were used to analyze freshness degradation; the Softmax model produced the best accuracy, 96.29% for un-iced shrimp and 95.73% for iced shrimp.

Cui et al. [9] created ML models, to forecast the shelf life of five marine fish species at various storage temperatures. They discovered that the RBF model outperformed the others, with prediction errors below 0.5, using the BP, GA-BP, RBF, and ELM algorithms in conjunction with indicators such as TVC, TVB-N, and K-value.

Wang et al. [10] combined analysis by GC-MS with an e-nose system to assess oyster freshness and identify key volatile compounds associated with spoilage. Although their results relate only to oysters, such classification methods as LDA, SVM, and RF resulted in more than 90% accuracy at 4°C and more than 95% accuracy at higher temperatures.

Combining ML algorithms with e-nose systems can greatly improve the precision and reliability of food freshness evaluation. ML methods play a crucial role in interpreting the complex signal patterns produced by e-nose sensors [12]. Recent developments also show that ML models can now run on low-power microcontrollers, enabling compact, stand-alone devices capable of performing real-time inference without any network connection. These systems are ideal for portable and energy-efficient applications because they process sensor data directly on the device and use less than 1 mW of power [13-15].

The findings from existing literature support the usage of MQ2, MQ4, MQ8, MQ135, temperature sensing, Arduino-based processing, GSM alerts, and Random Forest classification in developing a compact and cost-effective real-time food freshness monitoring system.

III. Proposed System

This section covers the complete workflow of the proposed seafood-freshness monitoring system. The process begins with sensor-based data acquisition, followed by dataset generation, preprocessing, ML model development, and real-time deployment. Fig. 1 illustrates the overall block diagram for the proposed portable e-nose model.

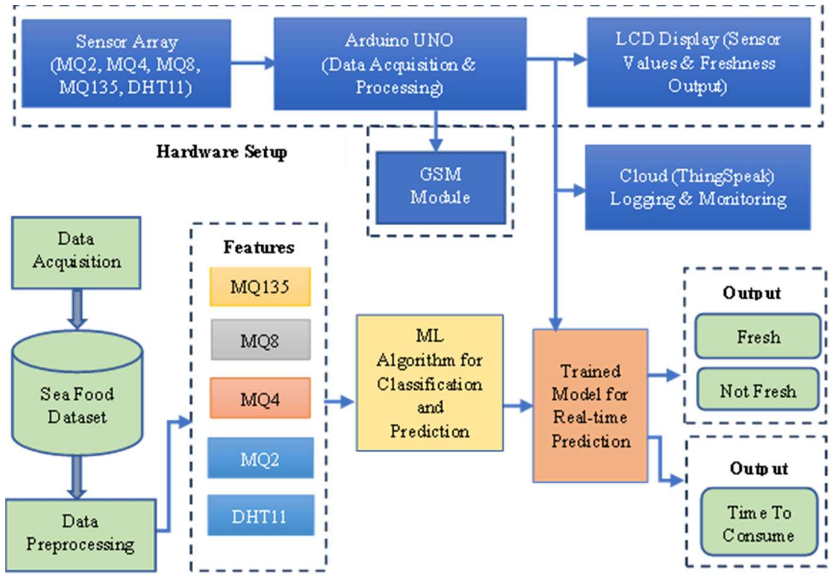

Figure 1. Framework for the proposed portable electronic nose model

A. Implementation Steps

Hardware Setup and Data Acquisition

The setup utilizes a sensor array comprising MQ2, MQ4, MQ8, MQ135 gas sensors, along with the DHT11 temperature sensor. These sensors are used for different gases that are associated with food spoilage, such as alcohol vapors, methane, hydrogen, and ammonia. Furthermore, temperature is also measured because it greatly affects the rate of spoiling.

An Arduino Uno is connected to the sensor's output. It sends the measurements to the processing unit after continuously sampling the sensors at predetermined intervals. It also manages the GSM module, buzzer, and LCD display to provide both local and remote user alerts. Because of its dependability, stability in MQ sensors' analog input performance, and compatibility with low-cost embedded systems, the Arduino Uno was chosen for this application.

Local Display (LCD) and Cloud Logging

After the initial processing, the real-time sensor data is sent to the ThingSpeak cloud platform for remote monitoring. Using the platform's IoT dashboard, the user can easily observe temperature patterns and gas concentration changes with respect to time without needing to check the device in person.

At the same time, the LCD display shows the live sensor readings and the system's decision (whether the item is fresh or spoiled) along with an estimated remaining shelf life. This approach makes the system more practical for everyday use.

Dataset Formation and Preprocessing

The gas sensor dataset consists of a record of temperature and readings from MQ2, MQ4, MQ8, and MQ135 sensors during the test. Every entry in this dataset has a binary label on whether each reading represents a normal condition or a spoilage-related level of a particular gas. After normalization and preprocessing, all incorrect and incoherent records were removed. Finally, the labels of sensors are combined into one final freshness label: a sample is fresh if all the labels are zero; otherwise, it is not.

A simple rule-based scoring system will give a numerical target for the prediction of shelf life. First, each sensor label is multiplied by a weight: 1×MQ2, 2×MQ4, 3×MQ8, and 5×MQ135. Then, the total score is mapped to an estimated number of hours that are left before spoilage. To reflect the influence of temperature, every time the temperature exceeds 32°C, the estimated shelf life will be decreased by 30%, since food spoils faster at higher temperatures.

After the preprocessing, the dataset is split into 80% for training and 20% for testing. This helps the model to learn realistic spoilage patterns from the sensor readings and also delivers a clean, structured dataset for the ML algorithms.

Feature Extraction

In order to train the model, five sensor readings are used as input features: the temperature from the DHT11 sensor and the gas values from MQ135, MQ8, MQ4, and MQ2. These are the major factors that influence the freshness of the food and the onset of spoilage.

To ensure that the dataset represents reality with respect to real-time setup, features selected are the same as the sensors used in hardware. No additional and artificially created features were used, to keep the system simple and understandable.

Machine-Learning Model Development

In this work, the Random Forest algorithm was employed for both the classification and regression models. In the classification part, the Random Forest classifier will look at the combined freshness label and determine if the food sample is fresh or spoiled. For predicting how many hours of shelf life are remaining, the Random Forest regressor makes use of the numerical target that we created earlier.

Random Forest has been chosen because it can handle nonlinear patterns, works well even if the sensor readings are a bit noisy, and manages features that have different value ranges. The dataset will be split into 80% for training and 20% for testing. To check how well the model performs, accuracy and a confusion matrix metrics will be used.

Real-Time Model Deployment

Following validation, the trained models are incorporated into the real-time system. In which, the processing module receives continuous live sensor readings from the Arduino Uno and produces two outputs: Fresh/Not Fresh classification and estimated remaining shelf-life (hours). These outputs are instantly displayed in both the Python command window and the LCD display. Furthermore, the GSM module notifies the user and sounds a buzzer when spoiling is detected. The users are guaranteed to receive information instantly, consistently, and easily due to real-time deployment. As a result, there is less chance of eating spoiled food, which enhances handling and storage decisions.

B. Hardware Description

The food freshness tracking system presented here includes a number of low-cost, reliable, and easily integrated electronic components. Some of these are, a microcontroller unit, temperature sensor, MQ series gas sensors and output modules for communication and user warnings. By using all these together real-time warnings can be provided by the system to monitor environmental conditions, and accurately detect gases associated with food spoilage.

MQ2 Gas Sensor (Light VOC and Alcohol Detection)

The MQ2 sensor shown in Fig. 2(a) is responsible for detecting smoke, alcohol vapors and light volatile organic compounds (VOCs) that appear in the early stages of food decomposition. Its metal-oxide layer varies its resistance upon exposure to these gases, and this change is converted into an analog signal that reflects the gas concentration.

MQ4 Gas Sensor (Methane Detection)

Methane, commonly produced during the anaerobic processing of organic decomposition is detected by the MQ4 sensor, which is shown in Fig. 2(b). The sensor produces a voltage that is proportional to the progression of disintegration, which helps in its detection.

MQ8 Gas Sensor (Hydrogen Detection)

Hydrogen (H_2) usually produced during the advanced spoilage reactions, is detected by the MQ8 sensor, which is shown in Fig. 2(c). This sensor is used due to its great sensitivity; means being able to detect greater deterioration in food components.

MQ135 Gas Sensor (Ammonia and Air Quality Gas Detection)

Ammonia, nitrogen oxides, and other common air pollutants are detected by the MQ135 sensor, which is shown in Fig. 2(d). MQ135 is a crucial sensor for identifying severe spoilage circumstances, because when food becomes spoiled then ammonia levels increase dramatically.

Temperature sensor DHT11

Digital temperature measurements from the DHT11 sensor, shown in Fig. 2(e), are crucial for freshness analysis because high temperatures increase the rate of spoilage. The sensor generates reliable calibrated readings that may be used to calculate shelf life and temperature-adjusted freshness.

(a) (b) (c) (d) (e)

Figure 2. a) MQ2 Gas Sensor, b) MQ4 Gas Sensor, c) MQ8 Gas Sensor, d) MQ135 Gas Sensor, (e) DTH11 Sensor

Arduino Uno

The central processing unit is the Arduino Uno. It reads the analog outputs from MQ sensors, takes the digital temperature data from the DHT11, processes the sensor readings, and transmits them to the ML module. It also sends information to the output devices like the GSM module, buzzer, and LCD display. Arduino Uno is chosen because it is reliable, simple to program, and ideal for ongoing real-time monitoring.

LCD Display Module

The 16x2 LCD display offers a straightforward and quick interface by displaying real-time sensor data, temperature, freshness categorization, and projected shelf life. Users can visually assess the food's condition with this without needing any outside equipment or software. This display module is equipped with an I2C interface, which typically includes an I2C controller module. This module converts the parallel data from the LCD into a serial format suitable for I2C communication. To connect the 16x2 LCD to a microcontroller (such as an Arduino), only four connections are needed: power (VCC), ground (GND), SDA (data line), and SCL (clock line). The interfacing of a 16x2LCD display with Arduino Uno is shown in Fig. 3.

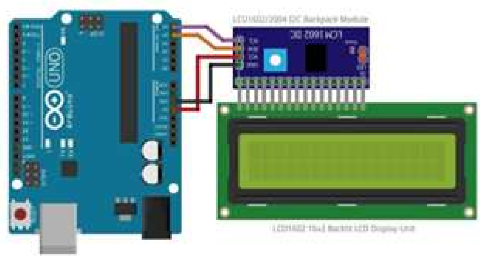

Figure 3. Interfacing of 16x2 LCD with Arduino Uno

SIM800C GSM Module

By sending SMS alerts to the user's mobile device, the SIM800C GSM module shown in Fig. 4 offers remote communication functionality. The module sends an alert when temperature changes or indicators of spoilage are discovered, maintaining constant monitoring even when the user is not physically near the device.

Figure 4. SIM800C GSM Module

All these components combine to create a cost-effective, dependable, and productive hardware platform that can handle real-time food-freshness detection and shelf-life prediction.

IV. RESULTS AND DISCUSSION

The hardware setup for the portable e-nose implemented for seafood freshness evaluation is shown in Fig. 5. The system includes the multi-sensor gas array, Arduino Uno microcontroller, LCD display module, GSM communication unit, and the laptop interface that is used for real-time monitoring and also ML analysis. The gas sensors are situated in the front for direct exposure to the VOCs emitted by seafood samples. The LCD module displays the acquired Gas Sensors values, while the laptop runs the Random Forest ML model used for validation. The predicated freshness output is displayed in both Python command window and LCD module. This setup enabled continuous data acquisition and stable system performance throughout the experiments.

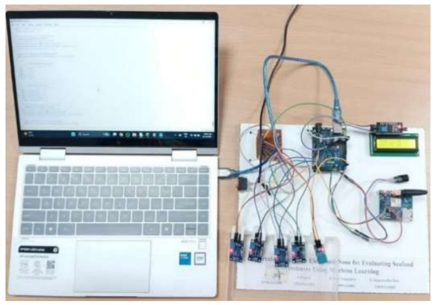

Figure 5. Hardware Setup of the Portable Electronic Nose System

The hardware with all gas sensor outputs turned off is shown in Fig. 6. Since there are no spoiling gases present, the sensor indicators continue to show very little activity. All sensors' low baseline readings are shown on the LCD, indicating that the system is stable and unaffected by outside influences. In order to calibrate drift and set reference thresholds for subsequent spoilage detection, this baseline was essential.

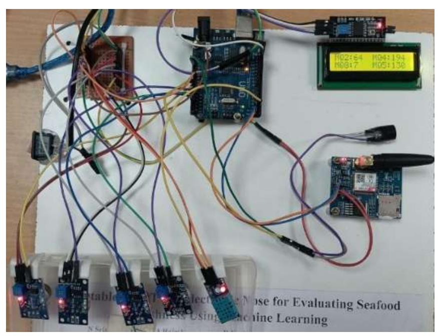

Figure 6. Hardware Setup Showing Baseline Condition (All Gas Sensor outputs OFF)

The system under test conditions is depicted in Fig. 7, where the MQ2 and MQ135 sensors react to the presence of gases linked to spoiling. When these sensors get triggered, it confirms that ammonia and other nitrogen-based gases released from the seafood have activated them. Once this happens, the system sends the sensor readings to the ML model, and the LCD display clearly shows the increased values for these sensors.

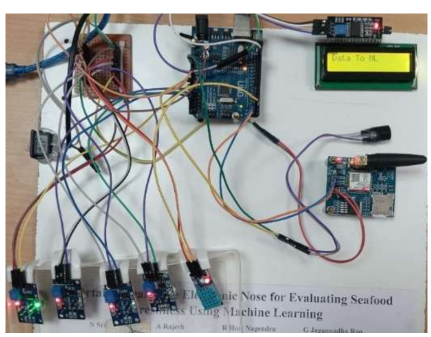

Figure 7. Hardware Setup When MQ2 and MQ135 Sensors Are Activated

The sensor readings under clean air conditions are shown on the LCD in Fig. 8(a), the surrounding room temperature and humidity are also shown (b). MQ2, MQ3, MQ4, and MQ5 (135) all continue to have low background values. In order to differentiate between fresh and spoiled states, these baseline values act as reference inputs. After the sample is exposed to spoilage related gases, Fig. 8(c) shows a clear rise in the readings of MQ2, MQ4, and MQ135. Among them, MQ135 shows the strongest response, indicating that it is highly sensitive to gases such as ammonia. These elevated values form strong feature inputs for the ML classifier, which clearly distinguish the contaminated condition from the baseline. This illustrates how the e-nose can identify food spoilage in its early stages.

Figure 8. (a) LCD Display Showing Baseline Sensor Values (All Gas Sensors OFF), (b) LCD Display Showing Room Temperature and Humidity values (c) LCD Display Showing Elevated Readings When MQ2 and MQ135 Are ON

Figure 9. (a) Random Forest Output in Python When All Sensors Are OFF, (b) Random Forest Output in Python When MQ2 and MQ135 Sensors Are ON

The Random Forest model output that matches the baseline sensor readings is displayed in Fig. 9(a). The random forest model classifies the sample as fresh seafood with an estimated freshness time of 12 to 18 hours because the incoming values are low for all sensors. This shows that the model has avoided false detections and correctly detected non-spoilage conditions. Also, as per the output display, the data was successfully sent to ThingSpeak cloud and Arduino Uno. In the model's output shown in Fig. 9(b), the system is detecting active spoilage. The MQ2 and MQ135 readings are considerably higher at this stage, and the Random Forest model marks these sensors with a value of 1, indicating the presence spoilage gases. Based on this, the system classifies the seafood as moderately spoiled, within an estimated 3–6 hours of shelf life remaining. This demonstrates how the model is able to monitor spoilage progression and give a real-time estimate of freshness.

V. Conclusions

The proposed system presents a simple, portable solution for real-time evaluation of seafood freshness, using low-cost gas sensors, temperature measurement, and machine learning techniques. It facilitates continuous data acquisition and transmission through the Arduino Uno and effectively identifies gases emitted during spoilage with the MQ series sensors. Local display is provided through an LCD, while a GSM module within the system enables realtime information and the issuance of SMS alerts in unsafe conditions for the convenience of users. The Random Forest model enabled accurate predictions of shelf life and classification of freshness, and data was made available on ThingSpeak for cloud-based monitoring. The low cost, small size, and low power made the system suitable for households, small retail shops, and short supply chains. Early spoilage detection and warnings could reduce food waste and avoid the consumption of unsafe seafood.

In the future, the system can be further improved by adding more gas sensors to supplement the current ones and aggregating more extensive data across varied environmental conditions. These will enhance its precision and make it more scalable for practical applications in food quality evaluation and IoT-based safety applications.

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