Proceeding Paper

The Development of a Mobile E-Nose System for Real-Time Beef Quality Monitoring and Spoilage Detection †

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Abstract: Ensuring the quality of meat is crucial to preventing health hazards caused by improper handling. To address this issue, a smart packaging system is necessary for continuous monitoring of beef quality and microbial population, benefiting both meat industries and end consumers. The presence of spoilage-causing microbes can be detected using an electronic nose (e-nose), a cost-effective and rapid instrument for beef quality classification. This research introduces the development of a mobile e-nose system for beef quality detection and monitoring. The system comprises a chemical gas sensor array, a data acquisition system, a data processing system, and a pattern recognition system. The gas sensors utilized in the sensor array include MQ135, MQ137, MQ9, MQ3, TGS 2620, TGS 2610, TGS 2600, and TGS 822. The experiment involved a dataset with 1800 data points. The experimental results demonstrate the system's ability to accurately distinguish between fresh and spoiled beef. Furthermore, it exhibits a promising classification accuracy of 95.89% using the Support Vector Machine model. Therefore, this system presents a potential solution for a low-cost, user-friendly, and real-time meat quality monitoring system. This research contributes to the development of an accessible and efficient meat quality monitoring system, addressing the need for continuous assessment and ensuring consumer safety.

Keywords: beef; SVM; electronic nose; odor analysis; volatile organic compounds

1. Introduction

Meat is the tissue of animals that is used as food. It originates from various animals, such as cows, pigs, chickens, and sheep. The most common types of meat include beef, pork, chicken, and lamb. Beef is the meat of a bovine animal, typically a cow. It is one of the most commonly consumed meats in the world and is a rich source of protein, iron, and other essential nutrients. Beef can be prepared in many different ways, such as grilling, frying, roasting, and stewing, and is used in a wide variety of dishes, such as burgers, steaks, stews, and soups [1]. Beef is also a common ingredient in many traditional and cultural dishes worldwide. There are different cuts of beef and different grades of beef, which are based on the amount of fat marbling in the meat. Beef is one of the most widely consumed meats in the world and is a staple in many cultures' diets [2].

Proper storage of beef is important to maintain its quality and safety for consumption. When beef is exposed to open air, beef spoilage occurs. Fresh beef that is exposed to open air will begin to spoil quickly due to the presence of bacteria and other microorganisms in the air [3]. These microorganisms can cause the beef to become contaminated, leading to spoilage and potentially making it unsafe to eat. Oxygen in the air can also cause the oxidation of beef, which can lead to changes in color, flavor, and texture. The open-air storage life of beef is about 15 h. Exposure to heat and humidity can also accelerate the

spoilage process. Bacteria grow rapidly at temperatures between 40 and 140°F (4–60 °C), and high humidity can create an environment that is conducive to bacterial growth [2–5]. It is important to note that fresh beef that has been exposed to open air for an extended period of time and shows signs of spoilage should not be consumed, as it can cause food poisoning. To prevent spoilage, it is important to handle beef safely and properly, including washing hands and utensils, properly storing the beef, and cooking it to the appropriate internal temperature to kill any bacteria [6].

The methods used to evaluate beef spoilage include sensory evaluation, microbial, enzymatic, and physical assessment. In microbial testing, beef is tested for the presence of bacteria, yeasts, and molds. The most common method is to take a sample of the beef and culture it on a growth medium [7]. The sensory evaluation method involves evaluating the appearance, odor, and taste of the beef to determine if it is spoiled. This can include visual inspections for discoloration, sliminess, or off-odors, as well as smelling and tasting the beef. Enzymatic testing involves measuring the activity of enzymes that are involved in the spoilage process [7,8]. For example, the activity of proteolytic enzymes can indicate the degree of protein breakdown, an indicator of spoilage [6]. In a physical testing method, the changes in the physical properties of the beef are measured, such as texture, firmness, and color, that can indicate spoilage. It is worth noting that testing methods can differ depending on the extent and type of spoilage. A combination of methods is often used to obtain a more accurate picture of the spoilage status of beef. Quality determination of beef using the volatile organic compound (VOC) analysis using an electronic nose (e-nose) device is a new approach [9,10].

An electronic nose, also known as an e-nose, is a device that uses sensors to detect and identify VOCs in the air [11]. It has wide applications in the healthcare industry for the detection of various pulmonary diseases [12–14]. These VOCs are produced by microorganisms as they grow and metabolize, and their presence can indicate spoilage. An electronic nose can be used to detect and identify these VOCs in beef, allowing for the early detection of spoilage. An electronic nose typically consists of a sensor array, a signal processing unit, and a pattern recognition algorithm. The sensor array is made up of different types of sensors, such as metal oxides or polymer films, that can detect specific VOCs [15,16]. The signal processing unit converts the sensor readings into an electronic signal, and the pattern recognition algorithm compares the electronic signal to a database of known VOC patterns to identify the variations of specific VOCs present in the beef.

In this paper, we have designed and developed an electronic nose for detecting and monitoring beef quality. The system consisted of four main components: a chemical gas sensor array, a data acquisition system, a data processing unit, and a pattern recognition module. The sensor array features a selection of gas sensors, including MQ135, MQ137, MQ9, MQ3, TGS 2620, TGS 2610, TGS 2600, and TGS 822. The experiment utilized a dataset consisting of 1800 data points. The experimental outcomes highlight the system's capability to effectively differentiate between fresh and spoiled beef. Signal preprocessing for the e-nose data was carried out using the Discrete Wavelet Transform, and classification was performed using the supervised classification method, Support Vector Machine.

2. Materials and Methods

2.1. Electronic Nose System

The e-nose system consists of a chemical gas sensor array, a data acquisition system, a data processing system, and a pattern recognition system. The whole e-nose setup designed and developed is shown in Figure 1. The gas sensors used for the sensor array are MQ135, MQ137, MQ9, MQ3, TGS 2620, TGS 2610, TGS 2600, and TGS 822. The VOCs detected by all these sensors are provided in Table 1. MQ and TGS gas sensors are types of gas sensors that use a metal oxide (such as tin dioxide) as the sensing element.

When a gas is present, it reacts with the metal oxide and changes the electrical resistance of the sensor. The change in resistance is then used to determine the concentration of the gas. The e-nose system uses these sensors in combination to detect and identify specific

chemicals emitted by the beef sample. The sensors work by measuring changes in electrical resistance, which are caused by the presence of a specific gas. Each sensor output is driven by a 1K resistor and applied to the Arduino Mega 2560 Rev3 developer board for data acquisition. From the microcontroller board, the signal continues to the personal computer installed with Matlab R2020b for further data processing and analysis. Thus, the e-nose system can analyze the data from the sensors to identify the variations of VOCs emitting from the beef. The sensor chamber has been partitioned into two segments, as illustrated in the figure: one for holding the sample and the other for equipment. We made the e-nose chamber from transparent plastic to make it easier to observe the sample's condition.
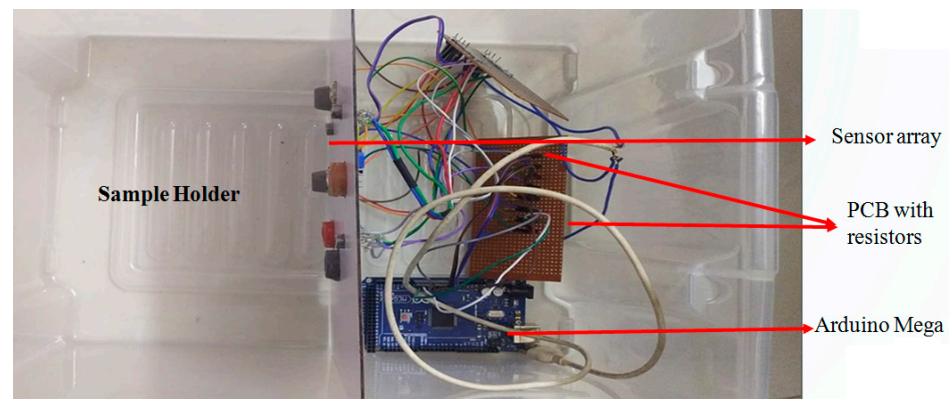

Figure 1. Block diagram of e-nose system.

Table 1. Details of sensors.

Model Number	Detected Compounds	Range (ppm)
MQ 135	Ammonia, Benzene, Carbon Dioxide, and Alcohol	10–200
MQ 137	Ammonia and Carbon Monoxide	5–500
MQ 9	Methane, Carbon Monoxide, and LPG	10–10,000
MQ 3	Alcohol, Carbon Monoxide, Benzene, Hexane, Methane, and LPG	25–500
TGS 822	Acetone, Ethanol, Benzene, and Methane	50–5000
TGS 2620	Carbon Monoxide, Ethanol, Isobutane, and Methane	50–5000
TGS 2610	Ethanol, Methane, Propane, and Isobutane	300–10,000
TGS 2600	Methane, Isobutane, Ethanol, and Carbon Monoxide	1–100

2.2. Sampling and Sensing

The major beef cuts include ribeye, rump, sirloin, tenderloin, flank, round, brisket, chuck, short loin, chuck, and short plate. For this work, we have used the bottom round of the beef cut. When beef is stored in aerobic (oxygen-rich) conditions, it can produce volatile organic compounds (VOCs) as a result of the breakdown of fat and protein. Some of the VOCs that can be produced include aldehydes, ketones, and alkanes. These compounds can contribute to off-flavors in beef and affect its sensory qualities [2,7]. We used 300 g of bottom-round beef for this experiment. To speed up odor detection, the beef sample was put next to the sensor array in the sample holder. The sample compartment was fully sealed off during the experiment, resulting in negligible airflow. For the experiment, the beef sample was continually monitored for 1800 min, which is adequate to record meat quality from fresh to spoiled. The measurements were collected during the day and night under variable conditions due to the ambient temperature and humidity. This homemade e-nose was developed to detect gases generated by mesophilic bacteria during the deterioration of beef. Mesophilic bacteria spread best between 20 and 45 degrees Celsius.

In this study, the term "beef quality standard" refers to the meat quality criteria set forth by the Agricultural and Resource Management Council of Australia and New Zealand [17]. Meat quality is categorized into four sensory classes, which are correlated

with the total viable count (TVC): Excellent (TVC < 3), Good (TVC 3 to 4), Acceptable (TVC 4 to 5), and Spoiled (TVC > 5). In this experiment, an equal amount of beef samples (300 g) was used for both microbial population quantification and e-nose measurements. To determine the microbial population in the beef samples, a hemocytometer was employed. Microbial population measurements were carried out every hour for a duration of 30 h to ensure greater accuracy in the results.

2.3. Data Analysis

The Discrete Wavelet Transform (DWT) is a widely used signal processing technique, including in electronic nose (e-nose) applications, for various purposes, including signal preprocessing. DWT is a versatile tool for e-nose signal preprocessing, as it can help enhance the relevant information in the signals while reducing noise. So, we used DWT for signal preprocessing. After the signal preprocessing phase, the data from the eight sensors were organized into a feature vector. Given our e-nose system's measurement cycle of 1800 min and a sampling frequency of 10 Hz, this resulted in a total of 18,000 data points. Consequently, the feature vector's size amounted to 144,000 (8 sensors multiplied by 18,000 data points).

In this initial study, we employed the Support Vector Machine (SVM) algorithm for the purpose of classification. SVM is a powerful machine learning algorithm used for classification and regression tasks. It works by finding the optimal hyperplane that best separates data into different classes while maximizing the margin between them. SVMs are particularly useful when dealing with binary classification problems but can be extended to handle multi-class scenarios. SVM is effectively used in e-nose-based studies [18,19].

3. Results and Discussion

In this section, we outline the experimental outcomes of our study, emphasizing that we conducted the coding processes using Matlab R2020b. Our dataset comprises a table generated from measurements carried out on a beef sample, spanning 1800 rows, corresponding to an1800 min measurement period. We supplied eight sensors and TVC data as inputs to our machine learning methods, producing binary classification results with two classes: fresh and spoiled beef. To accomplish this classification, we grouped the "excellent", "good", and "acceptable" classes as "fresh" and the remaining as "spoiled". This dataset, which examines the stages of beef deterioration, necessitates highly accurate classification due to its critical implications for human health. To achieve superior classification accuracy and reduce computation time while retaining key information, we adopted a feature vector with a size of 144,000, as previously explained. Figure 2a displays raw signals sampled from the sensors, which are affected by noise. Interestingly, the presence of noise persists despite temperature control measures. Consequently, the requirement for denoising techniques to mitigate the noise levels in these raw signals remains. Each color in the figure represents distinct responses from the gas sensors within the sensor array, indicated by their respective sensor resistance values in ohms. Furthermore, it isworth noting that each gas sensor generates noisy signals of varying magnitudes, underscoring the necessity for effective noise filtering to restore the integrity of the raw signals.

We employed cross-validation to conduct a thorough performance assessment of our classification model, allowing for an objective comparison with other models. Specifically, we adopted a 10-fold cross-validation approach. This method involves the division of the dataset into ten segments, each comprising nine training parts and one testing part, in successive cycles. The training and testing procedures are iterated through these ten steps to ensure that each segment is used for testing. The model's average classification accuracy is then computed as the arithmetic mean of the results obtained from these cycles. Upon analyzing the ROC curve depicted in the provided image, it becomes clear that the SVM classification algorithm has outperformed others in terms of classification accuracy, recall, and precision. The performance metrics for the SVM algorithm are succinctly outlined in the accompanying Table 2, and the ROC curve of the algorithm is depicted in Figure 2b.
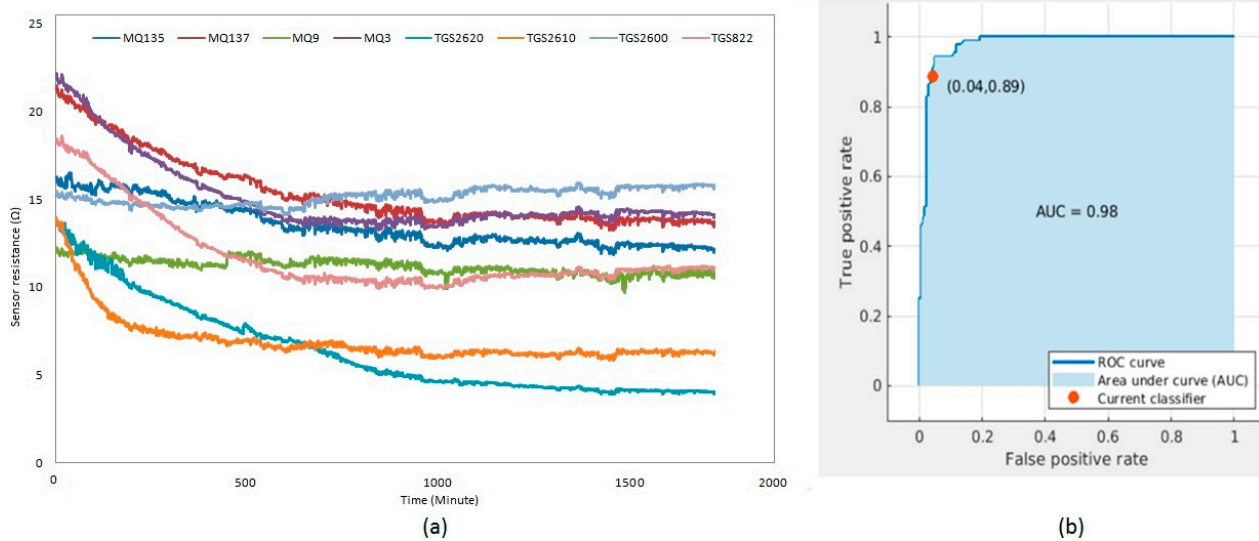
Figure 2. (**a**) Sensor array response to beef sample; (**b**) ROC curve of SVM model.

Table 2. Performance metrics.

Parameters	SVM Model
Accuracy (%)	95.89
Recall (%)	91.23
Precision (%)	98.12

4. Conclusions

Ensuring meat quality is imperative to prevent health risks stemming from mishandling. Addressing this concern necessitates a smart packaging system for continuous monitoring of beef quality and microbial presence, benefiting both the meat industry and consumers. Detecting spoilage-causing microbes can be achieved through an electronic nose (e-nose), an economical and swift tool for classifying beef quality. This paper introduces the development of a low-cost e-nose system tailored for beef quality monitoring. In terms of industry standards, this system showcases promising performance in distinguishing between fresh and spoiled beef using a straightforward machine learning technique, SVM. The experimental results highlight SVM's superiority, achieving an accuracy of 95.89%, a recall of 91.23%, and a precision of 9.12%. These findings point out the potential of this proposed system for further development as a cost-effective, user-friendly, and real-time meat quality monitoring solution.

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