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DEVELOPING A LOW COST ELECTRONIC NOSE FOR SPOILAGE ANALYSIS OF GROUND BEEF

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Abstract: A low-cost, easy-to-use e-nose is developed to detect the spoilage of ground meat. E-nose consists of hardware, software and data processing components. The main elements of hardware component are gas sensors sensitive to hydrogen sulfide (H_2S) and ammonia (NH_3). Using MIT App Inventor 2 an Android application is developed to run the hardware component, retrieve the data, pre-process and send it to Google Sheets. Classification model is developed, and data management is carried out in Google Colab and Google Script. Logistic regression method is used to develop classification models from the collected signals. The model classified the samples as "spoiled" and "fresh" based on the gas concentrations. The Nessler solution is used to determine the actual spoilage state. Ground beef samples stored in the refrigerator and at room temperature are used to obtain spoiled and fresh samples to develop a logistic regression model. A total of 36 samples are used to develop model. Another set of 24 samples is used to test model and prototype device performance. It is observed that all samples used in the testing phase were classified correctly. The cost of the system has been determined as approximately $100 considering January 2021 exchange rates.

Keywords: Food safety, Artificial intelligence, Machine learning, Logistic regression, Electronic nose

Kıyma Kokuşma Analizi İçin Düşük Maliyetli Elektronik Burun Geliştirilmesi

Öz: Kıyma örneklerinin bozulmasını belirlemek için düşük maliyetli, kullanımı kolay bir elektronik burun geliştirilmiştir. E-burun donanım, yazılım ve veri işleme bileşenlerinden oluşmaktadır. Donanım bileşeninin ana unsurları, hidrojen sülfür (H_2S) ve amonyağa (NH_3) duyarlı yarı iletken gaz sensörleridir. MIT App Inventor 2 kullanılarak, donanım bileşenini çalıştırmak, verileri almak, ön işlemeye tabi tutmak ve Google Sheets'e göndermek için bir Android uygulaması geliştirilmiştir. Google Colab ve Google Script kullanılarak sınıflandırma modeli geliştirilmiş ve veri yönetimi gerçekleştirilmiştir. Toplanan sensör sinyallerinden sınıflandırma modelleri geliştirmek için lojistik regresyon metodu kullanılmıştır. Model, gaz konsantrasyonlarına dayalı olarak kıyma örneklerini "bozulmuş" ve "taze" olarak sınıflandırmıştır. Nessler çözeltisi gerçek bozulma durumunu belirlemek için kullanılmıştır. Buzdolabında ve oda sıcaklığında saklanan dana kıyma örnekleri, lojistik regresyon modeli geliştirmek için bozulmuş ve taze örneklerin elde edilmesi için kullanılmıştır. Model geliştirmek için toplam 36 örnek kullanılmıştır. Model ve prototip cihaz performansını test etmek için başka bir 24 numune seti kullanılmıştır. Test aşamasında kullanılan tüm örneklerin doğru bir şekilde sınıflandırıldığı görülmüştür. Sistemin maliyeti Ocak 2021 kur değerleri dikkate alındığında yaklaşık 100 $ olarak belirlenmiştir.

Anahtar Kelimeler: Gıda güvenliği, yapay zeka, makine öğrenmesi, lojistik regresyon, elektronik burun

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1. INTRODUCTION

Consumer demand for beef has increased significantly over the past decade due to its high nutritional value and taste (Hong et al., 2012). Beef is a food tends to spoil and contaminate easily. Protein, which is the main component of beef, decomposes into ammonia, hydrogen sulfide, ethyl mercaptan, etc. during spoilage (Kong and Ma, 2003). Various physical, chemical, molecular and immunological methods have been used to determine whether the meat is spoiled, and many studies have been carried out to detect the pathogens that cause spoilage (Jay, 2000). However, the number of studies on methods of controlling and destroying pathogens on meat products is higher than the studies conducted to quickly detect spoilage in meat. The commercially developed PCR amplification and detection system is based on the DNA test technique that detects Salmonella within 24 hours, and the reliability of the device is quite good. Although this method demonstrates progress in pathogen detection technology, the detection time is relatively long (Baumler et al., 1997). Winters et al. (1997) reported that Campylobacter Jejuni was detected in contaminated chickens and turkeys using PCR, and the detection time was 8 hours. Tan & Shelef (1997) described an automated method for detecting Salmonella Enteritidis in broiler in combination with an immunomagnetic bead and indicated the time required for detection as 18 hours. Albayrak & Yousef (1997) reported a technique based on spectrophotometric assay, including colorimetric analysis of 2,3,3 TTC (tri-phenyl-tetrazolium) to determine the bacterial activity. These methods are time consuming (Bautista et al., 1995; Miyaomoto et al., 1998) and require chemical analysis/procedures.

There are three laboratory methods available in spoilage analyses of meat including detection of ammonia with Nessler solution, monitoring for hydrogen sulfide with lead acetate, and ammonia measurement. These methods require laboratory conditions, expertise and the use of different chemical substances. Therefore, sampling, storage of samples, and analysis are not practical for consumers or markets. Hence, it is vitally important to use fast, reliable and user-friendly methods.

Use of state-of-the-art technologies along with artificial intelligence, makes determination and characterization of different parameters of biological samples possible in shorter time and more economical way (Ouellette, 1999). One of these technologies that have gained importance in recent years is electronic nose (e-nose) systems. These devices can be used in different areas such as health, detection of environmental problems and even food quality.

E-noses mimic the complex human olfactory system. They consist of sensors similar to receptor cells in the human nose. The sensor signal is processed by a computer using sophisticated pattern recognition techniques, similar to the human brain, and the necessary classification is made (Barisci et al., 1997).

The human brain perceives all of the chemical gases as "smells" without classifying them. Therefore, it is desirable for the sensors in an e-nose system to be sensitive to chemicals responsible for generating smell (Stussi et al., 1996). There are many different sensors used in these devices. The most widely used are metal-oxide semiconductors (MOS), modified metal-oxide semiconductors (MMOS), conductive polymers (CP), and conductive oligomers (CO).

The main gases that are released during the spoilage of meat are NH_3 and H_2S. When these gases reach a certain concentration, they can be detected by the human nose. However, it is very difficult to detect if spoilage starts within the limits that the human nose cannot show sensitivity. In addition, each person's sensitivity to smell is subjective. Therefore, e-noses provide a more objective and precise method in such applications.

Various studies are conducted in the rapid detection of beef spoilage using e-noses. Wijaya et al. (2021) tested performance of discrete wavelet transform and long short-term memory (DWTLSTM) to process e-nose signal that is contaminated with noises. They reported the accuracy of this algorithm as 94.83%.

In another study Wijaya et al. (2017a) developed an e-nose system in beef quality monitoring. They used a sensor array consisting of 10 gas sensor, one temperature and a humidity sensor. Their system was able to classify beef quality with a classification accuracy of up to 93.64 % for binary classification.

Huang and Gu (2022) designed a metal-oxide sensor (MOS) based e-nose system in the quantitative detection of beef adulteration. They used an algorithm consisting of a one-dimensional convolutional neural network (1DCNN) and a random forest regressor (RFR). The algorithm performed with an R^2 value of close to 1 in the detection.

There are many commercial e-nose devices developed with different technologies and purposes. However, these are general-purpose devices, and their costs are quite high. Kızıl et al. (2015) used the DiagNose-II e-nose device in their study. They reported the price of the device to be € 9,000, including software, in 2015. Another widely used commercial e-nose device is the CyraNose 320. The US retail price of this device is $11,500 (Doty et al., 2020).

Therefore, it is necessary to develop purpose-specific, low-cost, and user-friendly devices. The aim of this study is to develop an e-nose that will be low-cost, and compatible with Android mobile phones employing artificial intelligence.

2. MATERIALS AND METHODS

2.1. Hardware Development

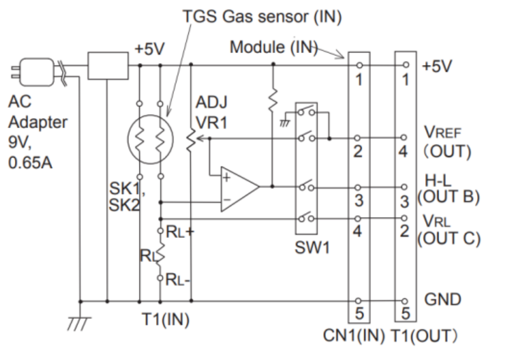
The main components of the electronic nose system are NH_3 and H_2S gas sensors (major gases released during the spoilage), data acquisition unit and data processing software. The NH_3 and H_2S sensors used in the design have a tin-dioxide (SnO_2) semiconductor active element. As the detectable gas concentration increases, the conductivity of the active element increases accordingly. Therefore, more electrons pass through this active element. Sensor output voltages will increase proportional to the gas concentration in the headspace of sample. The level of the NH_3 and H_2S concentrations in the environment can be determined by converting the sensor response into an output signal (Kızıl et al., 2001). Gas sensors exposed to gas concentration provide analog outputs between 0 and 5 V, depending on the concentration. These values are used in database development. Table 1 shows the NH_3 and H_2S gas sensors (Figaro Engineering Inc, Osaka, Japan) and their detection ranges.

Table 1. Sensors and technical features

Model	Target Gas	Detection Range (ppm)	Image
TGS 825	H_2S	5 – 100	
TGS 826	NH_3	30 – 300	

The SR-D1A (Figaro Engineering Inc, Osaka, Japan) circuit is used for each sensor in order to determine the current flowing over the sensors depending on the gas concentration in the environment during the operation. The current passing through the sensor is detected by this circuit as a signal and analog values was instantly transferred to the data processing unit. The schematic representation and technical specifications of this circuit are given in Table 2.

Table 2. SR-D1A sensor circuit and technical specifications

Item	Unit	Circuit Diagram
Operating voltage	100 – 240 V AC	
Power consumption	Sensor: approx. 1.6W Circuit: about 1.6W	
Output voltage	5 V ± 5% 300 mA	
Loading resistor	TGS 825: 10 kΩ TGS 826: 33 kΩ	
Operating temperature	-10 – +50 oC	
Dimensions	125x74x32 mm	
Weight	Circuit: 76 g AC adapter: 70 g	

An Arduino Mega microprocessor board is used in the prototype. This board has a low-cost, high-capacity microprocessor that can easily integrate different sensors (Ferrandez et al., 2022). Arduino Mega can accommodate more than one sensor and provides a dynamic technology development opportunity. A HC05 Bluetooth unit (ITEAD Intelligent Systems Co. Ltd., China) is integrated to the system to maintain a wireless communication between the device and mobile phone.

The temperature sensor used in the system is NTC 100 K thermistor. This sensor has an analog output and is preferred because it does not require calibration and is small in size. It measures the air temperature with high accuracy and sends it to the micro-processor unit. The reason for using the temperature sensor in the designed system is to observe the possible effects of the temperature on the sensor data by visualizing the ambient temperature while the device is running.

The prototype system is designed by considering the dimensions and technical characteristics of the material. Here, the goal is to combine the microprocessor, sensors, bluetooth module and SR-D1A circuits on a main body of the smallest possible dimensions. The schematic representation of the developed system and the device are shown in Figure 1. As shown in Figure 1, the signals released from the gas sensors are first transferred to the SR-D1A circuits. These circuits send the signals as voltage values (between 0 and 5 V) to the Arduino Mega. The data processed here is transmitted to the mobile phone via Bluetooth module. Here, the classification of the sample is made using artificial intelligence model.

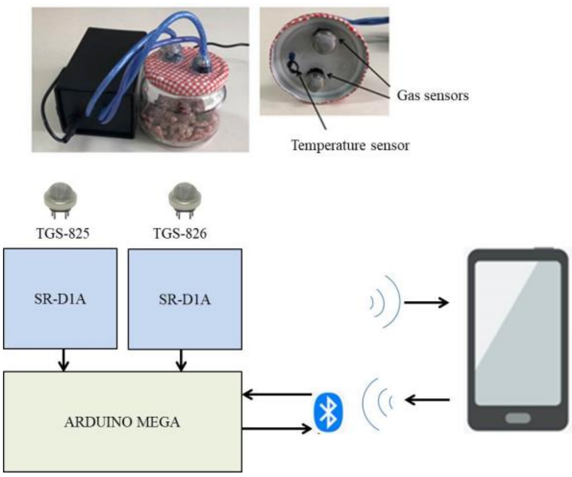


Figure 1:
Schematic of prototype e-nose

2.2. Mobile Application and Software Development

The device is designed to be used with smartphones using Android operating systems. The Android application is developed in MIT App Inventor 2, a cloud-based software development platform. MIT App Inventor 2 offers users the opportunity to program by bringing together the blocks representing almost every operation with the drag-and-drop technique (Adiono et al., 2019).

The software that handles data transfer and processing has 3 segments. In the first segment, the control of the device, the visualization of the data flow and spoilage classification result was handled via Android application.

In the second segment, raw sensor data processed within the microprocessor, transferred to Google Drive where the Google Sheets operates, and a dataset is created to train classification model. The dataset is then saved in comma separated values (CSV) file format to be used in Google Colab platform for the development of the artificial intelligence model.

In the third segment, the artificial intelligence application, which will be detailed below, is developed on the Google Colab platform. The data management order of the prototype is demonstrated in Figure 2.

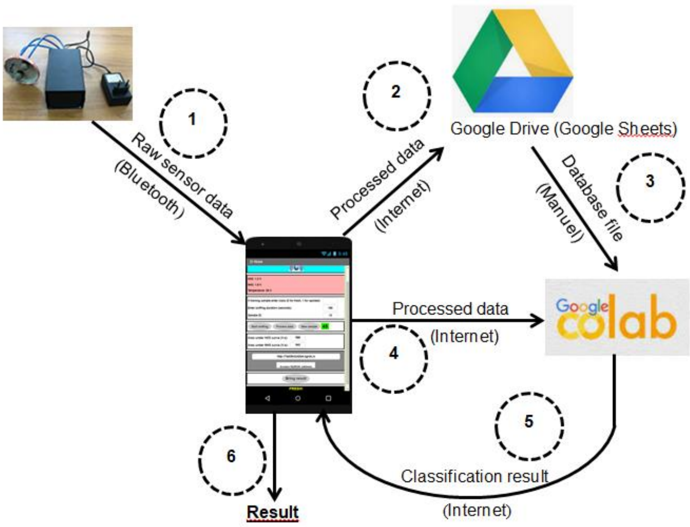


Figure 2:
Data management order

2.3. Sampling Component

The sample container is made of a 400 ml glass jar. The reason for using glass jars is that it does not cause odor, is easily available and can be easily cleaned. The gas and temperature sensors mounted on the lid compatible with this jar. Figure 1 above shows both the sampling arrangement and the placement of the sensors inside the cover.

2.4. Data Processing

The device sends the sensor data to the application for processing at a rate of 1 reading per second for 3 minutes. The response of each sensor actually plots a curve when recorded. The areas under these curves are recorded for each sensor as the value representing that sample in sniffing. The following equation is used to normalize the data (Balasubramanian et al., 2005).

$$V_b = \frac{V_i - V_{min}}{V_{min}} \tag{1}$$

where; V_b is the normalized voltage of a sensor at i seconds; V_i is the raw sensor voltage value read in i seconds; V_{min} is the minimum sensor value recorded for 3 minutes. Examples of raw and normalized readings during measurement are shown in Figure 3.

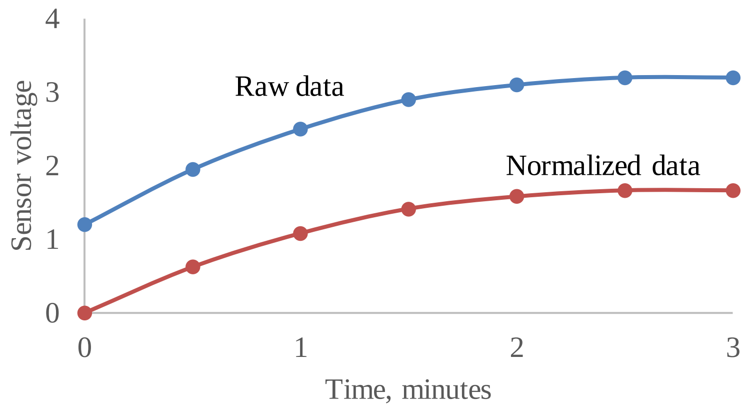


Figure 3:
Raw and normalized data

The area under the curves are calculated and instantly sent to the Google Sheets file via internet connection. The following equation is used while calculating the areas under the curves (Kızıl et al., 2015);

$$A = \sum_{k=1}^{T} f(t_k)\Delta t \tag{2}$$

where; A is the area under the curve (V.S); t, is unit time interval (S); T is the total time the curve was recorded (S); k is the identification number of the unit rectangles that make up the total area.

The processed sensor data can be seen both on the application screen and instantly sent to Google Sheets and stored. In order for Google Sheets to receive and store incoming data, a URL is used as an address. In fact, as soon as the file is created in Google Sheets a URL address of that file automatically appears in the address bar. Some coding should be done to inform how to receive and store the data coming to this page. The coding process is carried out on the Google Script platform, which is accessed via Google Drive. The script code is given in Table 3.

Table 3. Google script code

```
function doGet(e) {
var ss = SpreadsheetApp.openByUrl("https://docs.google.com/spreadsheets......./d/1edit#gid=0");
var sheet = ss.getSheetByName("Sheet1");
  addUser(e,sheet);
}
function doPost (e) {
 var ss = SpreadsheetApp.openByUrl("https://docs.google.com/spreadsheets......edit#gid=0");
 var sheet = ss.getSheetByName("Sheet1");
  addUser(e,sheet);
 }
function addUser(e, sheet) {
```

```
var h2s = e.parameter.h2s ;
var nh3 = e.parameter.nh3 ;
var class = e.parameter.sinif ;
var sampleNo = e.parameter.sampleNo ;
sheet.appendRow([h2s, nh3, class, sampleNo]);
```

2.5. Development of Classification Model

The training data set is downloaded from Google Sheets in CSV file format for use in the artificial intelligence model. The artificial intelligence model is written in the Python programming language. This language is preferred in machine learning applications because it works fast and is close to machine logic. Another reason for choosing this language is that it is open source (Dalcin et al., 2011; Pérez et al., 2011).

The artificial intelligence model is developed in the cloud-based Google Colab platform. The cloud solutions are used today to overcome hardware problems. Cloud systems provide free GPU access without compromising the computer's GPU capacity (Lazuardi et al., 2019). Google Colab is configured with the leading Keras, TensorFlow, PyTorch and OpenCV artificial intelligence libraries (Carneiro et al., 2018).

Logistic regression model is used as classification model. This model is generally preferred for binary classifications. Logistic regression employs a linear function that is also called logit (Eqn. 3)

$$x = b_0 + b_1x_1 + \cdots + b_rx_r \tag{3}$$

where; $b_0, b_1, \dots b_r$ the predicted weights**.**

The logit function is actually the sigmoid function of (x). This function creates binary classifications in the form of [0,1] (Figure 4).

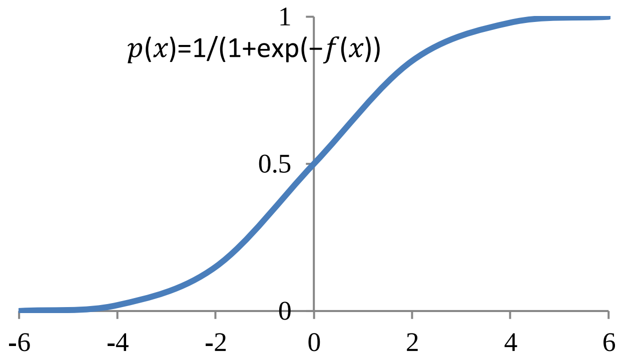


Figure 4:
Logistic function curve

In logistic regression the best weights $(b_0, b_1, \dots b_r)$ are determined so that the function (**x**) predicts actual responses of observations. This is called training phase. The stages of training and testing of the model are explained in the flowchart below (Figure 5). The codes used in the model development phase are given in Table 4. Line numbers of the codes in the chart are matched with dashed lines in Figure 6. After the model is trained, Ngrok software is used to provide access to the model created in Google Colab. Ngrok is a reverse proxy software that allows users to use local server in the internet environment by tunneling it. When Ngrok runs, it produces an URL address where the model is published. When this address is entered in the

Android application, the sensor data is sent to this URL, the model runs and the classification result is sent to the application over the internet.

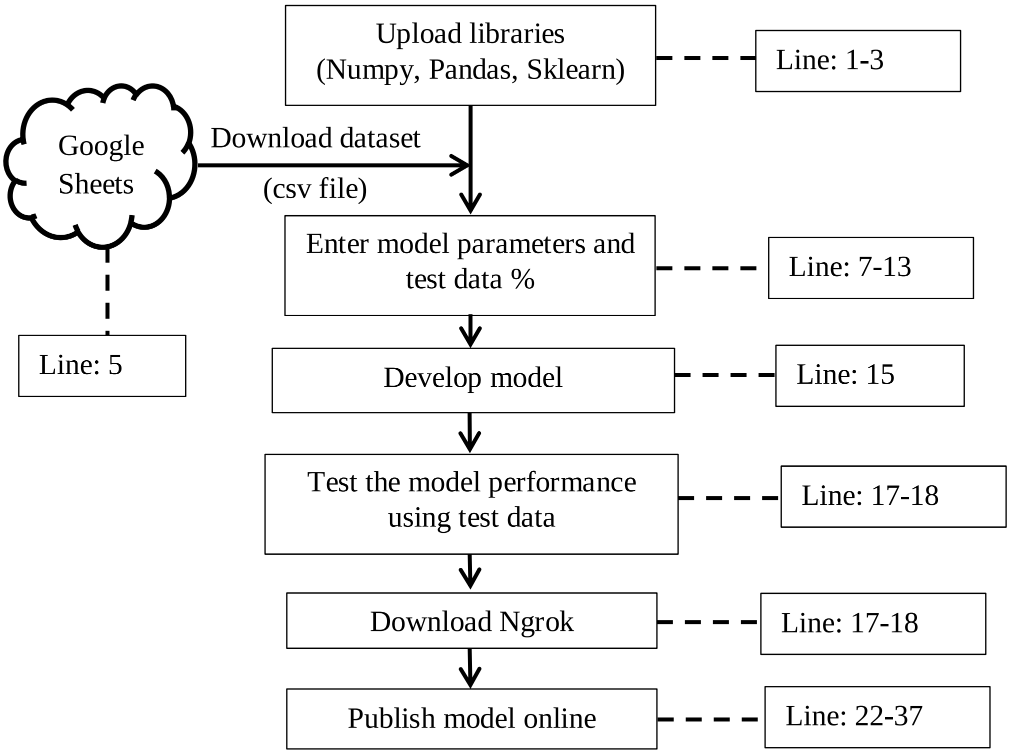


Figure 5:
Model development stages in Google Colab.

Table 4. Classification model codes

Line	Codes
1	import pandas as pd
2	import numpy as np
3	import sklearn
4	sensor_data = pd.read_csv("SENSORTEST.csv")
5	x = sensor_data.drop("class", axis=1)
6	y = sensor_data["class"]
7	from sklearn.model_selection import train_test_split
8	x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state = 1)
9	from sklearn.linear_model import LogisticRegression
10	logmodel= LogisticRegression()
11	logmodel.fit(x_train, y_train)
12	predictions = logmodel.predict(x_test)
13	from sklearn.metrics import accuracy_score
14	print(accuracy_score(y_test, predictions)*100)
15	!pip install flask-ngrok
16	from flask_ngrok import run_with_ngrok
17	from flask import Flask, jsonify
18	app = Flask(__name__)
19	run_with_ngrok(app)
20	@app.route("/<int:sensor1>/<int:sensor2>")
21	def home(sensor1,sensor2):
22	p = []

```
    p += [sensor1,sensor2]
    arr = np.array([p])
    predict= logmodel.predict(arr)
    if predict == [1]:
      result = {'result':'fresh'}
    else:
      result = {'result':'spoiled'}
    return jsonify(result)
app.run()
```

In order to train the logistic regression model, it is necessary to determine the spoilage status of samples with traditional analysis methods. In other words, the data obtained from the gas sensors must be matched with chemical analyzes to predict the model weights. A flow chart of the developed system is given in Figure 6.

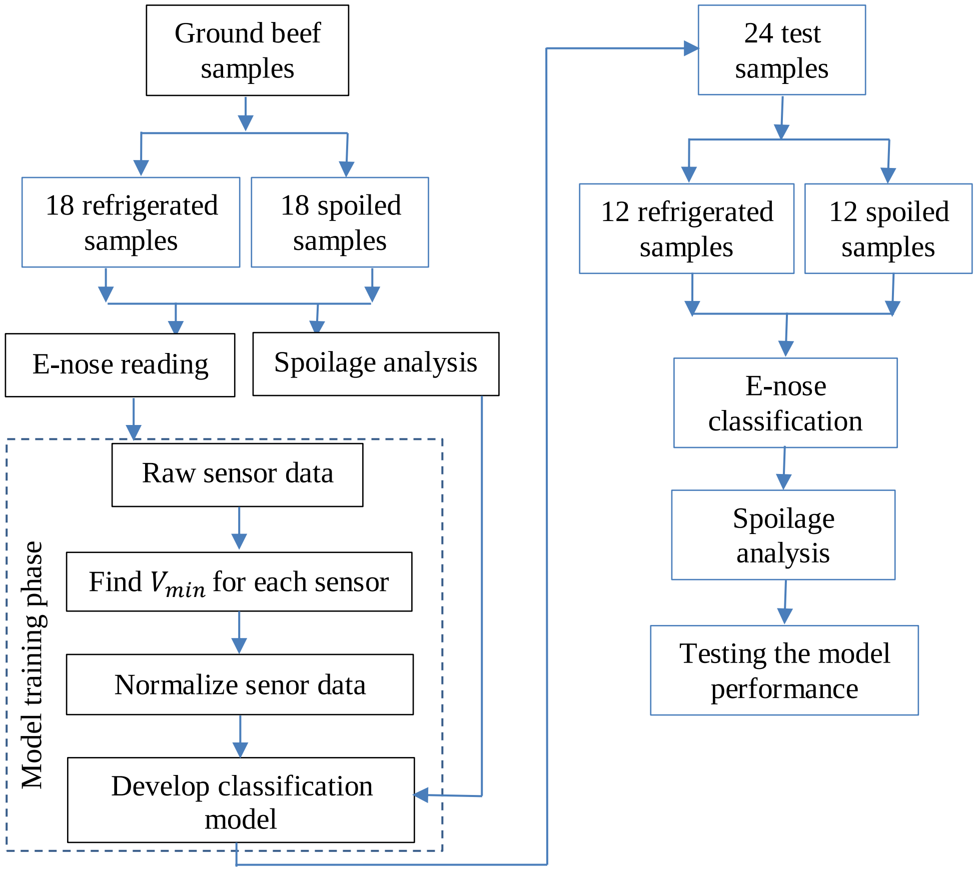
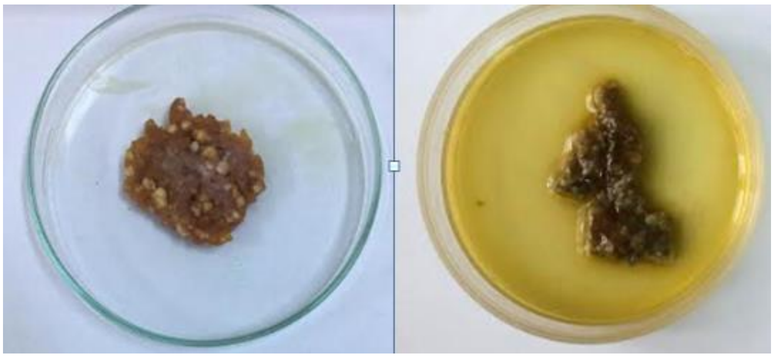


Figure 6:
Flowchart of the developed system

2.6. Spoilage Analysis

In order to prepare the training dataset, sample readings corresponding to the sensor data and the spoilage status should be determined by traditional analysis methods. It is also needed in the testing of classification performance of the model. The Nessler's solution (ChemBio, CB2740), which is one of the commonly used laboratory methods, is used to determine the spoilage status of samples.

A small piece of the sample is placed in a petri dish. Color changes are observed by pouring 2-3 ml of Nessler's solution on it. According to this method, if the sample is spoiled its color changes from orange to dark orange depending on the level of spoilage (MEB, 2013) (Figure 7). If the sample is determined to be spoiled, it is labeled as "1" otherwise "0" is used for fresh samples.



a. b.

Figure 7.
Fresh and spoiled ground beef samples
a. Fresh, b. Spoiled

3. RESULTS AND DISCUSSION

3.1. Android Application

After the software and hardware are created and the model is developed, the performance of the prototype is tested. For e-nose analysis; after the device is connected to the power supply and the sensors are warmed up within 15-20 minutes, the lid is mounted on the sample jar. It is necessary to connect the device to the Android application running on the phone via Bluetooth. When the connection is established, instant sensor data appear on the screen just below the Bluetooth icon. If the sample is for training (the spoilage status is determined by chemical analysis method) the class of the sample (0 for fresh, 1 for spoiled) should be entered. It is also required to enter sniffing duration (180 seconds in this study) and, if desired, the sample number. Here, sniffing means exposing the sensors to the headspace of ground beef samples in the jar.

After these parameters are entered, when the Send button is clicked, the sensors' data is recorded for 180 seconds. The elapsed time appears to the right of the New Sample button. When the time is completed, the Process data button clicked and the areas under each sensor curves are calculated. Simultaneously, both the class, sample number and these field values are recorded in the Google Sheets database. After each reading, the sample jar is separated from the lid and left outside until the sensor values stabilize.

After collecting enough data for training the model, logistic regression model is developed on Google Colab as described above and the URL (Ngrok) address where this model works is obtained for classification of unknown samples. Similar procedures are applied during the estimation of spoilage status of unknown samples (model testing). However, after calculating the areas under sensor response curves, the Ngrok URL address obtained from Google Colab should be entered to perform logistic regression analysis. Access Ngrok address should be clicked after the address is entered. The Bring Result button brings the classification result at the bottom of the screen as "Fresh" or "Spoiled". The user interface of the Android application is given in Figure 8.

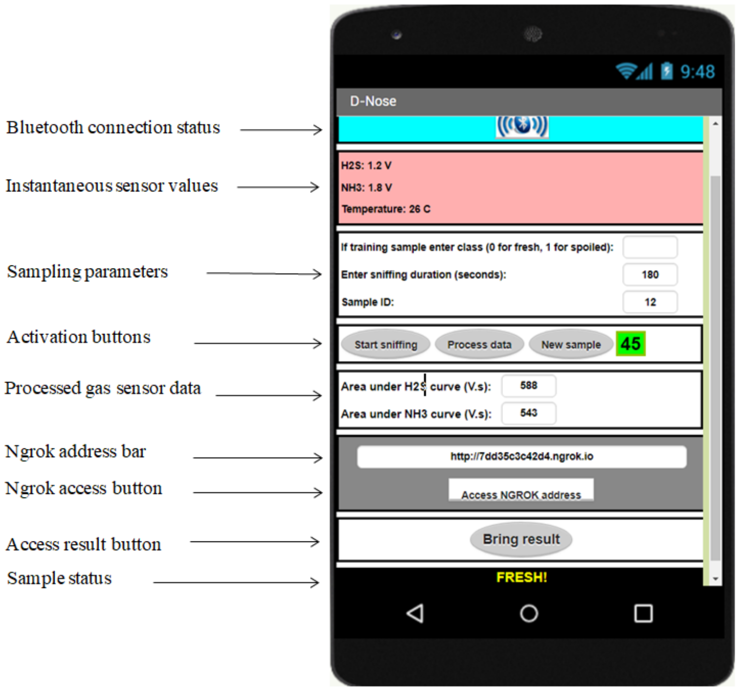


***Figure 8**:*
Android application user interface

3.2. Training and Testing of the Model

Seventy-five grams of sample obtained from daily slaughtered beef from local markets are put into 36 jars. Eighteen samples are kept in the refrigerator. The remainders are stored at room temperature. In addition, 500 g sample obtained from the same sample kept outside in a different container. Small pieces from this sample are taken every 2 hours and analyzed with Nessler's solution to detect the onset of spoilage. Once the spoilage is detected, 18 samples left outside to spoil are also taken to the refrigerator and kept there for about 3 hours until they reach the same temperature as the other samples already refrigerated. All thirty-six samples are sniffed with the e-nose. The sensor data is sent to Google Sheet for training database development.

Following the training phase, the classification performance is tested using different samples obtained from different stores. Twenty-four new samples obtained from local stores belong to 8 different cows are used to test the model performance. Twelve of these samples are stored in the refrigerator while the remainders stored at room conditions as in training phase. The model was able to correctly classify all 24 samples in testing phase. Comparison of the findings of this study with similar e-nose studies is given in Table 5. As it is seen from the table both our e-nose and the systems developed or used by other researchers provides a promising method in the monitoring of beef spoilage.

Table 5. Comparison of literature

Literature	Material	Learning model	Model performance	Cost of e-nose
Balasubramanian et al. (2005)	Beef strip loins	L-1-Out*, QDA**	L-1-Out:100% for unspoiled, 43.75 %. QDA: 100% for unspoiled, 93.78 % for spoiled	$ 11,500
Limbo et al. (2010)	Minced beef	PCA***, CA****	Successful	N/A
Xiao et al. (2014)	Beef strip loins	Linear fitting regression	90 % accuracy	Custom made
Wijaya et al. (2017b)	Beef/pork adulteration	Naïve Bayes classifier	75 % accuracy	Custom made
Huang and Gu (2022)	Beef/pork adulteration	1DCNN-RFR*****	R^2 of 0.9852	$ 26,693
OUR STUDY	**Ground beef**	**Logistic regression**	**100 % accuracy**	**$ 100**

* Live-one-out, **Quadratic discriminant, *** Principal component analysis, ****Cluster analysis, ****** One-dimensional convolutional neural network.

4. CONCLUSION

Sensor, data processing/handling, and artificial intelligence technologies are developing rapidly. It is also becoming easier and cheaper to access these technologies. Sensors and related electrical/electronic materials obtained at low prices make it possible to develop new technologies that will facilitate our daily life.

The transfer, storage, processing and making meaningful of the data obtained from the sensors have been very important problems for technology developers until recent years. With recent technology, the amount of data that needs to be processed is reaching levels that could not be stored and processed in the internal systems of the devices. Cloud-based data collection and processing technologies developed to solve this problem providing the convenience of working with almost unlimited volume of data. Today, the use of cloud systems operating over the Internet is becoming popular.

In this context, it is aimed to design an electronic nose device by using the above-mentioned sensor and data technologies. Only the sensors and circuits mentioned above constitute the cost of the device. These materials are available online at very low prices. The overall cost of the materials used within the scope of this project is approximately $ 100 in January 2021.

The use of data storage/processing and artificial intelligence model is carried out completely free of charge via the cloud system. Using MIT App Inventor 2, which is also an open-source software development platform, the application of the device is developed completely free of charge.

It is determined that the developed application, device, model and the sampling system specific to this project work successfully. The prototype device is able to classify ground beef samples as spoiled or fresh using the logistic regression model. Today, food safety is one of the most important issues concerning public health. In this context, it is seen that the prototype has a very high potential to be used as an alternative to conventional methods.

CONFLICT OF INTEREST

The authors acknowledge that there is no known conflict of interest or common interest with any institution/organization or person.

AUTHOR CONTRIBUTION

Kemal Eren KIZIL, conducted literature research, experimental and theoretical research, system design and software development,

Simge ÖZALP, supervised the study and interpreted the results.

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