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E-Nose Application for Detecting Banana Fruit Ripe Levels Using Artificial Neural Network Backpropagation Method

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ABSTRACT

Bananas are one of the largest horticultural commodities in Indonesia because in each region of Indonesia there are different types of bananas. Bananas are climacteric because they will feel the experience even though they have been harvested. Currently, the introduction of banana ripeness is still done in a conventional way by utilizing sight and smell. However, this method is not effective in determining fruit maturity because we cannot distinguish between ripe bananas and bananas that are in the early stages because they have almost the same color and aroma. So a system is designed that resembles the human sense of smell to accurately identify the level of ripeness of the fruit. The system is named Electronic Nose or abbreviated as e-Nose. The design of the e-Nose will be done using the Artificial Neural Network Backpropagation method. The results obtained from the application of E-Nose to detect the level of ripeness of bananas with the Artificial Neural Network Backpropagation method, which is a tool capable of predicting the ripeness condition of the bananas being tested so that accurate predictions are obtained and the prediction results are displayed on the website. The accuracy results obtained from the use of the Backpropagation Neural Network method for 3 categories (immature bananas, ripe bananas, and rotten bananas) are 100%, with an epoch of 2000.

1. Introduction

Bananas are horticultural products whose harvest time is when they reach the early indicators of maturity. Bananas are usually picked directly in ripe condition (maturation) with a green color on the skin. The characteristics of bananas that are ready to harvest are that the fruit part is filled and the fruit linger is gone, even though the fruit to be harvested is still green and the flesh is still hard. This is because bananas are climacteric fruits, therefore bananas must be harvested immediately when the previous characteristics have been met so that when they are in the hands of banana consumers, they can reach the optimum ripening process. Climacteric fruit is a fruit that experiences a spike in respiration and ethylene production after harvesting [2]. As a climacteric fruit, bananas produce a lot of gas in the ripening process, one of which is ethylene gas. In climacteric fruit, ethylene gas plays a very important role in the physiological and biochemical changes that occur during the ripening process.

At this time the introduction of banana ripeness is still done conventionally by utilizing the senses of sight and smell, whereas this method is done by looking at the condition of the skin of the fruit and the aroma of the fruit. However, this method is not effective in determining fruit maturity, this is because we cannot distinguish ripe bananas from bananas that have almost reached the rotten stage. After all, the colors of the two conditions are almost the same. To be able to recognize bananas based on the level of maturity, a system that can work accurately is needed.

With technological advances that are growing rapidly at this time, Electronic Nose (e-Nose) is one of the solutions for detecting fruit ripeness which is included in a non-destructive method. The development of the Electronic Nose (e-Nose) has reached all aspects such as the health sector, agriculture, animal husbandry, etc.

In this research, a system will be built to identify the ripeness level of bananas using Electronic Nose (E-Nose). The system design is carried out using the Artificial Neural Network Backpropagation method to identify gas patterns that will be the reference for categorizing banana ripeness levels based on aroma, which is formed by 13 input nodes, 1 hidden layer, and 3 output nodes. The e-Nose system consists of a device part and a server part. The system classifies the level of ripeness of bananas into the categories of unripe bananas, ripe bananas, and rotten bananas.

2. Methods and Procedures

The e-Nose system is divided into device section, server section, and machine learning methods.The device section consists of a microcontroller and sensor array. Furthermore, the data is processed on the server and the prediction result are obtained from the mechine learning method. Figure 1 is a block diagram of the electronic nose system (E-Nose).

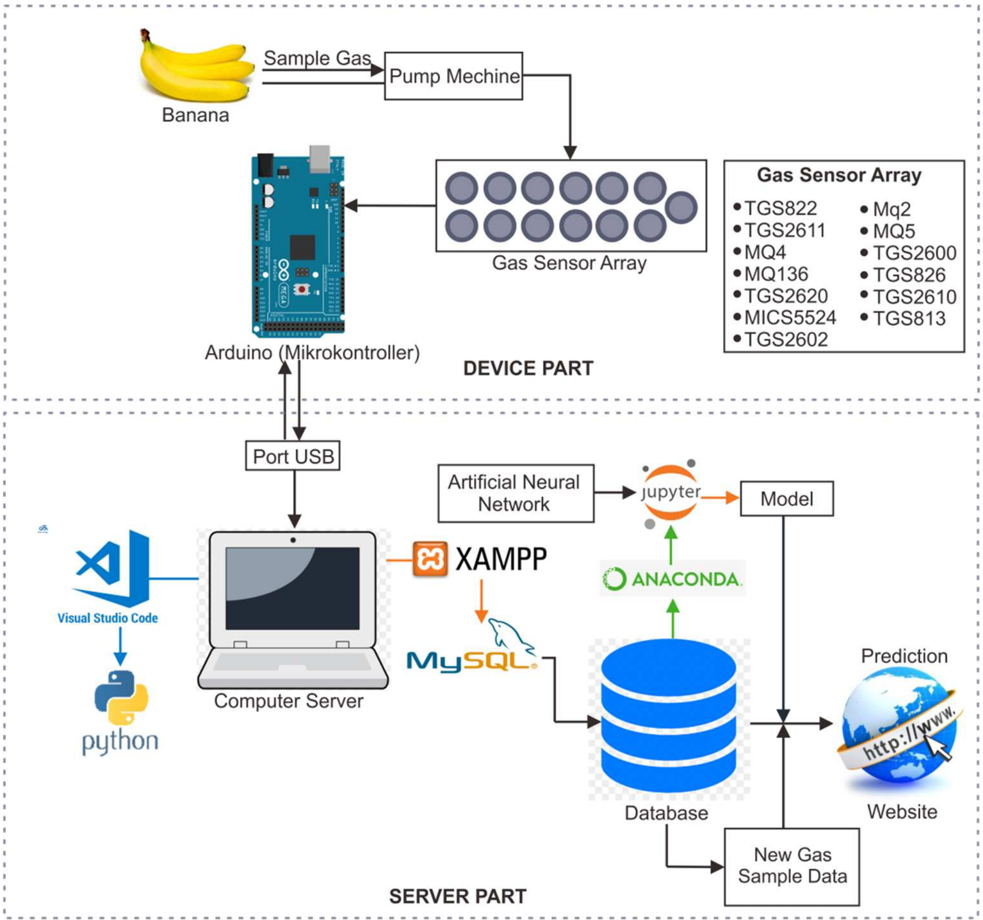

Figure 1. Block diagram of the electronic nose system (E-Nose)

2.1 Device Section

The device section consists of a microcontroller, sensor array, and pump mechine. This section serves as input data from the sensor readings on the banana gas sample. In this section, the microcontroller functions as a control center, so that all data obtained by the sensor array is collected and then processed on the microcontroller. The pump mechine in this tool serves to suck gas from bananas and the gas is flowed into the sensor room. Sensor room is sensor array consisting of 13 gas sensors, namely the TGS 822 sensor, TGS 2611 sensor, MQ 4 sensor, MQ136 sensor, TGS 2620 sensor, MICS sensor 5524, TGS 2602 sensor, MQ 2 sensor, MQ 5 sensor, TGS sensor. 2600, TGS 826 sensor, TGS 2610 sensor, TGS 813 sensor. Furthermore, the data from the sensor array is sent to the server computer via the USB port. Figure 2 is device section of e-Nose and Table 1 displays the sensor characteristics for each chemical.

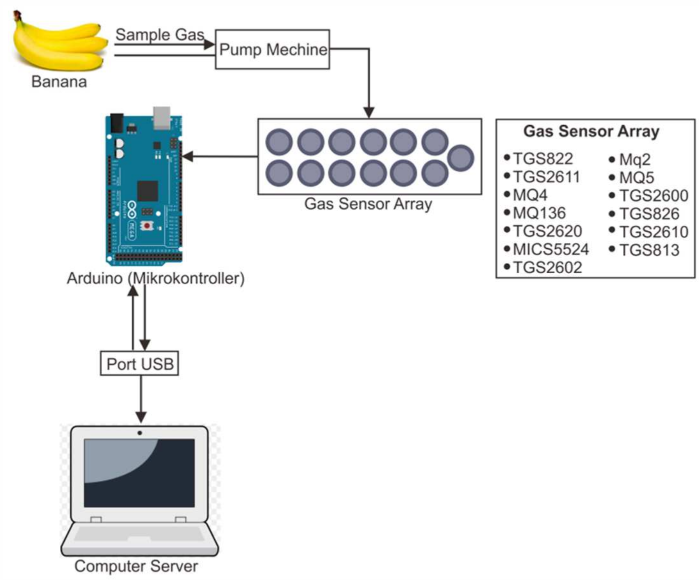

Figure 2. Device section of e-Nose

Table 1. Sensor Array

Sensor	Chemical
MICS 5524	Carbon Monoxide, Ethanol, Hydrogen, Ammonia, Methane
TGS 826	Amonia and Amines
MQ-136	Hidrogen Sulfide and Sulfide
TGS 822	Alcohol and Organic Solvent
MQ-4	Methane, Biogas, Natural Gas
TGS 813	Methane, Propane, Isobutane, Natural Gas, Liquefied Gas
TGS 2602	Cigarette Smoke, Cooking Odor, VOC, Ammonia, Hydrogen Silfide, Alcohol
MQ-5	Butane, Propane, Methane, Liquefied Gas, Natural Gas
TGS 2610	Liquefied Petroleum Gas, Combustible Gas, Propane, Butane
MQ-2	Propane, Smoke, Combustible Gas
TGS 2620	Carbon Monoxide, Ethanol, Organic Solvents, Other Volatile Gases
TGS 2600	Smoke, Cooking Odor, Hydrogen, Carbon Monoxide, Air Pollutants
TGS 2611	Methane, Natural Gas

2.2 Server Section

The server part functions as a data collection center, data processing, decision making, and also as a part that will send information in the form of prediction results to the website. In this section there is Visual Studio Code software with the python programming language, this software is used to run data receiving programs from the USB port to the database. Furthermore, there is xampp software that functions as a MySQL connector, and MySQL is used as a database. And then, Anaconda software functions as a GUI desktop application which is to process data using applications that are already available on Anaconda Navigator, so with this software data from sensor arrays is processed, and also made the website uses the application. Figure 3 is server section.

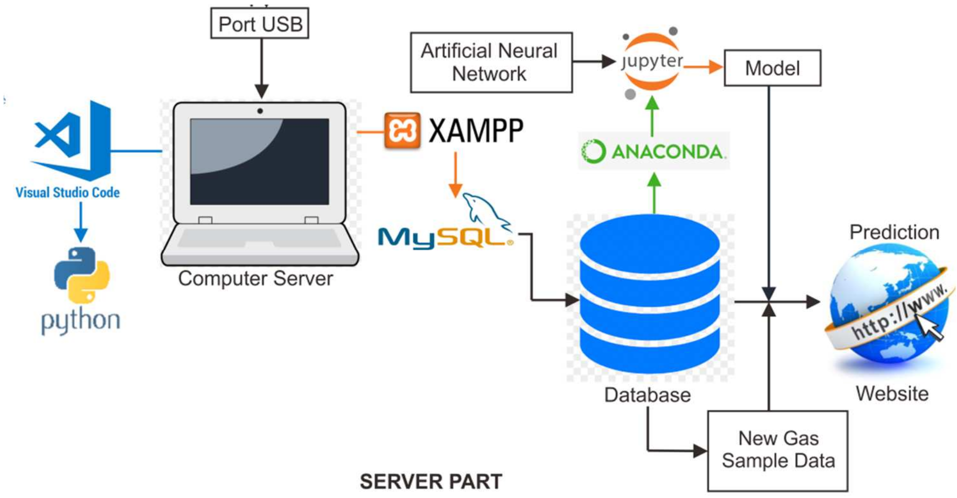

Figure 3. Server section

2.3 Machine Learning

The method used in this e-nose is an artificial neural network with a backpropagation training method. Backpropagation serves to minimize errors or errors in the output of the Artificial Neural Network. The backpropagation architecture is shown in Figure 4. The architecture is formed by 13 input nodes, 1 hidden layer, and 3 outputs. The Tensorflow framework is applied to create a backpropagation model. The training process is configured with 2000 epochs.

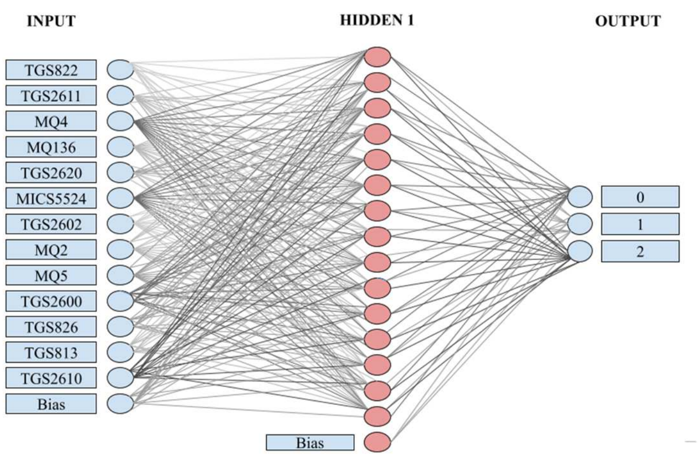

Figure 4. Backpropagation Architecture

3. Results and Discussion

In this tool, the data that is processed to create a model is 1821 data for each category (unripe bananas, ripe bananas, rotten bananas). Furthermore, labeling is carried out on the data in each category, where the label '0' is an unripe banana, the label '1' is a ripe banana, and the label '2' is a rotten banana. The labeling is done manually because the data obtained is clear for the 3 categories. Figure 5 is data that has been labeled.

1	id,tgs822,tgs2611,mq4,mq136,tgs2620,mics5524,tgs2602,mq2,mq5,tgs2600,tgs826,tgs2610,tgs813,kluster
2	1,36,161,120,34,161,65,130,74,41,85,43,87,5,0
3	2,37,161,120,36,157,64,129,74,41,85,41,83,6,0
4	3,35,160,120,36,158,65,126,74,41,85,42,84,6,0
5	4,36,161,120,34,159,65,130,73,41,85,41,85,5,0
6	5,35,161,120,34,158,65,130,74,41,86,41,85,5,0
7	6,35,161,119,35,160,66,128,74,41,86,41,84,4,0
8	7,36,161,120,35,156,66,126,74,41,85,41,85,5,0
9	8,35,161,119,35,157,66,128,74,41,85,41,83,5,0
2468	2467,68,173,164,44,222,93,252,109,47,103,94,131,3,1
2469	2468,72,174,166,45,217,93,250,110,47,105,95,136,4,1
2470	2469,71,174,168,44,226,93,253,111,47,105,97,132,3,1
2471	2470,70,173,167,45,229,95,259,111,47,107,95,133,3,1
2472	2471,70,173,166,45,224,96,259,110,47,107,98,137,3,1
2473	2472,69,173,164,44,228,95,260,110,48,106,95,137,2,1
2474	2473,71,173,162,44,219,95,257,109,46,106,94,130,3,1
2475	2474,71,173,158,42,219,95,255,107,46,104,97,134,3,1
4198	4197,142,196,197,60,279,144,329,232,54,172,130,162,4,2
4199	4198,145,195,198,58,284,144,337,232,53,173,133,163,5,2
4200	4199,143,195,198,59,291,142,342,233,53,174,130,161,4,2
4201	4200,144,196,196,61,283,148,343,233,54,173,129,159,5,2
4202	4201,144,195,197,59,285,148,337,232,54,171,130,164,3,2
4203	4202,141,195,196,61,280,146,333,231,53,173,131,160,4,2
4204	4203,144,196,198,58,290,147,337,232,53,172,131,164,4,2

Figure 5. The dataset

Figure 6 is the result of the training model evaluation with a test loss of 3.4184401975778655e-09 (3.4184401975778655 x 10^-9 = 0.0000000034184401975778655) and test accuracy of 1.0.

```
Test loss: 3.4184401975778655e-09
Test accuracy: 1.0
```

Figure 6. Model evaluation

Figure 7 is a graph of training accuracy and validation accuracy resulting from the training process carried out. The training accuracy is 1.0 and 1.0 for validation accuracy.

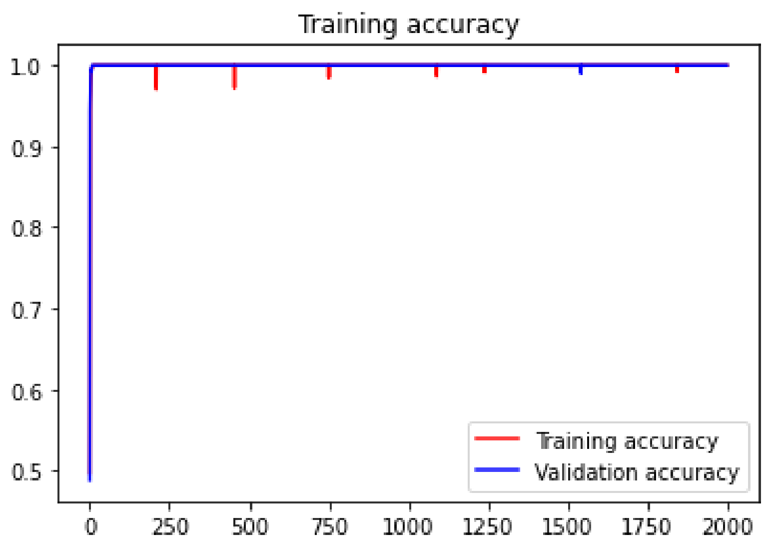

Figure 7. Training Accuracy

Figure 8 shows the model's performance based on precision, recall, and f1+score. The next stage is to deploy the model on a web application.

```
In [20]: from sklearn.metrics import classification_report
         print(classification_report(y_test, y_test_pred))

              precision    recall  f1-score   support

           0       1.00      1.00      1.00       568
           1       1.00      1.00      1.00       534
           2       1.00      1.00      1.00       537

    accuracy                           1.00      1639
   macro avg       1.00      1.00      1.00      1639
weighted avg       1.00      1.00      1.00      1639
```

Figure 8. Classification report

Figure 9 is main website display. Figure 10 shows the prediction on web for the unripe banana. Figure 11 depicts the predicted ripe banana. And then rotten banana is shown on Figure 12.

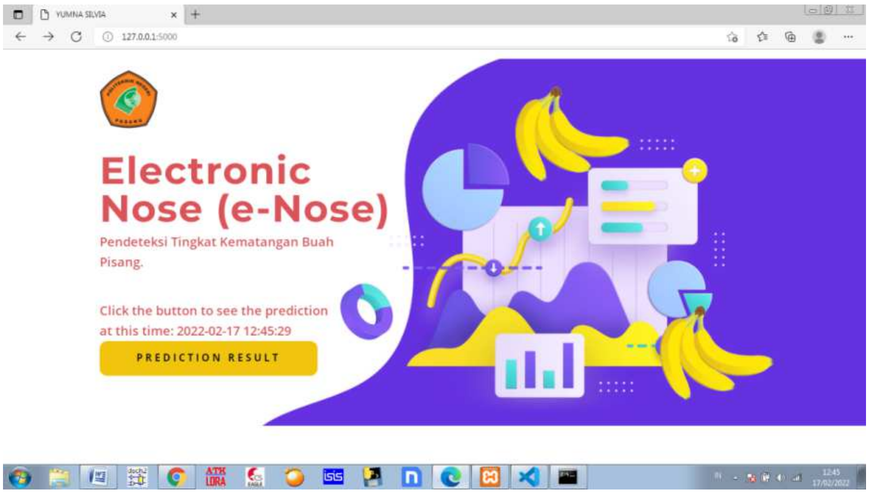

Figure 9. Main Website Display

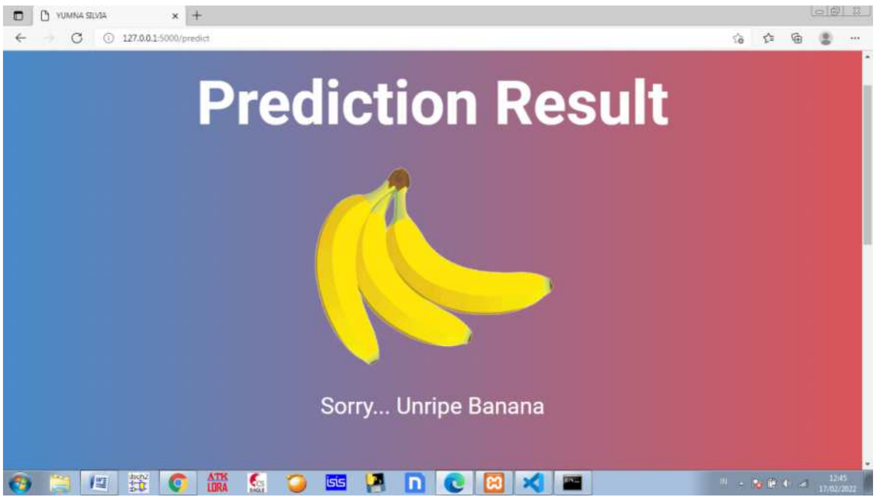

Figure 10. Display Web display of unripe banana

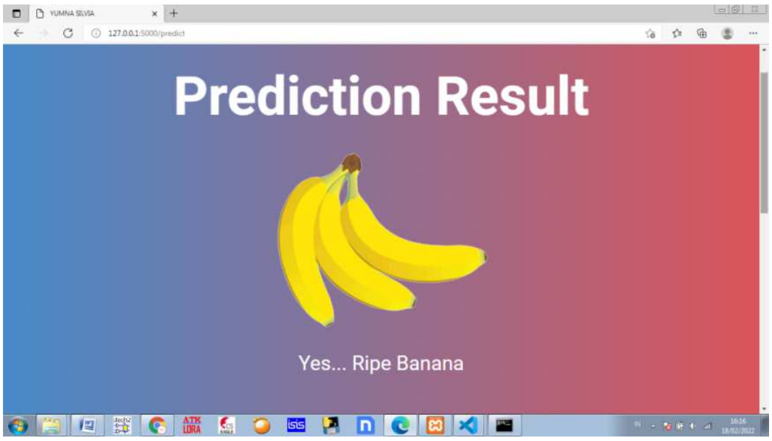

Figure 11. Web display of ripe banana

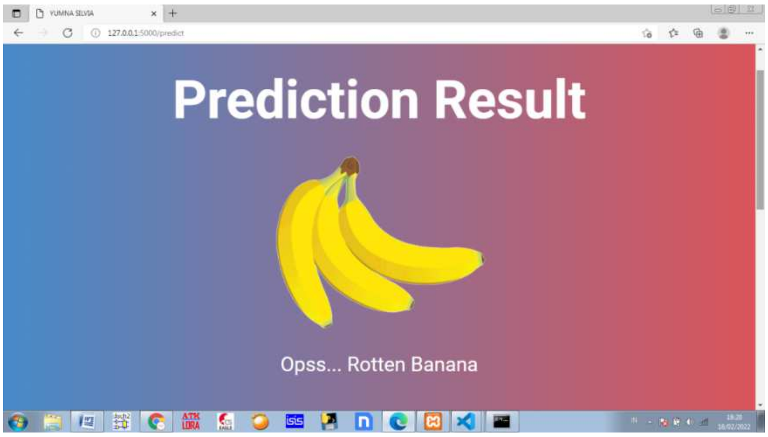

Figure 12. Web display of rotten banana

The model succeeded in categorizing three levels of banana ripeness. The effect of the banana fruit maturity level category on the ADC value and the voltage generated from the gas sensor array, namely the more rotten the banana ripeness level, the greater the ADC value and the resulting voltage, can be seen in Figure 13. The time of sending data from hardware to database is equal to 15 seconds so that for 1 minute as much as 4 data are collected. Meanwhile, the delivery time from the database to the website is predicted to be the same.

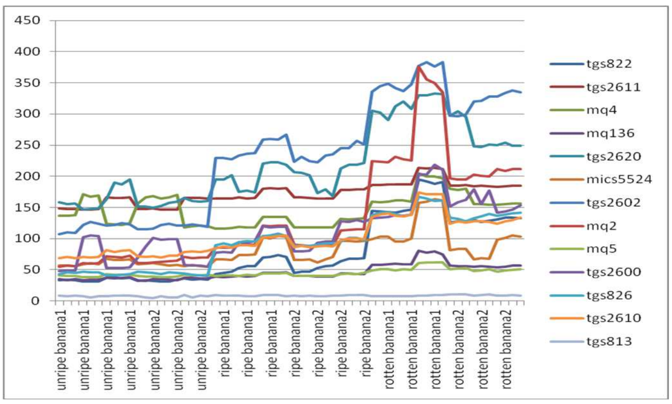

Figure 13. Comparison graph of all gas sensor tests

4. Conclusion

Based on the experiments, the e-Nose system succeeded in categorizing the ripeness level of bananas, namely unripe bananas, ripe bananas, and rotten bananas. The website server displays the prediction results smoothly until this paper is made. After several tests, the accuracy of the e-Nose model is 100%.

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