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

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1. Introduction
Bananas are horticultural products whose harvest time is when they reach the early indicators of maturity. 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.

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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 machine 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 machine. 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 machine 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.

![Device section of e-Nose](image)

Figure 2. Device section of e-Nose

| Sensor      | Chemical                                                                 |
|-------------|-------------------------------------------------------------------------|
| MICS 5524   | Carbon Monoxide, Ethanol, Hydrogen, Ammonia, Methane                   |
| TGS 826     | Amonia and Amines                                                      |
| MQ-136      | Hydrogen 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 Sulfide, 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                                                   |

Table 1. Sensor Array

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.

![Server section](image)

**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.

![Backpropagation Architecture](image)

**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.
Figure 5. The dataset

Figure 6 is the result of the training model evaluation with a test loss of $3.4184401975778655e-09$ ($3.4184401975778655 \times 10^{-9} = 0.000000034184401975778655$) 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.
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
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.
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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