Electronic Nose Based on Sensor Array for Classification of Beef and Rat Meat Using Backpropagation Artificial Neural Network Method

Diana Rusjayanti
Department of Computer Engineering, Universitas Wiralodra, Indramayu, Indonesia

Indri Yanti
Department of Computer Engineering, Universitas Wiralodra, Indramayu, Indonesia

Muh Pauzan
Department of Computer Engineering, Universitas Wiralodra, Indramayu, Indonesia

Abstract: The differentiation of beef and rat meat is crucial for food safety and consumer protection. This research aims to create a tool to distinguish between beef and rat meat and to analyze the training data patterns for both types of meat. A sensor array consisting of three gas sensors—TGS822, TGS2602, and TGS2610—was used to detect the presence of Metal Oxide Semiconductor (MOS) gases in the meat samples. The classification method employed was a backpropagation artificial neural network (ANN). Results indicate that the classification tool performs well in differentiating beef from rat meat, with distinct patterns observed in the training data for each type of meat. The model achieved a precision of 100%, a recall (sensitivity) of 80%, and an accuracy of 90%. However, the TGS2610 sensor did not show a significant difference between beef and rat meat, suggesting no variance in the gas content detected by this sensor. These findings highlight the potential of using such sensors in practical applications for meat detection and underscore the need for further refinement in sensor selection and system integration to improve classification performance.

Keywords: Artificial Neural Network, Backpropagation, Electronic Nose, Meat Classification, Sensor Array.

Correspondents Author:
Indri Yanti, Department of Computer Engineering, Universitas Wiralodra, Indramayu, Indonesia
Email : indriyanti.ft@unwir.ac.id

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Introduction

Meat is an important source of protein for human nutrition, but identifying the quality and purity of meat is crucial for food safety. Food fraud, such as mixing rat meat with beef, can cause serious health problems for consumers(Lestari, 2020; Arvita Kholestyana and Hana Maria Salsabila, 2023). To address this issue, there are international regulations and standards like the Codex Alimentarius, which provide guidelines for hygiene, labeling, and preventing food fraud. In Indonesia, The government is responsible for protecting public by setting rules and oversight in whole food supply chain (Lukman *et al.*, 2023), BPOM and the Ministry of Agriculture enforce regulations to ensure the safety and quality of meat products, including the implementation of GMP and HACCP. By adhering to these standards, the food industry can protect consumers and maintain public trust.

Research on differentiating rat and beef meat utilizes various methodologies such as DNA barcoding, PCR-RFLP, proteomics, ELISA, GC-MS, FTIR, immunohistochemistry, and Western blotting. Each method offers distinct advantages: DNA-based techniques such as PCR-RFLP provide precise genetic differentiation, while proteomics and ELISA focus on protein markers. Chemical analyses like GC-MS and FTIR detect unique volatile compounds and molecular vibrations, respectively. Immunological methods such as immunohistochemistry and Western blotting use antigen-antibody interactions for tissue and protein differentiation. However, gaps remain in integrating advanced technologies for improved accuracy and cost-effectiveness, standardizing protocols, validating methods for practical application, and addressing accessibility challenges in industrial contexts. Addressing these gaps promises enhanced food safety, regulatory compliance, and consumer confidence in meat.

A classification method that has been proven effective in pattern recognition is the backpropagation neural network method (Wiranto et al., 2023; Faradiba, 2017). Artificial neural networks are mathematical models inspired by neural networks in the human nervous system. The backpropagation method is a technique used in artificial neural network training, which allows artificial neural networks to learn complex patterns and recognize patterns that are not easily visible to humans. The backpropagation neural network method has been widely applied in various scientific disciplines such as prediction of agriculture and mining stock (Meizir & Rikumahu, 2019), prediction and forecast in banking (Sovia et al., 2018), computer network security (Guan & Yang, 2019), and in green energy such as photovoltaic power prediction (Chen et al., 2017).

In the context of recognizing and classifying types of meat, the use of backpropagation neural networks has great potential. Artificial neural networks can learn from data examples that include various features and characteristics of rat and beef meat, such as texture, color, chemical composition, odor, and others. In this case, artificial neural networks can involve deep layers to recognize complex patterns and gain a deeper understanding of the unique characteristics of each type of meat. To support the recognition and classification process, the use of MOS gas sensors can also be involved. MOS (Metal-Oxide-Semiconductor) gas sensors are used to collect data on the odor and gases produced by meat (Ismarti, 2021; Simamora, 2017). This sensor is able to detect and measure odor related to the distinctive characteristics of rat and beef meat. Data obtained from the MOS gas sensor can be used as an important feature in the classification process using the backpropagation neural network method.

Various studies have previously been carried out regarding the classification of the type and freshness of meat using other approaches, such as image processing. Several studies on meat classification using image processing such as minced meat classification using digital imaging system coupled with K-Nearest Neighbors (KNN) (Stendafity et al., 2023), chicken meat freshness classification using convolutional neural network, input data was from camera (Garcia et al., 2022). Classification of beef meat region based on RGB image by means of convolutional neural networks (Alp & Şenlik, 2023). Apart from that, several studies have used image analysis using K-Nearest Neighbor (KNN), including research discussing image classification of beef and pork based on color and texture characteristics. The results of the research show that image classification of beef and pork based on color and texture characteristics can be done with fairly high accuracy, namely 92.5%. However, the weakness of this research is that it only uses images of beef and pork taken from one source, so the results cannot necessarily be generalized to images of beef and pork from different sources (Astuti, 2016). Other research that uses image analysis but with a different type of classification is convolutional neural network (CNN). CNN is used to classify beef and pork images. This research collected 3000 images of beef and pork image data which were divided into 3 classes, namely beef, pork and blended meat. The accuracy obtained was 98.33% for image classification of beef and pork. This research does not discuss other factors that can influence the accuracy of meat image classification, such as image quality, lighting, and shooting angle (Alhafis, 2022). Input data from camera for meat classification has been studied by (Asmara *et al.*, 2017) and (Alzaga, Buenaventura and Loresco, 2022). The other input is from gas sensors, such as the reading value was used to classify the freshness of meat carried out by (Juannata, Wijaya and Wikusna, 2022). Other research that uses signal processing in its classification is carried out to classify the purity of beef using an electronic nose with the PCA

(Principal Component Analysis) and SVM (Support Vector Machine) classification methods (Daiva, 2018).

Based on the description above, the classification of meat was employed by laptop/personal computer so that is make it not practical in term of application, and no previous studies are using gas sensors for rat meat classification. Therefore, this research aim is to develop an electronic nose (e-nose) which is practical and portable for classifying types of meat. This research used two types of meat, rat and beef meat. The electronic nose used in this research consists of a sensor array: TGS 822, TGS 2602, and TGS 2610. These sensors function are to detect the odor of the rat meat. During testing, the e-nose was operated using a data acquisition system connected to a sensor array. The sensory signals generated by the sensor array during testing are recorded by the data acquisition system.

Research Method

The method used in this research is experimental research which will produce a prototype of the e-nose tool used to classify types of meat using backpropagation artificial neural networks (ANN).

Research step

This research has several stages to be able to design and create a meat type classification tool using backpropagation ANN. Figure 1 shows a series of stages in this research.

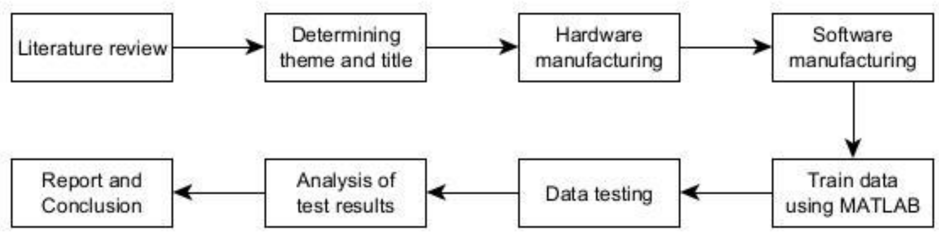

Figure 1 The research steps

Figure 1 shows the flow of research design from start to finish, in outline what will be applied to this research. The first stage is conducting a literature review. Literature reviews are important to determine the steps to be taken in research which are then used to determine themes, titles and gaps from previous research. The next stage is hardware design. Next, is the software design stage, which is related to the use of MATLAB to obtain weight and bias values from the training data which will be used in the Arduino IDE for the testing process. After getting the test results, the data will be analyzed, concluded and reported.

Block diagram

The block diagram of this research consists of 3 parts input, processing or control and output as shown in Figure 2. At input, 3 Taguchi type sensors are used, namely the TGS 822 gas sensor, TGS 2602 gas sensor, and TGS 2610 gas sensor with each sensor function shown in Table 3.7. Data from the three sensors will be processed using Arduino Mega with a classification method, namely the backpropagation artificial neural network. The output section is used to display the results of processing by the system. The system output is in the form of classification results displayed on the I2C 16x2 LCD, while the SD card is used to store data and a fan is used to clean the air in the chamber.

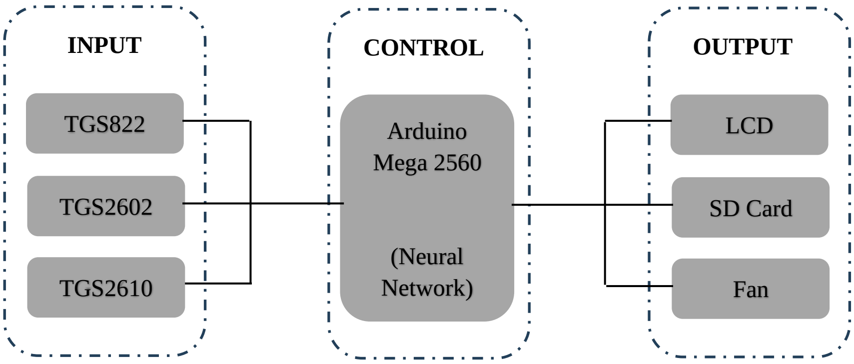

Figure 2 block diagram

Hardware design begins with creating a schematic of the electronic nose circuit. Figure 3 shows a circuit schematic that illustrates the connections between components involved in this research using KiCad software.

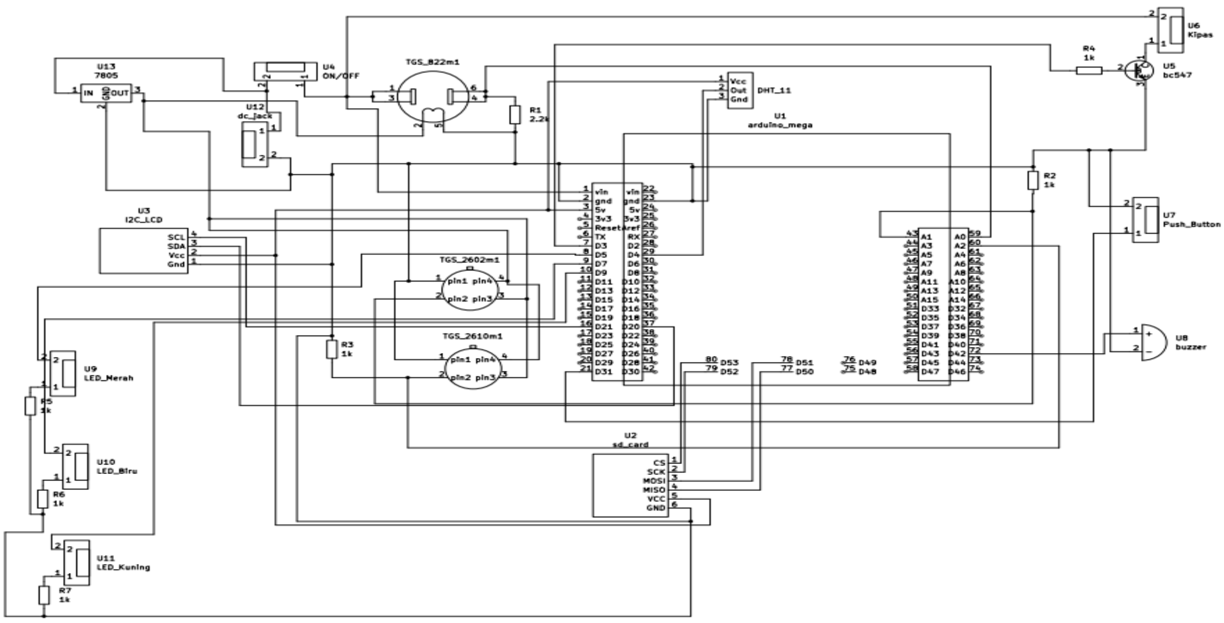

Figure 3 schematics for e-nose

In collecting data from sensor readings installed on the electronic nose, there are three different types of Taguchi Gas Sensor (TGS) Metal Oxide Semiconductor (MOS) gas sensors, namely TGS 822, TGS 2602, and TGS 2610. The purpose of using these three sensors is to expand and enrich the dimensions in the recognition of odor patterns input into Artificial Neural Networks, thereby increasing the ability to recognize aromas with varying levels of difficulty and characteristics.

Apart from using the three TGS sensors, it is also equipped with a DHT11 temperature and humidity sensor. The temperature and humidity used in this research are only for monitoring the environment and do not carry out signal processing (Qothrunnada et al., 2024). The Arduino Mega 2560 in the circuit schematic is used to control other components (Haura et al., 2023; Pauzan & Yanti, 2021; Karimah et al., 2023). The experimental results on this tool will be displayed on the I2C 16x2 LCD screen. Next, the data obtained would be saved on the SD card.

Architecture of artificial neural networks

The classification method for this research uses artificial neural networks (Kohonen et al., 1991), more specifically, namely backpropagation artificial neural networks. This system uses 3 parameters which are input from the three Taguchi sensors (TGS 822, TGS 2602, and TGS 2610), so in this system 3 neurons are used which are symbolized by x, while the hidden layer (z) used in this research is 1 fruit with 10 neurons. In the output layer (y), the system has 1 neuron which is denoted by y and the training target uses a binary number representation. A target value of 0 indicates beef, while a target value of 1 indicates rat meat. Figure 4 shows the artificial neural network architecture used in this research.

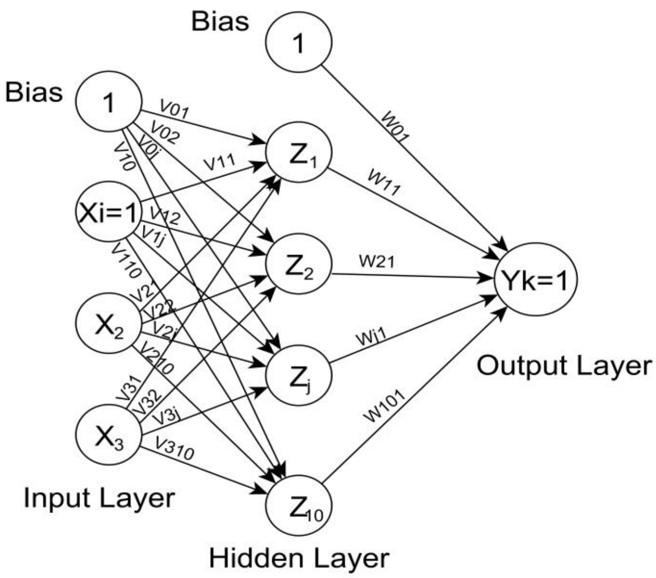

Figure 4 architecture of artificial neural networks

The architecture shown in Figure 4 uses the TANH activation function on layer 1 and sigmoid on layer 2. This activation function was chosen because it was adapted to the one used in MATLAB. MATLAB is used for the training process on training data to obtain the various values needed, one of which is the weight value.

Data analysis

Data analysis in this study was carried out using a confusion matrix. Confusion matrix is a matrix that contains the results of classification predictions and actual data carried out by the classification system (Hasan et al., 2021). The confusion matrix rules are shown in Table 1.

Table 1 Confusion matrix

		Actual value	
		True	**False**
Prediction value	**True**	TP (True Positive)	FP (False Positive)
	False	FN (False Negative)	TN (True Negative)

Based on data from the confusion matrix, the precision, recall and accuracy values that are usually found in machine learning evaluations can be calculated. Precision is the level of accuracy between the information requested by the user and the answer provided by the system. Mathematically, the precision value can be calculated based on equation (1) (Rahayu et al., 2021; Azhari et al., 2021).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Sensitivity or also called recall is the level of success of the system in retrieving information. Mathematically, the recall value can be calculated based on equation (2).

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Accuracy is defined as the level of closeness between the predicted value and the actual value. Mathematically, the accuracy value can be calculated based on equation (3).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Result and Discussion

Starting from schematic and continue to pcb design, then soldering components and put it in the casing. The result is shown in Figure 5.

Figure 5 electronic nose for meat classification

The meat classification tool has two parts or chambers. The first chamber is used to place the PCB board which has been assembled according to the footprint, the I2C 16x2 LCD functions to display values or characters on the device and the LED as an indicator on the device. The second chamber is to place the gas sensor array, namely TGS822, TGS2602, and TGS2610, as well as the DHT11 temperature sensor. The second chamber is also used to place meat samples. Therefore, the second chamber is made closed so that the aroma of the meat sample can be smelled well and does not mix with the ambient air. In the second chamber there is a fan which will turn on for 3 minutes after the testing process is complete automatically to clean the remaining air/gasses in the chamber.

Data training

At the training stage, the training data taken is raw and fresh beef and rat meat. Three gas sensors are used to obtain different results from the two types of the samples. The graph in Figure 6 shows the pattern produced by the three gas sensors that detect beef, while the graph in Figure 7 shows the pattern produced by the three sensors that detect rat meat.

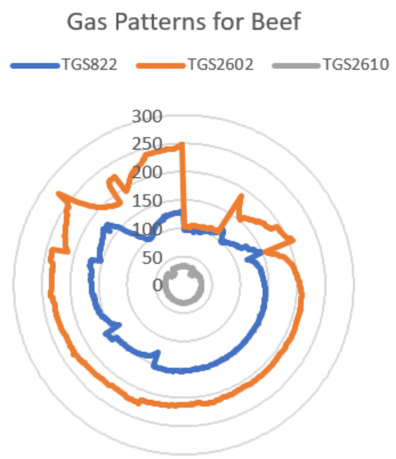

Figure 6 Gasses pattern of sensor array for beef

Figure 6 shows that different gas patterns were detected in the beef samples from the two sensors. However, there are several intersecting patterns. These intersecting things will be difficult to distinguish by human smell, so tools based on artificial intelligence are needed.

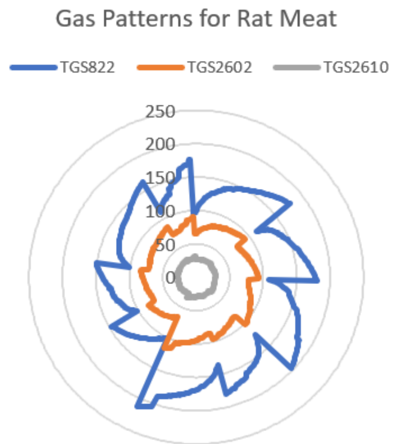

Figure 7 Gasses pattern of sensor for rat meat

The research involves 1000 training data, namely 500 beef data and 500 rat meat data along with data fluctuations during testing from both meat samples. Based on Figure 6 and Figure 7, it shows the combination of patterns from the three different sensors between beef and mutton so that this data can be used as training data.

After getting different patterns from the two types of meat, training was then carried out in MATLAB to get all the parameter values used in the backpropagation neural network. Figure 8 is a cross-entropy vs epoch graph showing the best validation performance at a particular epoch. Cross-entropy is a measure commonly used to evaluate the performance of classification models. Apart from that, a MATLAB Function is also obtained which contains training coding. The backpropagation artificial neural network training coding was then converted into the Arduino programming language and then used to test meat samples.

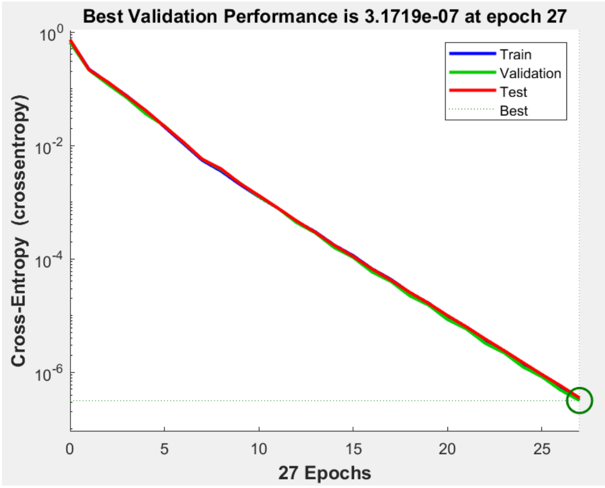

Figure 8 Graphic cross-entropy vs epoch

In Figure 8, the graph depicts the cross-entropy versus the 27 epochs generated from MATLAB (nnstart). The best validation performance observed is 3.1719e-07, which occurs at epoch 27. This performance metric, cross-entropy, is a measure used in machine learning and neural networks to assess the difference between predicted and actual values. A lower cross-entropy value indicates better model performance, suggesting that the neural network trained on this dataset achieved its highest accuracy at epoch 27, with a remarkably low error rate of 3.1719e-07. This graph serves as a visual representation of the model's learning progress over the epochs, showcasing how the cross-entropy loss decreases as the network iteratively learns and improves its predictions.

Data testing

After the training stage, the next stage is the testing stage on the tool to determine the precision, recall and accuracy. At the end, the tool employed for classifying types of beef and rat meat. This tool predicts by looking at the combination of values from three types of gas sensors TGS822, TGS2602, and TGS2610. The beginning step is chopped the meat with a weight of 60 grams then put it into the second chamber, then the meat sample is detected by gas sensors, the values are sent to Arduino Mega, the board do classification. The value results from each sensor will be displayed on the LCD screen and the value will be stored on the micro-SD. During tool testing, the temperature in the second chamber was stable at 20°C. Equipment testing data on samples of both types of meat is shown in Table 2.

Table 2 Testing result for e-nose

No.	Sample	Output	Classification	Ground Truth
1	A	0	Beef	Beef
2	B	0	Beef	Beef
3	C	0	Beef	Beef
4	D	0	Beef	Beef
5	E	0	Beef	Beef
6	F	0	Beef	Beef
7	G	0	Beef	Beef
8	H	1	Rat	Beef
9	I	0	Beef	Beef
10	J	1	Rat	Beef
11	K	1	Rat	Rat
12	L	1	Rat	Rat
13	M	1	Rat	Rat
14	N	1	Rat	Rat
15	O	1	Rat	Rat
16	P	1	Rat	Rat
17	Q	1	Rat	Rat
18	R	1	Rat	Rat
19	S	1	Rat	Rat
20	T	1	Rat	Rat

Classification with the output 0 indicates beef, while 1 indicates rat meat. Ground truth (actual) for sample data 1-10 is beef, while 11-20 is rat meat. In the 8th and 10th data, classification result is error, namely the ground truth was beef but the classification showed rat meat. The causes of misclassification include the sensitivity of the gas sensor. In addition, it is possible that the training data is not clean or contains noise, which can confuse the model and cause classification errors. Table 3 shows the confusion matrix for test data.

Table 3 confusion matrix with data testing

$N = 20$		Actual value	
		True	**False**
Prediction value	**True**	8	0
	False	2	10

Based on the research that has been carried out, it can be concluded that the odor of beef and rat meat is difficult to differentiate directly by humans because in terms of color and odor they are very similar, so it is required tools that can classify them. However, the pattern in the training data between beef and rat meat has a different shape. In the test data, the precision obtained was 100%, the recall or sensitivity was 80% and the accuracy was 90%. The TGS2610 sensor did not show any significant differences between beef and rat meat. This means that both types of meat do not contain the gas detected by the TGS2610. The researcher would like to thank Department of Computer Engineering, Faculty of Engineering, Universitas Wiralodra, which has facilitated research activities in the form of borrowing electronics, embedded systems and IoT laboratories for this research.

Conclusions

Based on Table 3 and equations (1), (2), and (3), precision is 100%, sensitivity (or recall) is 80%, and accuracy is 90%. Precision and sensitivity relate to the model's performance in identifying positive cases, sensitivity focuses more on the model's ability to capture all true positive cases, while precision focuses more on the model's ability to provide correct positive predictions from all the positive predictions made. Accuracy measures how many of all predictions were correct. In this context, an accuracy of 90% means that 90% of all predictions made by the model are correct. This shows that the model provides good predictions. In the confusion matrix analysis, three things, namely precision, sensitivity, and accuracy, are sufficient to describe the performance of the tool that has been created.

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