Design and Development of a Coffee Blending Device with Carbon Monoxide (CO) Level Identification Based on Artificial Neural Networks

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ABSTRACT

Coffee is categorized into three types Robusta, Arabica, and Liberica. The roasting process is the most crucial step in developing the aroma, flavor, and underlying color that determine coffee quality. The coffee roasting process produces complex aroma compounds that impart the desired taste and aroma characteristics of coffee. This research aims to design a coffee content detection tool by determining the carbon monoxide (CO) level in Arabica, Robusta, and Liberica coffee. The research uses the Backpropagation artificial neural network method with 2 hidden layers, including 4 input layers and 3 output layers, to identify the tested coffee varieties. The highest carbon monoxide (CO) levels were found in Arabica Special coffee, with an ADC level of 662 carbon monoxide gas. The lowest carbon monoxide (CO) levels were detected in Liberica coffee, with an ADC level of 105 carbon monoxide gas. Coffee identification was carried out using an artificial neural network method with a success rate of 98% for Liberica coffee, 100% for Arabica coffee, and 98% for Robusta coffee.

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1. Introduction

Coffee is one of the agricultural commodities widely enjoyed by the public. Products made from coffee are highly popular among consumers, leading to an increasing number of community businesses that offer coffee-related products [1][2]. Coffee has health benefits, and regular consumption can reduce the risk of several diseases [3][4]. Consumer awareness of health and coffee flavour has an impact on the demand for high-quality coffee [5]. Improper coffee processing can affect the coffee powder quality, which should adhere to the SNI 01-2983-1992 standard [6]. To enable the evaluation of well-processed coffee, one approach is to consider the carbon monoxide levels [7][8]. Freshly roasted coffee is not pleasant and suitable for consumption[9][10]. After roasting, there is a gas formation process that occurs within the coffee beans. The roasting process also produces complex aroma compounds that provide the desired taste and aroma characteristics in coffee[11]. The roasting process in coffee bean processing has a significant impact on coffee quality, leading to changes in the coffee content[12][13][14]. The gas composition released from whole coffee beans during the grinding process has been reported by Clarke and McRae as 87% carbon dioxide (CO2), 7.3% carbon monoxide (CO), and 5.3% nitrogen (N2), with the remainder (less than 1%) being volatile organic compounds (VOC) [15]. Coffee that is freshly roasted may not taste good because the carbon monoxide content tends to still be present inside it, which is not healthy [16]. This study involves the development of a coffee-making device that identifies CO levels using electronic sensors, specifically aroma sensors. The system testing utilizes LabVIEW Virtual Instruments (Vi) programming. The device's mechanism is designed to take into account the fineness level, and the CO identification will be synchronized with the fineness level of each coffee. This research is conducted with the aim of designing a coffee content detection device by determining the carbon monoxide (CO) level in Arabica, Robusta, and Liberica coffee. It seeks to identify the best coffee for consumption based on the carbon monoxide (CO) content using an Enose sensor. It utilizes the Backpropagation artificial neural network method with 2 hidden layers to identify the tested coffee varieties.

2. Research Methodology

An Electronic Nose (E-Nose) is an instrument capable of recognizing complex characteristic information [17][18][19]. The E-Nose is the result of responses from multiple sensors with partial specificity and the aroma reactions to various volatile compounds, functioning in a manner similar to the human nose [20][21]. The working mechanism of the nose in animals or humans is based on identifying gases emitted by volatile organic compounds (VOC) in the air, recognized based on previously stored aromas in the brain [22]. there are types of electric nose sensors.

The MQ135 sensor is sensitive to compounds such as NH3, NOx, alcohol, benzene, smoke (CO), and CO2. Its analog resistance value changes when exposed to gases. Due to its practicality and low power requirements, this sensor is suitable for use as a pollution hazard indicator [23]. The MQ-7 gas sensor is used in equipment to detect carbon monoxide (CO) gas in automobiles, industries, or everyday life. This sensor has high sensitivity to CO, is long-lasting, and stable. To measure accurately, it uses a 5V AC/DC heating power supply and a 5V circuit power supply. Its measurement range is between 20 and 2000 ppm [24]. The TGS 2602 sensor has low alcohol concentration and high sensitivity to air contaminants from outdoor gases like ammonia and H2S. Due to its small chip size, this sensor only requires a heating current of 56mA and is mounted in a TO-5 component package [25]. The TGS 2620 sensor has high sensitivity to organic solvent vapours and other easily evaporating vapours, making it suitable for organic vapor detectors/alarms. Due to the miniaturization of the sensing chip, the TGS 2620 requires only 42mA of heating current and is housed in a standard TO-5 package [26].

In addition to being a beverage associated with bitterness, coffee is also known for its acidity. That's why some people are reluctant to drink coffee because they fear that its acidity may affect their health. After coffee is roasted, there is a gas formation process that occurs within the coffee because [27]. Roasted coffee may taste less enjoyable because the carbon monoxide content tends to remain within the coffee. Degassing is the continuous release of CO gas (naturally) over a specific period of time [28].



Figure 1. Mechanical Design

The physical description of the testing equipment can be seen in Figure 1. Part A is where coffee beans are placed for grinding into coffee powder. Part B serves as the location for attaching all E-

nose sensors. Meanwhile, Part C functions as the container used to collect the ground coffee during the testing process. Part D consists of a monitor screen that displays the output values obtained from four sensors, namely MQ-135, TGS 2602, TGS 2620, and MQ-7.

In simple terms, the Artificial Neural Network (ANN) JST Backpropagation process can be divided into two parts, which are training and testing. Training is the learning process of the artificial neural network system, where it learns the input values and how to map them to the output until an appropriate model is obtained [29][30]. Additionally, testing is the process of checking the accuracy of the model obtained from the training process an example of a backpropagation network with two hidden layers can be seen in the following figure 2.



Figure 2. Backpropagation artificial neural network 2 hidden layers

The results of training in MATLAB with ANN JST Backpropagation with 19 epochs have approached the predicted target value. A regression value of 1 indicates a good fit between the input data and the target data, as seen in Figure 3.

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4 b	€ Zeo	w +		Output Document 3
Algorithms				
Data Division: Random	(divideranc	n		
Training: Levenbe	rg-Marguard	t (trainlm)		
Performance: Mean Sq	uared Error	(mse)		
Calculations: MATLAB	1			
Progress				
Epoch:	0	19 iterations		1000
Time:		0:00:15		
Performance: 0.	.294	1.47e-13	3	0.00
Gradient: 0.	.206	7.70e-08	1	1.00e-07
Mu: 0.00100		1.00e-17] 1.00e+10
Validation Checks:	0	0		6
Plots				
Performance	(plotperform)		
Training State	(nlottrainetat	- -		
indining state	(proter unified	7		
Error Histogram	(ploterrhist)			
Regression	(plotregression)			
Fit	(plotfit)			
			1 epochs	
Plot Interval: 1				

Figure 3. Display of artificial neural network training

3. Results And Discussion

In circuit design, the economic value of the components used must be taken into consideration. Before creating the circuit and system, a block diagram is first designed. This is to achieve the goal of having a circuit that leads to the desired outcome, as illustrated in the block diagram shown in the figure 4.

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Figure 4. Block Diagram

Based on Figure 4, the functions of each block diagram are as follows: Sensors are used to identify the formation of carbon monoxide (CO) gas is MQ-135, MQ-7, TGS 2602, and TGS 2620. The Arduino microcontroller is used for programming to display the gas reading results to the output. The monitor is used as a display medium for the values of the generated gas.Artificial Neural Network is the method used in this research. The type of ANN used is backpropagation with 2 hidden layers.

To easily understand the system's operation, you can refer to the system flowchart diagram shown in the figure 5.



Figure 5. System Flowchart

The working principle of this device is as follows: when the AC motor is activated, and the roasted coffee is ground into coffee powder, the coffee is left in the coffee container. The gas sensors, including MQ-135, MQ-7, TGS 2602, and TGS 2620 used in this research, will identify the various gases formed after the coffee grinding process. The Arduino software will program the sensors to identify carbon monoxide (CO) gas. The gas data is used as input data for the identification process using artificial neural networks in the Matlab software, and the identification results are then displayed on the monitor.

Data was collected on the sensor responses to different types of coffee, including arabica, liberica, and robusta, with varying roasting levels, namely light, medium, and dark. The measurements were taken over a duration of 1 minute and 10 seconds.



Figure 6. Sensors Respon E-Nose



Figure 7. Sensors Respond E-nose

In Figure 6 and 7, it can be observed that the highest carbon monoxide (CO) level was found in special Arabica coffee with a carbon monoxide gas level of 662, while the lowest carbon monoxide (CO) level was detected in Liberica coffee with a carbon monoxide gas level of 105.

For the training sample data collection, three types of coffee were used: Robusta, Arabica, and Liberica. The sampling process was conducted by collecting 70 data samples from the MQ-135, TGS 2602, TGS 2620, and MQ-7 sensors. All data was fed into the artificial neural network for training to obtain weight and bias values for coffee identification using the Artificial Neural Network method.

 $\frac{70}{70}x100\% = 100\%$

The success rate in identifying Arabica coffee powder reaches 100%.

$$\frac{69}{70}$$
 x100% = 98%

The success rate in identifying Robusta coffee powder reaches 98%.

$$\frac{69}{70}x100\% = 98\%$$

The success rate in identifying Liberica coffee powder reaches 100%.

The results achieved showed the ability to identify Liberica coffee with a success rate of 98%, Arabica coffee with 100%, and Robusta coffee with 98%.

4. Conclusion

The highest carbon monoxide (CO) levels were found in Arabica Special coffee, with an ADC level of 662 carbon monoxide gas. The lowest carbon monoxide (CO) levels were detected in Liberica coffee, with an ADC level of 105 carbon monoxide gas. The Artificial Neural Network method can identify Liberica coffee with a success rate of 98%, Arabica coffee with 100%, and Robusta coffee with 98%.

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References

- M. Münchow, J. Alstrup, I. Steen, and D. Giacalone, "Roasting conditions and coffee flavor: A multistudy empirical investigation," Beverages, vol. 6, no. 2, pp. 1–14, 2020, doi: 10.3390/beverages6020029.Y. Zheng, "Estimation of Disease Transmission in Multimodal Transportation Networks," Asian J. Public Opin.
- [2] A. Samoggia and B. Riedel, "Consumers' perceptions of coffee health benefits and motives for coffee consumption and purchasing," Nutrients, vol. 11, no. 3, 2019, doi: 10.3390/nu11030653.
- [3] I.Elmadfa and A. L. Meyer, "Patterns of drinking and eating across the European Union : implications for hydration status," vol. 73, pp. 141–147, 2015, doi: 10.1093/nutrit/nuv034.
- [4] R. Poole, O. J. Kennedy, P. Roderick, J. A. Fallowfield, P. C. Hayes, and J. Parkes, "Coffee consumption and health: umbrella review of meta-analyses of multiple health outcomes," BMJ, vol. 359, p. j5024, 2017, doi: 10.1136/bmj.j5024.
- [5] H. Ashihara and A. Crozier, "Biosynthesis and catabolism of caffeine in low-caffeine-containing species of Coffea," J. Agric. Food Chem., vol. 47, no. 8, pp. 3425–3431, 1999, doi: 10.1021/jf981209n.
- [6] M. S. Butt and M. T. Sultan, "Coffee and its Consumption : Benefits and Risks Coffee and its Consumption : Benefits," vol. 8398, 2011, doi: 10.1080/10408390903586412.
- [7] A. E. Özen, M. del Mar Bibiloni, A. Pons, and J. A. Tur, "Fluid intake from beverages across age groups: A systematic review," J. Hum. Nutr. Diet., vol. 28, no. 5, pp. 417–442, 2015, doi: 10.1111/jhn.12250.

- [8] I. Elmadfa and A. L. Meyer, "Patterns of drinking and eating across the European Union : implications for hydration status," vol. 73, pp. 141–147, 2015, doi: 10.1093/nutrit/nuv034.
- [9] M. T. L. Kreuml, D. Majchrzak, B. Ploederl, and J. Koenig, "Changes in sensory quality characteristics of coffee during storage," Food Sci. Nutr., vol. 1, no. 4, pp. 267–272, 2013, doi: 10.1002/fsn3.35.
- [10] R. F. LeBouf and M. Aldridge, "Carbon monoxide emission rates from roasted whole bean and ground coffee," J. Air Waste Manag. Assoc., vol. 69, no. 1, pp. 89–96, 2019, doi: 10.1080/10962247.2018.1515125.
- [11] S. Schenker, C. Heinemann, M. Huber, R. Pompizzi, R. Perren, and F. Escher, "Impact of roasting conditions on the formation of aroma compounds in coffee beans," J. Food Sci., vol. 67, no. 1, pp. 60–66, 2002, doi: 10.1111/j.1365-2621.2002.tb11359.x.
- [12] R. Susanti, A. Hidayat, N. Alfitri, and M. Ilhamdi, "Identification of Coffee Types Using an Electronic Nose with the Backpropagation Artificial Neural Network," vol. 7, no. September, pp. 659–664, 2023.
- [13] X. Wang and L. T. Lim, "Effect of roasting conditions on carbon dioxide degassing behavior in coffee," Food Res. Int., vol. 61, pp. 144–151, 2014, doi: 10.1016/j.foodres.2014.01.027.
- [14] B. A. Anderson, E. Shimoni, R. Liardon, and T. P. Labuza, "The diffusion kinetics of carbon dioxide in fresh roasted and ground coffee," J. Food Eng., vol. 59, no. 1, pp. 71–78, 2003, doi: 10.1016/S0260-8774(02)00432-6.
- [15] S. Smrke, M. Wellinger, T. Suzuki, F. Balsiger, S. E. W. Opitz, and C. Yeretzian, "Time-Resolved Gravimetric Method to Assess Degassing of Roasted Coffee," J. Agric. Food Chem., vol. 66, no. 21, pp. 5293–5300, 2018, doi: 10.1021/acs.jafc.7b03310.
- [16] P. Mirmiran, M. Carlström, Z. Bahadoran, and F. Azizi, "Nutrition, Metabolism & Cardiovascular Diseases Long- term effects of coffee and caffeine intake on the risk of pre-diabetes and type 2 diabetes : Findings from a population with low coffee consumption," Nutr. Metab. Cardiovasc. Dis., pp. 2–7, 2018, doi: 10.1016/j.numecd.2018.09.001.
- [17] S. Xu et al., "Detecting and monitoring the flavor of tomato (Solanum lycopersicum) under the impact of postharvest handlings by physicochemical parameters and electronic nose," Sensors (Switzerland), vol. 18, no. 6, pp. 1–15, 2018, doi: 10.3390/s18061847.
- [18] H. Harianto, M. Rivai, and D. Purwanto, "Implementation of Electronic Nose in Omni-directional Robot," Int. J. Electr. Comput. Eng., vol. 3, no. 3, 2013, doi: 10.11591/ijece.v3i3.2531.
- [19] P. Tyagi, R. Semwal, A. Sharma, U. S. Tiwary, and P. Varadwaj, "E-nose: a low-cost fruit ripeness monitoring system," J. Agric. Eng., vol. 54, no. 1, 2023, doi: 10.4081/jae.2022.1389.
- [20] C. F. Tsai and I. P. J. Jioe, "The analysis of chlorogenic acid and caffeine content and its correlation with coffee bean color under different roasting degree and sources of coffee (Coffea arabica typica)," Processes, vol. 9, no. 11, 2021, doi: 10.3390/pr9112040.
- [21] F. Röck, N. Barsan, and U. Weimar, "Electronic nose: Current status and future trends," Chem. Rev., vol. 108, no. 2, pp. 705–725, 2008, doi: 10.1021/cr068121q.
- [22] S. Firestein, "Howtheolfactorysystem makessense of scents," vol. 413, no. September, 2001
- [23] Huanwei Electronics, "Datasheet MQ-135 Gas Sensor," Hanwei Electronics Co.,Ltd, vol. 1, pp. 3–4, 2014.
- [24] Figaro, "TGS 2602 for the detection of Air Contaminants," Figaro Eng. Inc., pp. 1–2, 2005, [Online]. Available: http://www.figarosensor.com/products/docs/TGS2602-B00 (0913).pdf

- [25] Fígaro, "TGS 2620 for the detection of Solvent Vapors.," Prod. Inf., 2014.
- [26] Hanwei Electronics, "MQ-7 Gas Sensor Datasheet," vol. 1, pp. 3–5, 2016.
- [27] J. Depaula and A. Farah, "Caffeine consumption through coffee: Content in the beverage, metabolism, health benefits and risks," Beverages, vol. 5, no. 2, 2019, doi: 10.3390/beverages5020037.
- [28] S. Smrke, M. Wellinger, T. Suzuki, F. Balsiger, S. E. W. Opitz, and C. Yeretzian, "Time-Resolved Gravimetric Method to Assess Degassing of Roasted Coffee," J. Agric. Food Chem., vol. 66, no. 21, pp. 5293–5300, 2018, doi: 10.1021/acs.jafc.7b03310.
- [29] R. Susanti, R. Nofendra, M. Syaiful, and M. Ilhamdi, "The Use of Artificial Neural Networks in Agricultural Plants The Use of Artificial Neural Networks in Agricultural," vol. 2, pp. 62–68, 2022.
- [30] R. Susanti, Z. Ressy Aidha, M. Yuliza, and S. Yondri, "Artificial Neural Network Application for Aroma Monitoring on The Coffee Aorma Profile and Intensity," 2021.