Prediction of Powdered Coffee Brands Based on Aroma Using Electronic Nose and Artificial Neural Networks

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Abstract. The way to find out the brand of coffee powder on the market is by looking at the packaging. If you don't know the brand, you can guess by smelling it. The purpose of this study was to predict the brand of coffee powder based on aroma using an electronic nose and artificial neural network (ANN). The method used is to take samples of 3 brands of coffee powder on the market and detect the aroma using an electronic nose. The electronic nose used has 6 sensors. The sensor reading value is used as an artificial neural network (ANN) input. The output of the artificial neural network is the brand of coffee powder. The data used are 240 data, namely 180 data for ANN training and 60 data for validation. The validation results show that the highest accuracy of ANN in predicting the brand of coffee powder is 67.78% in ANN training of 50 thousand iterations.

1. Introduction

Powdered coffee is a processed product from coffee beans. Powdered coffee is obtained by grinding roasted coffee beans using a grinder. There are various brands of powdered coffee on the market. Each brand of powdered coffee has its own aroma and taste. Various kinds of coffee drinks can recognize the brand based on the packaging. If the packaging is not there, it will be quite difficult to know the brand.

Currently, in electronics, various electronic components have been developed, including the electronic nose (e-nose). The e-nose consists of one or a combination of gas sensors used to detect gas. Each gas sensor has a different ability and sensitivity in detecting aroma. Currently, there are many studies that utilize e-nose. E-nose is used to detect products that have an aroma, including agricultural products.

In computing, a method for data processing based on a biological model approach is developed, namely an artificial neural network (ANN). ANN works like a human biological brain that works based on input to produce output. In ANN there are layers or layers and each layer is given a certain weight. ANN will be able to work well after training on the data until a small error value is obtained. Between layers in ANN has a certain amount of weight after training.

Several researchers have used e-nose and artificial neural networks in detecting agricultural products based on aroma. Ulfa et al. conducted a study to identify and classify powdered coffee based on the type of coffee using e-nose and ANN. The gas sensor used is the TGS series. The results showed that the ANN made was able to recognize the types of coffee, namely arabica coffee, robusta coffee and liberica coffee with 73.3% success [1]. Hulda et al, conducted a study to detect pure and mixed luwak coffee powder using enose. Classification of data using Principal Component Analysis (PCA) method. E-nose combined with the PCA method has succeeded in detecting pure luwak coffee powder and mixed luwak coffee powder with a success rate of 100% [2]. Shiddiq et al, conducted a study using e-nose to evaluate the quality of honey. The gas sensor used is the MQ series of 6 units. The six sensors can distinguish solutions of two types of honey, namely SNI honey, forest honey, and date palm juice [3]. This study aims to predict the brand of powdered coffee based on aroma using an electronic nose and artificial neural network (ANN).

2. Methods

The research was carried out from June-September 2022 at the Agricultural Mechanization Laboratory of Polinela. The equipment used is an e-nose which consists of 6 MQ series sensors, namely MQ2, MQ3, MQ5, MQ8, MQ9, MQ135 and an Arduino board, digital camera, and scale. The material used is coffee purchased in the market with 3 different brands.

2.2 Research procedure

Making an e-nose with 6 sensors, namely MQ2, MQ3, MQ5, MQ8, MQ9, MQ135 and assembling it with the Arduino UNO board, making a coffee chamber as a place for coffee aroma data retrieval, preliminary testing of e-nose in detecting coffee aroma, data retrieval the aroma of powdered coffee by placing 50 grams of powdered coffee in the coffee chamber for 10 minutes and recording sensor readings. Each is repeated 3 times. Sensor readings are analog values. The analog value is converted into digital data using the following equation:

Voltage = (Sensors value x 5)/1023……………………………………………………1)

Each sensor used has a different character in responding to gas. The sensitivity of the MQ series sensors in responding to gas is shown in Table 1.

Table 1. Sensors Type of gas and type gas responded

Sensors type	**Type gas responded**	**Sensitivity**
MQ-2	Flammable gas, smoke and propane	300-10000 ppm
MQ-3	Alcohol	20-500 ppm
MQ-5	LPG, LNG Natural gas, iso-butane, propane Town gas	200-10000 ppm
MQ-8	Hidrogen (H2)	100-1000 ppm
MQ-9	Carbon monoxide (CO) and metane	10-500 ppm CO 300-10000 ppm metane
MQ-15	Benzena, ammonia and sulfide	10-1000 ppm

The data collection scheme is as shown in Figure 1 and the location for the coffee bean aroma is shown in Figure 2.

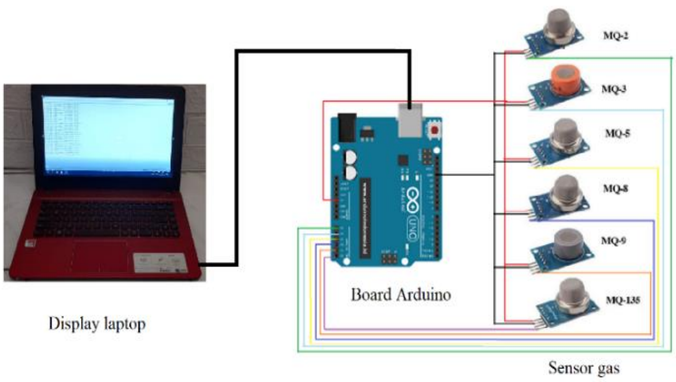

Figure 1. Data collection scheme

Figure 2. Coffee chamber

Creating an artificial neural network (ANN) with input is the digital data of each sensor reading. JST's output is a brand of powdered coffee. The data used are 240 data with 180 data division used for training and 90 data used for testing (validation). The ANN architecture is made as shown in Figure 3.

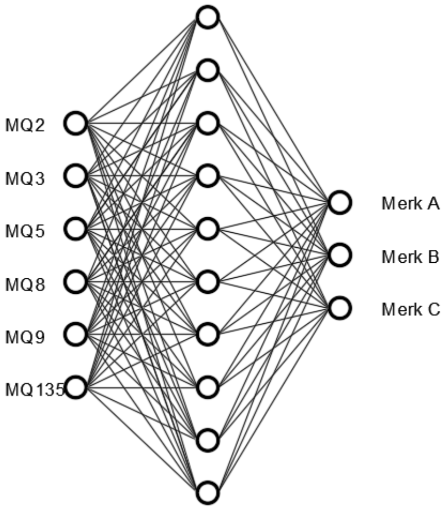

Figure 3. Artificial Neural Network Architecture

3. Results and Discussion

E-nose is an electronic nose that works to imitate the human nose. Inside the e-nose there are a series of sensors for smell of aroma. Aroma or odors are drawn across the sensor array and induce reversible physical and/or chemical changes in the sensing material causing changes in electrical properties including conductivity [4]. Each cell in the array behaves like a receptor by responding to different aroma to varying degrees [5].

The gas molecules interact with the solid-state sensor by absorption, adsorption or chemical reaction with a thin or thick film of the sensor material. The sensor device detects the physical and/or chemical changes brought about by this process and these changes are measured as an electric current signal. Conductivity sensor devices are used to determine changes in conductivity, piezoelectric sensors are used to determine changes in mass, optical sensors are used to determine optical changes and MOSFET sensors are used to determine work functions [6]. How the e-nose works as shown in Figure 3.

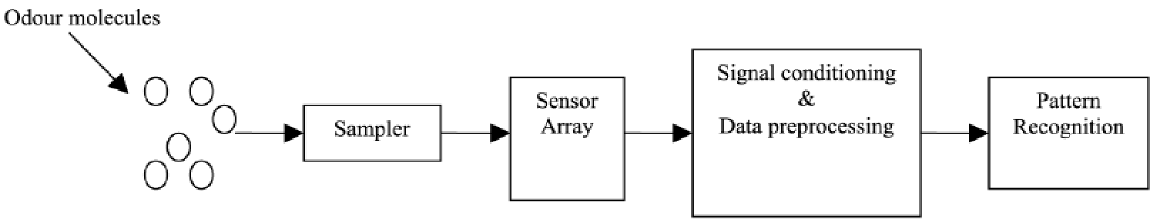

Figure 3. E-nose system [6]

In this study, the sensors used are MQ-2, MQ-3, MQ-5, MQ-8, MQ-9 and MQ-135 sensors. Each sensor has a different sensitivity in detecting aroma / odor depending on the series used. Table 1 presents the types of sensors and the gas they respond to.

On the gas sensor there is a heater that functions to trigger the sensor to work to detect the objectivity of the type of gas to be sensed. On the sensor there is also a resistance value that varies according to the value of the gas density to be sensed. The higher the concentration value of the gas being sensed, the lower the resistance value. And if the lower the concentration value of the gas that is sensed, the higher the resistance value

3.1. Output e-nose

The e-nose output is in the form of digital numbers as a result of analog voltage conversion from each sensor. Data collection for 10 minutes resulted in 90 data for each sensor. For 3 replications, 240 data were obtained for each sensor. The data is used for training as much as 180 data and 90 data for validation. Examples of sensor readings for each brand of powdered coffee are as shown in Table 2, Table 3 and Table 4.

Table 2. Sensor readings on brand 1 powdered coffee (training data)

Repeat	MQ2	MQ3	MQ5	MQ8	MQ9	MQ135	Brand
1	396	631	683	590	459	476	1
2	394	630	679	584	458	473	1
3	396	635	682	587	462	476	1
4	399	641	684	588	465	478	1
5	399	641	680	585	468	477	1
6	403	645	681	588	474	475	1
7	407	650	682	587	480	482	1
8	406	646	676	588	481	479	1
9	410	649	677	581	487	451	1
10	411	648	674	585	492	481	1
11	416	651	675	570	501	485	1
12	420	654	676	581	509	488	1
13	423	656	675	589	513	490	1
14	426	658	676	581	518	492	1
15	430	661	676	586	523	495	1
.	.	.	.	.	.	.	1
.	.	.	.	.	.	.	1
.	.	.	.	.	.	.	1
60	421	673	660	563	559	506	1

Table 3. Sensor readings on brand 2 powdered coffee (training data)

Repeat	MQ2	MQ3	MQ5	MQ8	MQ9	MQ135	Brand
1	428	674	697	601	523	508	2
2	429	674	696	601	526	509	2
3	431	676	697	600	530	510	2
4	433	677	697	601	534	512	2
5	434	678	696	606	539	512	2
6	435	678	695	600	542	513	2
7	437	680	695	607	547	514	2
8	439	681	696	593	552	516	2
9	441	683	696	602	556	517	2
10	443	684	696	607	558	518	2
11	445	684	696	600	562	519	2
12	447	687	696	611	565	521	2
13	452	690	699	605	570	525	2
14	454	689	699	597	572	527	2
15	453	690	698	614	573	526	2
.	.	.	.	.	.	.	2
.	.	.	.	.	.	.	2
.	.	.	.	.	.	.	2
60	422	526	675	568	563	512	2

Table 4. Sensor readings on brand 3 powdered coffee (training data)

Repeat	MQ2	MQ3	MQ5	MQ8	MQ9	MQ135	Brand
1	398	648	664	565	510	483	3
2	397	646	663	564	511	483	3
3	401	646	664	565	516	485	3
4	404	649	667	567	521	488	3
5	407	649	668	568	525	490	3
6	409	640	667	567	527	491	3
7	411	650	667	567	531	492	3
8	414	633	667	567	534	494	3
9	415	634	666	567	536	494	3
10	416	633	666	566	537	494	3
11	419	645	667	567	541	496	3
12	420	623	666	565	543	497	3
13	422	619	667	566	545	498	3
14	423	614	665	565	546	498	3
15	425	623	667	565	549	501	3
.	.	.	.	.	.	.	3
.	.	.	.	.	.	.	3
.	.	.	.	.	.	.	3
60	629	671	571	566	509	421	3

3.2 Artificial Neural Network (ANN)

In this study, the data used for ANN training is 180 data consisting of 60 data from brand 1, 60 data from brand 2, and 60 data from brand 3. The data used for validation is 90 data, consisting of 30 brand data. 1, 30 brand 2 data, and 30 brand data 3. The ANN inputs used consist of 6 inputs, namely, MQ-2, MQ-3, MQ-5, MQ-8, MQ-9 and MQ-135. Data training is made with 6 levels of training/iteration, namely 50 thousand, 100 thousand, 150 thousand, 200 thousand, 250 thousand and 300 thousand. The table of training and validation results is as in Table 3.

Table 3. Results of training and e-nose validation

Training (iteration)	RMSE	Accurate (data)			validation (%)
		brand-1	brand-2	brand-3	
50.000	0,002961	30	20	11	67,78
100.000	0,002441	30	17	7	60,00
150.000	0,001173	30	16	7	58,89
200.000	0,001519	30	15	11	62,22
250.000	0,000864	30	15	11	62,22
300.000	0,000870	30	14	9	58,89

Based on Table 3, it is known that the RMSE (root mean square error) value or the lowest training error was in the 300 thousand training with an error value of 0.000870 while the highest error occurred in the 50 thousand training, which was 0.002961. Prediction tests were carried out for 3 brands of powdered coffee with each brand totaling 30 sensor readings. The total reading of the three brands is 90 sensor reading data.

Prediction results show that for brand-1 correctly detected a number of 30 data or 100% at all levels of training. Prediction results for brands-2 detected 14-20 data or 47-67% for all levels of training. Predictive results for brand-3 were detected between 7-11 data or 23-37% for all training levels. Overall for 90 data, the one that gives the highest prediction accuracy is the 50 thousand data training with a training error value of 0.002961 and validation results 67.78%. Larger training iterations do not guarantee high prediction accuracy.

4. Conclusions

Based on the previous description, it can be concluded that the combination of the use of an electronic nose (e-nose) and an artificial neural network (ANN) can be used to predict the brand of powdered coffee. The highest prediction accuracy occurred in 50,000 data training with 67.78% accuracy results.

5. References

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