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Preferences of Acceptance for Gayo Arabica Coffee Based on Sensory Test Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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ABSTRACT

Gayo Arabica coffee has more than one variety, and each variety has their own taste. The sensory test can be done to see the level of consumer acceptance for Gayo Arabica coffee based on several considered variables. Sensory evaluation through a fuzzy approach is expected to result in several data accumulations from various panelists, making it easier for decision-making. This research is purposed to develop an Adaptive Neuro-Fuzzy Inference System (ANFIS) model, which can be used in predicting panelist acceptance levels towards various varieties of Gayo Arabica coffee products by using different membership functions. Attributes in the sensory test involved fragrance, acidity, body, aftertaste, and flavour as input variables, whereas consumer acceptance level was used as output variables. By 60% of the data were used as training data and 40% of the data were used as testing data with ANFIS model. The result of the research showed that ANFIS model with *generalized bell* and *gaussian* membership function has the lowest error value, which is 12.71% and 13.88%. That result indicates that ANFIS model with both membership functions is suitable to be used in estimating the acceptance level for Gayo Arabica coffee by consumers.

1. INTRODUCTION

Gayo Arabica coffee is an excellent coffee that originated in Gayo Plateau, Aceh Province, Indonesia [1, 2] and has several varieties with different taste, aroma, and acidity [3]. For the Gayo people, coffee is synonymous with life because most of the population in this highland area depends on coffee for their livelihood [4]. The environment in which coffee plants grow affects the quality of the taste of the coffee produced. Coffee grown on high land will have higher quality as well. Several studies have reported that the height of the planting site affects taste [5], physical quality, and biochemical content [6]. According to Worku et al. [7], higher areas contain more complex chemical compounds than coffee grown in lower areas.

To produce a coffee product that meets consumer expectations, usually, a sensory test is performed by panellists who have competence in assessing the taste of coffee. A sensory test is a discipline used in assessing the characteristics of a food or beverage product by utilizing the five human senses to observe colour, aroma, texture, and taste [8, 9]. Sensory test data can be statistically analysed using fuzzy logic.

Fuzzy logic models can imitate human intelligence when solving problems [10]. In addition, fuzzy logic is also suitable for analysing uncertain data, as in this study, where the sensory tests carried out certainly produce different and ambiguous judgments depending on the preference of each panellist. The membership function used in the fuzzy model determines the level of accuracy of the results obtained [11].

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a model that combines a Fuzzy Inference System (FIS) in decision making and prediction based on a learning algorithm against a set of historical data with an artificial neural network [12, 13]. ANFIS has been widely used in various fields, such as surveys [14, 15], economics and agriculture [16, 17], forecasting [18], supply chain [19], food [20, 21], decision making [22, 23], energy [24] and so on.

The development of the neuro-fuzzy system or ANFIS was carried out by Jang [25]. The learning process in neuro-fuzzy with a number of data pairs is useful for updating the fuzzy inference system parameters [26]. The fuzzy inference system used is assumed to have two inputs, namely x and y, and one output, namely f. The Sugeno fuzzy model is a fuzzy inference system often used in ANFIS [8]. The set of general rules for the Sugeno-order-1 model with two IF-THEN fuzzy rules is as follows [27]:

$$\text{Rule 1: if } x \text{ is } A_1 \text{ and } y \text{ is } B_1\text{, then } f_1=p_1x+q_1y+r_1 \quad (1)$$

$$\text{Rule 2: if } x \text{ is } A_2 \text{ and } y \text{ is } B_2\text{, then } f_2=p_2x+q_2y+r_2 \quad (2)$$

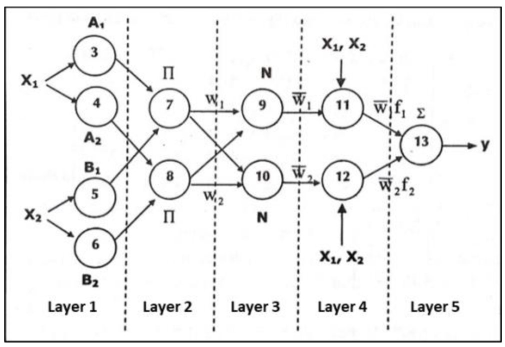


Figure 1. Architecture of two-inputs ANFIS network [27]

ANFIS structure based on its functions is presented on Figure 1 where the output of each node in layer i is written as $0_{1,i}$. Explanation of each layer in the architecture of ANFIS network is as follows [27]:

Layer 1: Each node i in this layer is an adaptive node with a node function:

$$O_{1,i} = \mu_{A_i}(x); \qquad i = 1,2, or \tag{3}$$

$$O_{1,i} = \mu_{B_{i-2}}(y); \qquad i = 1,2 \tag{4}$$

where, x is input for node i, and A_i or B_{i-2} is a linguistic variable that is connected with this node. In other words, $O_{1,i}$ is the level of membership of a fuzzy set A ($A=A_1$, A_2, B_1, or B_2) and determines the degree to which the given *input* x or y satisfies *quantifier A*. The parameter membership function of A can be approximated with the generalized bell function:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{5}$$

where, $\{a_i, b_i, c_i\}$ is the parameter set. The parameters in this layer are the premise parameters with a_i as the standard deviation value of the cluster results, b_i is a fixed value of 1, and c_i is as the result of the average value of the cluster results.

Layer 2: Each node i in this layer is a fixed node labelled Π, where the output is the product of all input signals:

$$O_{1,i} = w_i = \mu_{A_i}(x)\, \mu_{B_i}(y); \qquad i = 1,2 \tag{6}$$

Each node output shows the strength of a rule. In general, several *T-norm* operations that can express *fuzzyAND* logic can be used as a node function in this layer.

Layer 3: Each node i in this layer is a fixed node labelled N, the i node in calculating the ratio of the strengths of the i rule to add up all the strengths of the rule:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_{1+}\, w_1}; \; i = 1,2 \tag{7}$$

If more than two rules are formed, the function can be expanded by dividing w_i by the total number of w for all rules. The output of this layer is called the normalizing power.

Layer 4: Each node i in this layer is an adaptive node with a node function:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i + q_i y p_i + r_i); \; i = 1,2 \tag{8}$$

where, $\overline{w}_i$ is the normalized activation degree of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of the node. The parameters in this layer are called consequent parameters.

Layer 5: The single node at this layer is a fixed node labelled Σ, which adds up the entire *output* as the sum of all input signals:

$$\textit{All inputs}{=}O_{5,i} = \Sigma \overline{w}_i f_i = \frac{\Sigma \overline{w}_i f_i}{\Sigma \overline{w}_i}; \; i = 1,2 \tag{9}$$

The hybrid algorithm in ANFIS learning will regulate the c_{ij} parameters with two techniques, namely the forward technique and will set the parameters$\{a_i, b_i, c_i\}$the backward technique [28]. Jang et al. [27] suggested that the network input will propagate forward to the fourth layer in a forward step, where the c_{ij} parameters are identified using the least-square method. As for the backward step, the error signal will propagate in the backward step and the parameters $\{a_i, b_i, c_i\}$ will be corrected using the gradient-descent method.

The use of ANFIS in the data evaluation of sensory for food and beverages is still not widely used and is a new science; however, several studies have shown that the ANFIS method was very good because it was able to predict and solve difficult analysis problem of food or beverage quality. Russo et al. [29] used the ANFIS model to analyse the sensory test results of the taste and aroma of espresso coffee by using input variables such as coffee mixture, extraction time, and water temperature used when brewing coffee. The result showed that the model had a high accuracy level and was suitable for use in the sensory test. Other sensory test data processing using ANFIS was carried out by Bahram-Parvar et al. [8]. ANFIS was used as a simulation tool in predicting panellists' acceptance of the taste of ice cream by using sensory test input variables (flavour, body, texture, viscosity, and tenderness) as input variables and consumer acceptance of the output variables. The results obtained indicated that the ANFIS model could be used to estimate consumer acceptance of the taste of ice cream with an error value only by 5.11%. There are still very few articles or studies that look directly at the level of consumer acceptance for coffee products by using the results of the sensory test as an input variable and analysed using the ANFIS method, so this research was conducted to see whether the ANFIS method was appropriate to use as an analysis method for the sensory test of Gayo Arabica coffee.

This research is purposed to develop an ANFIS model that can predict panellist acceptance levels towards various varieties of Gayo Arabica coffee products by using different membership functions. Attributes in the sensory test involved fragrance, acidity, body, aftertaste, and flavour as input variables, whereas consumer acceptance level was used as output variables. Different types and fuzzy memberships are used to get the best model and more precise prediction results. The tested membership functions were *Generalized bell*, Gaussianmf, Gaussian2mf, and Pimf. As much as 60% of the data is used as training data and 40% as test data with the ANFIS model. It is hoped that the ANFIS model can be properly used in estimating the level of acceptance of Gayo Arabica coffee by consumers.

2. MATERIALS AND METHOD

There were four varieties of Gayo Arabica coffee used in this study, namely Ateng Super, Bor-Bor, Tim-Tim, and Abyssinia. Each coffee was brewed into an espresso cup with a double shot size, of which the volume size is 60 ml coffee. Each coffee brew was assessed by 10 experienced panellists consisting of 6 women and 4 men. The panellists' criteria included being a coffee connoisseur, not being sick, such as flu, coughs, mouth sores, and other diseases that could affect sensory tests, not wearing perfume, and have not smoked or eaten in the previous 30 minutes [30-32]. The assessment of each flavour component follows the score as in Figure 2, where the panellists made an assessment based on the preference for the acceptance of each Gayo Arabica coffee sample (Table 1).

The ANFIS model was begun by separating the data into input data and output data. The sensory assessment components in fragrance, acidity, body, aftertaste, and flavour became the input variables and consumer acceptance was the output variable. Fragrance is the aroma of coffee that is assessed by inhaling the aroma of coffee during brewing; acidity is the level of acidity of the coffee, body is the level of consistency of the coffee, aftertaste is the length of time for coffee tastes to stay in the mouth after drinking, and flavour is the combination of the overall taste of the coffee. Overall acceptability or panellists' acceptability was used as the output data. Overall acceptability is the panellists' level of acceptance for the Gayo Arabica coffee taste. The data obtained was separated into training data by 60% and testing data by 40%, which was selected randomly. Training data was used for learning the ANFIS algorithm, while testing data was used to see the accuracy of the algorithm that had been trained.

Fragrance		**Aftertaste**	
Soft	Strong	Thin	Heavy
1	10	1	10
Acidity		**Flavour**	
Low	High	Soft	Strong
1	10	1	10
Body		**Overall acceptability**	
Thin	Heavy	Less Favourite	Favourite
1	10	1	10

Figure 2. Score of sensory test assessment of Gayo Arabica coffee taste

The prediction results will be compared with the initial data to see the accuracy of the ANFIS model with the values of Mean Squared Error (MSE), Median Absolute Deviation (MAD), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The MAPE value is less than 10%, so the accuracy of the prediction results is excellent, the MAPE value is in the range of 10% - 20%, the accuracy is good, the MAPE value is in the range of 21% - 50%, the accuracy level is not good (reasonable), whereas if the MAPE value is more than 50%, the accuracy rate is poor (inaccurate) [33].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|.100 \quad (10)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (11)$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (12)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)^2}{N}} \quad (13)$$

3. RESULT AND DISCUSSION

3.1 Evaluation of the sensory test results for Gayo Arabica coffee

The taste of Gayo Arabica coffee as a result of panellist preferences (Table 2) shows that Bor-Bor Gayo Arabica coffee is the coffee with the highest acceptance rate, so it can be said that Bor-Bor has a better taste than other coffee varieties. Bor-Bor has a strong viscosity (body) and a high average aftertaste value compared to other varieties, a high aftertaste value indicates that the taste of Bor-Bor will last a long time on the tongue after drinking.

The Tim-Tim and Ateng Super varieties have the same level of taste acceptance and are second only to Bor-Bor, while the Abyssinia variety has the lowest acceptance rate. Tim-Tim has the strongest fragrance and higher acidity than other varieties. This result is supported by Wahyuni et al. [2] research which shows that teams processed with the full wash method produce a stronger coffee aroma. The three coffee varieties include Bor-Bor, Tim-Tim, and Ateng Super, which have the highest level of acceptance, it can also be seen that the three varieties have a high average flavour value. Regueiro et al. [34], and Chambers and Koppel [35] said that flavour is the most difficult component to assess because of the combination of aroma and taste in the mouth, so the flavour component plays an important role in the acceptance score of the food or drink being tested.

Table 1. Preference assessment component

Function	Component	Description	Assessment score
Input (X)	Fragrance (x_1)	The aroma of coffee when brewing	1-10
	Acidity (x_2)	Coffee acidity level	
	Body (x_3)	Coffee viscosity level	
	Aftertaste (x_4)	The taste that stays in the mouth	
	Flavour (x_5)	Combination of flavours on the tongue	
Output (Y)	Coffee varieties (y_1)	Varieties of Ateng Super, Bor-bor, Tim-Tim, and Abyssinia	-
	Overall acceptability (y_2)	Panellists' acceptance of the taste of Gayo Arabica coffee	1-10

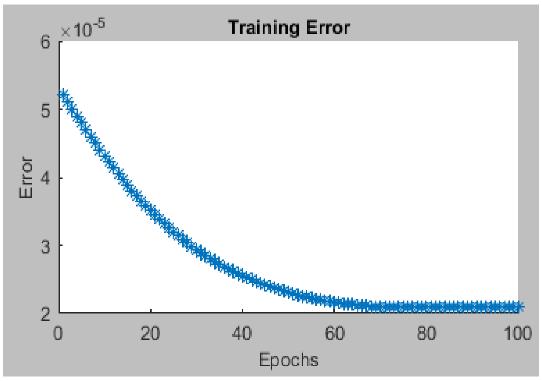
Table 2. Sensory test results for assessing the taste of various varieties of Gayo Arabica coffee

Taste	Ateng Super	Bor-Bor	Tim-Tim	Abyssinia	Overall Average
Fragrance	6.10	7.30	7.45	5.50	6.59
Acidity	7.15	8.00	8.55	7.20	7.73
Body	6.05	7.25	6.25	7.25	6.59
Aftertaste	7.20	7.95	7.00	6.90	7.26
Flavour	7.45	7.65	7.67	7.08	7.45
Overall Acceptability	7.30	7.40	7.30	7.20	7.33

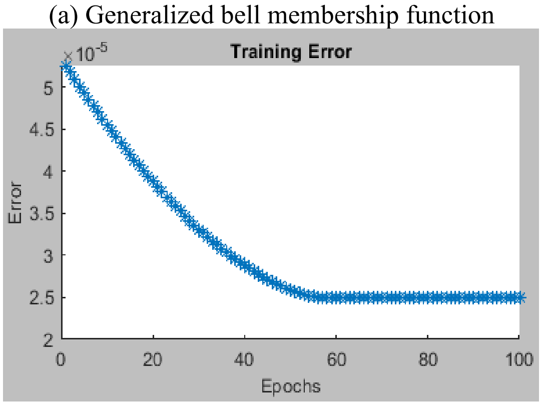
3.2 ANFIS results

Different fuzzy membership types and functions are used to obtain the best model and more precise prediction results. The tested membership functions were *Generalized bell, Gaussianmf, Gaussian2mf, and Pimf*. That was done because each membership function produces different levels of accuracy and prediction results errors [36-38]. Suwindra et al [39] said that data analysis to determine the relationship between variables begins with determining membership functions such as *Generalized bell*, *Gaussianmf*, *Gaussian2mf*, *and Pimf.* The same thing is also used by Mashaly & Alazba [40] in their research to develop the ANFIS method using 8 membership functions, where *Gaussianmf, Gaussian2mf*, and *Pimf* are 3 membership functions that have the best accuracy. The membership function *Generalized bell* is the lowest error level in predicting the triangular-shaped (Tri.) and trapezoidal-shaped (Trap.) [41].

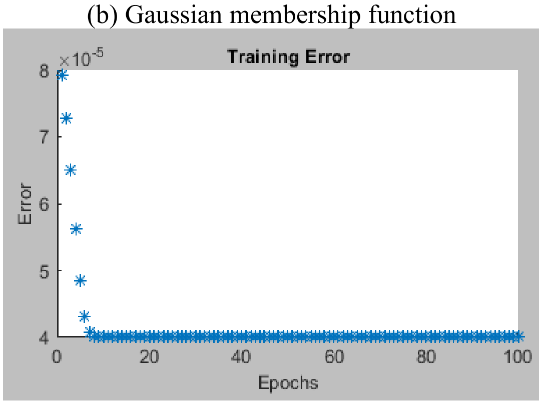
A total of 25 observational data are used in the process of training data, where each training process uses 100 epoch values to get small error training. The plot of the comparison of the error value with the number of epochs of the ANFIS model of the respective membership functions is shown in Figure 3.



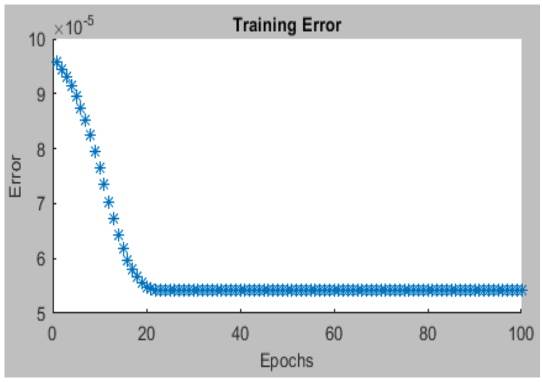
(a) Generalized bell membership function



(b) Gaussian membership function



(c) Gaussian2 membership function



(d) Phi membership function

Figure 3. Comparison of error values from training data of each membership function from 100 epochs tested to predict consumer acceptance of the overall taste of Gayo Arabica coffee

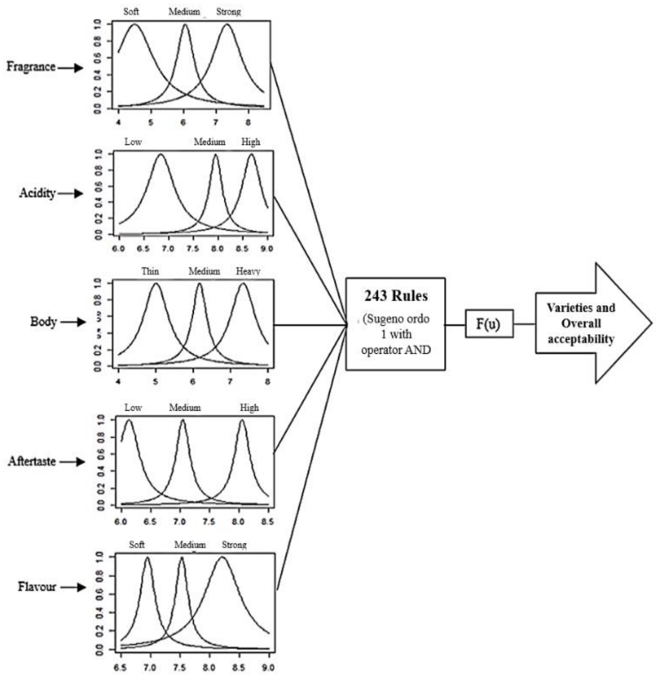


Figure 4. ANFIS architecture with *generalized bell* membership function to perform data prediction

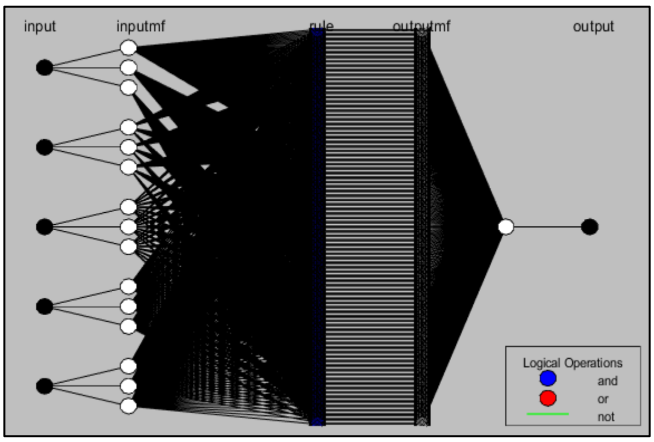


Figure 5. ANFIS Architecture for neuro-fuzzy with five input variables

Figure 4 and Figure 5 show ANFIS architecture illustrations with five inputs including fragrance, acidity, body, aftertaste, flavour, and the output, which is the consumer acceptance of the taste of Gayo Arabica coffee. Each input variable has three linguistic labels from its member function. The number of input variables and linguistic labels made rules as many as 35, so the number of rules used in this study was 243.

The formed ANFIS network will be trained with artificial neural network parameters, which are epoch and learning rate. The learning rate value is fixed at 0.01 for each training with each epoch value. The learning rate value will determine the speed of the ANFIS model to reach the point of minimization or the optimum level, the smaller the learning rate, the better [42]. Wahab [43] stated that the accuracy of the prediction results depends on the number of epochs used because this number of epochs will determine the number of repetitions carried out in learning data in the training process. ANFIS training can be stopped if the epoch value has reached the optimum level [8].

After being tested for 100 times, *Gbell* membership function training got optimal at epoch 60, *Gaussian* membership function error training got optimal at around epoch 50, *Gaussian2* membership function training got optimal at epoch 7, and *Gbell* membership function error training got optimal at epoch 20. This shows that the optimization level for the number of epochs is different for each membership function used. Although the neural network process with *Gbell* and *Gaussian* membership functions requires many epochs, the error training level obtained is small (Table 3).

Table 3. Comparison of error value of ANFIS model with different membership functions

MF	MAD	MSE	RMSE	MAPE
Gbellmf	0.90	1.71	1.31	12.71
Gaussmf	0.93	1.85	1.36	13.22
Gauss2mf	1.74	6.35	2.52	23.98
Phimf	1.91	8.21	2.87	26.13

The MAPE values of the ANFIS model with *Generalized bell* and Gaussian membership functions were 12.71% and 13.22%, means that the two MAPE values were at a good level of accuracy (range 10-20%). This indicates that the results of training with *Gbell* and *Gaussian* were the best results for data prediction.

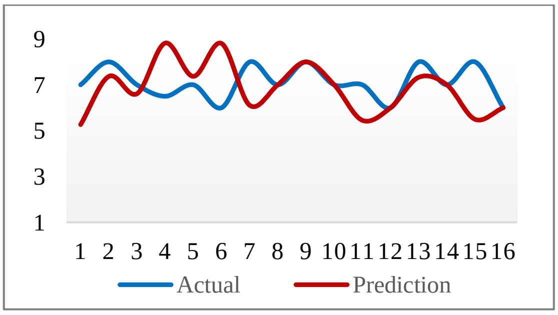
The MAPE values of the ANFIS model with the membership functions of *Gaussian2* and *Phi* were by 23.98% and 26.13%, where the two MAPE values were in the range of 20-50%, which indicates that *Gaussian2* and *Phi* were not good for data prediction in this study. Several other studies such as Mensah et al. [44], Salleh et al. [45], Giovanis [46], Sohrabpoor [47], Khoshnevisan et al. [48] also showed that the *Generalized bell* membership function was the best membership function with the highest level of accuracy and the lowest error used in the prediction process using ANFIS.

The results of the overall comparison of the prediction data and the actual data on panellists' acceptance of the taste of coffee are good (Figure 6), as shown on the results of the prediction values using the ANFIS model, *Gbell* and *Gaussian* membership functions tended to follow and approach the actual data pattern. In the ANFIS model with *Gaussian2* and *Phi* membership functions, there were several observations that were predicted to be far from the actual data. The MAPE values of both *Gbell* and *Gaussian* predictions, which were in the range of 10% to 20%, indicate that the ANFIS method with those membership functions had been well established and was able to analyse data related to human opinion in sensory testing on the prediction of consumer acceptance levels based on Gayo Arabica coffee taste. The prediction results of coffee varieties using the ANFIS method showed results that were very close to the actual data of coffee variety (Table 4).

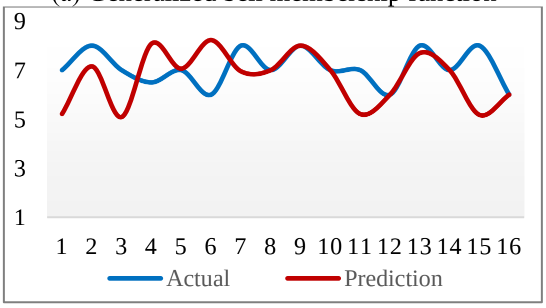
Research using the ANFIS method in the food sector using several membership functions has also been carried out by Khoshnevian et al. [48] in predicting grain yield based on energy input. The membership functions used included *Generalized bell*, *Gaussian*, and several other membership functions. The prediction result using the *Generalized bell* membership function was the best prediction result with a MAPE value of 0.08 or 8% and an RMSE of 0.083. The results of this study, as described above, indicated that the ANFIS method was very good for use in the food and beverage industry, it was also good for use in the evaluation of sensory test results.

Table 4. Comparison between actual data (testing data) and prediction result data of Gayo Arabica coffee varieties

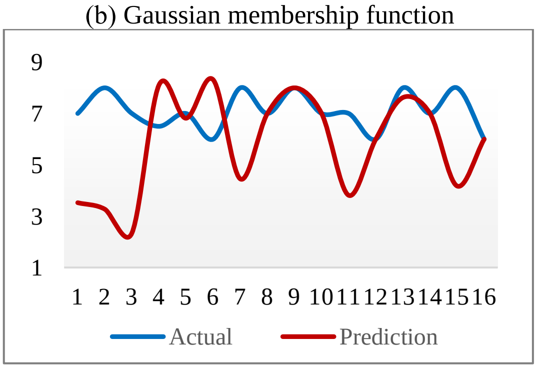
Respondent	Coffee Varieties	Input (Sensory Data)					Actual Data of Consumer's Acceptance	Prediction Data of Consumer's Acceptance of Gayo Arabica Coffee Taste			
		Fragrance	Acidity	Body	After taste	Flavour		*Gbellmf*	*Gaussmf*	*Gauss2mf*	*Phimf*
1	Ateng super	6.0	7.0	5.0	7.0	7.5	7.0	5.22	5.26	3.52	3.07
	Bor-bor	8.0	8.0	7.0	8.0	7.0	8.0	7.15	7.37	3.27	2.24
	Tim-tim	7.0	9.0	5.0	7.0	8.0	7.0	5.09	6.61	2.34	1.38
	Abyssinia	6.0	7.0	7.0	7.0	7.0	6.5	8.08	8.82	8.11	7.96
2	Ateng super	6.0	7.5	6.0	7.0	8.0	7.0	7.06	7.37	6.82	6.97
	Bor-bor	7.0	8.0	7.5	7.5	7.5	6.0	8.23	8.81	8.31	8.00
	Tim-tim	9.0	8.0	4.0	6.0	8.5	8.0	6.95	6.11	4.45	4.10
	Abyssinia	6.0	6.5	7.0	7.0	7.0	7.0	7.00	7.00	7.00	7.00
3	Ateng super	6.0	7.0	6.0	6.5	9.0	8.0	8.00	8.00	8.00	8.00
	Bor-bor	7.5	8.0	7.0	8.0	7.0	7.0	7.00	7.00	7.00	7.00
	Tim-tim	7.0	9.5	5.0	7.5	8.0	7.0	5.21	5.45	3.81	3.19
	Abyssinia	5.0	8.0	7.5	7.0	7.0	6.0	6.00	6.00	6.00	6.00
4	Ateng super	6.0	7.0	6.0	8.0	7.0	8.0	7.70	7.33	7.62	7.90
	Bor-bor	7.0	8.0	8.0	8.0	8.0	7.0	7.00	7.00	7.00	7.00
	Tim-tim	7.0	9.0	5.0	6.5	7.0	8.0	5.18	5.50	4.18	4.10
	Abyssinia	6.5	7.0	8.0	7.0	7.0	6.0	6.00	6.00	6.00	6.00



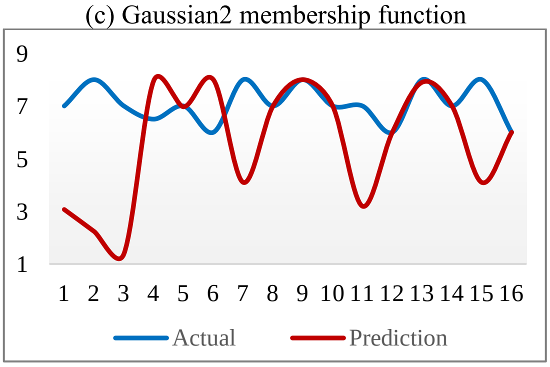
(a) Generalized bell membership function



(b) Gaussian membership function



(c) Gaussian2 membership function



(d) Phi membership function

Figure 6. Comparison between actual data and prediction data based on testing data of the ANFIS model from each membership function

4. CONCLUSIONS

The ANFIS method with *Generalized bell* and *Gaussian* membership functions are better to be used in predicting panellists' acceptance of the taste of Gayo Arabica coffee products compared to the membership functions of *Gaussian2* and *Phi* because they resulted in a small error value. The MAPE value for panellists' acceptance with Generalized bell was 12.71% with an accuracy level of 82.29%. The MAPE value for predicting panellists' acceptance with Gaussian was 13.22%, with an accuracy level of 81.88%. These results are very useful to be used in selecting types of coffee varieties with the category of taste level desired by panellists.

The contribution of this study is clear that the use of the ANFIS method with generalized bell and gaussian membership functions is highly recommended in predicting consumer acceptance of a product. Especially in assessing the taste attributes of a food or beverage product with various types or varieties. This research has demonstrated a logical predictive rule of some consumer preferences that can be studied with a constructive approach through the ANFIS method. Therefore, from managerial implications, it can be said that the ANFIS method is very useful to be used in predicting consumer acceptance of a product, especially related to the sensory taste test.

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