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Utilization of Artificial Neural Network for Assessment of Relationship Marketing Influence of Tomato (Solanum lycopersicum) Farmers

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ABSTRACT

Tomato plants have the potential to be a significant source of income because they are consumed daily and have high economic value. However, tomato production is constrained by suboptimal distribution, which is evident from low consumer loyalty due to inadequate relationship marketing. The Lembang region of West Java Province, Indonesia, a prominent horticultural center for tomatoes, serves as the research location. This study aims to analyze the impact of relationship marketing by tomato farmers on consumer loyalty, with the goal of making recommendations to enhance trust and ensure the continuity of tomato production. The analysis employs techniques such as the Adaptive Neuro-Fuzzy Inference System (ANFIS) and MicMac methods, which complement and reinforce each other. The analysis results reveal that relationship marketing is the primary factor in building consumer loyalty among tomato farmers in the Lembang area, as demonstrated by the ANFIS program's prediction accuracy of 97.1%. The variables that affect the loyalty of tomato farmers in consumers are price suitability, crop sales, trust in consumers. The implications of this research indicate a relevant relationship between demand and supply so that production continuity and price stability can be maintained.

1. INTRODUCTION

Horticulture commodities, which are consumed daily, can serve as significant sources of income and have commercial value [1]. In West Java, Indonesia, tomatoes are horticultural commodities with high economic value and are used not only for consumption but also for nutritional and medical purposes [2].

In the development of tomato production, consumers are important in determining the value chain of this commodity [3], and to increase the competitive advantage of agricultural products including tomato plants, one of the strategies is to create consumer loyalty [4]. Consumer loyalty can eliminate the possibility of consumers switching to competitors [5]. The absence of consumer loyalty will threaten the existence of a business including the tomato commodity business [6]. Indonesia is the country that produces the highest number of tomatoes compared to other countries in ASEAN [7].

Following Indonesia, the Philippines and Thailand hold the second and third positions, respectively, as the largest tomato producers in the ASEAN region. Indonesia's high tomato production allows it to compete with other countries, especially ASEAN. However, Indonesia currently faces challenges in distributing tomatoes, which may hinder its competitiveness in the import-export market. For this reason, the role of distributors in helping tomato farmers is needed in solving this problem [8].

According to the latest data from Indonesia's Central Bureau of Statistics (BPS), in 2022 West Java became the highest tomato-producing province in Indonesia. West Java Province reportedly produced 267,407 tons of tomatoes throughout 2022, the highest of all provinces in Indonesia. In the farmer's economic system, the distribution of agricultural products directly impacts rural culture and the farming community. This is because the process involves many parties, thus giving rise to various roles and networks in society which ultimately have implications for the farmers themselves [9]. In other cases, production will not be maximized without marketing [10]. Hence the need for marketing. There is a relevant relationship between agricultural production and marketing and the role of consumers.

The Lembang region, located in West Bandung, West Java, is one of the largest central producers of vegetable commodities, including broccoli, beans, chili, tomatoes, mustard greens, and peppers. Tomatoes are one of the commodities where market demand for tomato commodities from year to year is increasing so there must be a good distribution role. Relationship marketing between farmers and markets or consumers has low trust or commitment, higher functional conflict, and low uncertainty [11], and the phenomenon that exists, especially among tomato consumers, there are still many who have low consumer loyalty. Given this context, this study examines the relationship between relationship marketing and consumer loyalty, aiming to enhance trust in the continuity of tomato production. The research location was carried out in West Bandung Regency Lembang, West Java Province, Indonesia. The research respondents were consumers of tomato farmers in Lembang West Bandung with a purposive sampling.

2. METHODOLOGY

2.1 Analysis technique

In this study, the data collection technique used to obtain sample data was the purposive sampling method. Data collection was carried out using a questionnaire instrument distributed in the form of a questionnaire with a Likert scale weighing 1-5 ranging from strongly disagree to strongly agree. The sampling determined through purposive sampling was 230 samples of partner farmers in the Lembang area.

Based on the collected sample data, it is adjusted to the analysis technique for the data. The analysis technique used in this study uses the Adaptive Neuro-Fuzzy Inference System or Adaptive Network-Based Fuzzy Inference System (ANFIS) method to analyze the effect of relational marketing on tomato farmers. Where the ANFIS system is an adaptive neural network based on a fuzzy inference system [12]. The use of ANFIS artificial neural networks in this study is based on the consideration that the analysis results can describe models that are easy to understand, very flexible, tolerate data that is considered inappropriate, can model nonlinear data, and can build rules that can be applied in the form of rules that apply to the influence of marketing relationships on farmers [13]. Based on sample data, the ANFIS analysis method can model qualitatively and the mechanism of the decision-making process through rules developed by ANFIS [14]. Artificial neural networks can recognize certain patterns, learn new things, create predictive models, and even solve problems without the need to apply mathematical modeling based on historical data used as training data [15-17].

To support the model that will be developed using ANFIS, preliminary analysis is conducted to assess the influence of each variable on marketing relationships. This study utilizes the MicMac application to analyze the impact of each variable. The MicMac application serves as a tool to systematically rank variables (elements) based on their influence on the output variable.

ANFIS Method

Adaptive Neuro Fuzzy Inference System (ANFIS) is a network based on fuzzy inference system. Neuro-fuzzy is a combination of two systems, namely a fuzzy logic system and artificial neural networks. Neuro-fuzzy systems are based on fuzzy inference systems that are trained using learning algorithms derived from artificial neural network systems. Thus, neuro-fuzzy systems have all the advantages possessed by fuzzy inference systems and artificial neural network systems. From its ability to learn, neuro-fuzzy systems are often referred to as ANFIS (adaptive neuro fuzzy inference systems). One well-known form of structure, as illustrated in Figure 1, utilizes the Takagi-Sugeno-Kang fuzzy inference model.

Layer 1 (Fuzzification Layer)

Make $O_{1,i}$ is the output of each node in layer 1. Each node i in this layer is an adaptive node with node function $O_{1,i} = \mu A_i(x)$ for i = 1, 2; or $O_{1,i} = \mu B_i(y)$ for i = 1, 2, where x is the input to node i and Ai is the linguistic label (small, large, etc.) corresponding to this node function. Elsewhere $O_{1,i}$ is the membership function of A1 and its membership degree is specific to x given sufficient quantization of A_i. Commonly used membership functions are Bell and Gaussian.

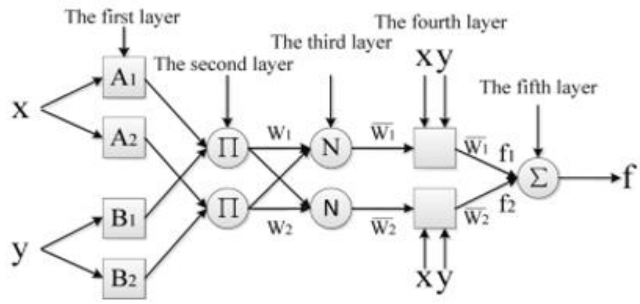


Figure 1. ANFIS architecture

The bell form membership function is expressed as:

$$f\ x; a_i, b_i, c_i = \frac{1}{1 + \frac{x - c_i{}^{2b_i}}{a_i}} \tag{1}$$

With parameter *b* usually positive. Parameter *c* is located in the middle of the curve. The Gaussian membership function is expressed as:

$$\mu_A(x_t) = e^{\frac{-(x_t - c)^2}{2\sigma^2}} \tag{2}$$

Layer 2 (Product Layer)

Each node in this layer consists of a prod t-norm operator as a node function. This layer synthesizes the transmission of information with layer 1 and multiplication of all incoming signals and sends the product out. The output of the product layer is expressed as:

$$O_{2,i} = w_i = \mu A_i(x).\mu B_i(y); i = 1,2 \tag{3}$$

Each node in this layer serves as a measure of the strength of the rule. The output of this layer acts as a weight function.

Layer 3 (Normalization Layer)

Each node in this layer normalizes the weight function obtained from the previous product layer. The normalized output is calculated by:

$$O_{3,1} = w_t \frac{w_i}{w_1 + w_2}, and\ i = 1,2 \tag{4}$$

The function can be expanded if there are more than two rules by dividing it by the total number *w* for all rules.

Layer 4 (Defuzzification Layer)

The nodes in this layer are naturally adaptive. The defuzzification output of this layer is calculated by the formula:

$$O_{4,1t} = w_{1t}^{*} Z_t^{(1)} = w_{1t}^{*}(\alpha_1 Z_{t-1} + \beta_1 Z_{t-2} + \gamma_1), \tag{5}$$

$$O_{4,2t} = w_{2t}^{*} Z_t^{(2)} = w_2^{*}(\alpha_2 Z_{t-1} + \beta_2 Z_{t-2} + \gamma_2) \quad (6)$$

where, α_i, β_i, γ_i are the set of node parameters and are called consequence parameters.

Layer 5 (Total Output Layer)

A single node at this layer synthesizes the information sent to layer 4 and returns the overall output using the following fixed function:

$$O_{5t} = \hat{Z}_t = w_{1t}^{*} Z_t^{(1)} + w_{2t}^{*} Z_t^{(2)} \quad (7)$$

2.2 MicMac analysis

The MicMac method (Matrix of Crossed Impact Multiplications Applied to a Classification) is a structural analysis method first introduced by Dupperin and Michael Godet in 1973. This method offers to solve complexity by ranking the elements of a system in a systematic and structured manner and through the form of relationships between variables. The MicMac method is often applied to identify key factors [18]. The advantage of the MicMac method is its structural analysis which can update previously qualitative data into quantitative through matrix properties [19]. In addition, according to a study [20], another advantage of MicMac is its ability to categorize and determine the arrangement of strategic variables and their mutual influence. So that it can provide a more convincing and reliable basis for consideration when addressing the proposed problem. Using this MicMac method, the main variables of a system can also be identified and analyzed [21].

Furthermore, the MicMac method in its analysis is based on the depiction of two axis values, namely driver power (DP) and dependent variables (D) [19], so that the variables can be categorized or grouped into each sector/cluster/quadrant [22-24]. There are three basic steps in the MicMac method: identifying variables, explaining the relationship between variables, and identifying key variables [25, 26]. Based on various problems related to the sustainability of tomato agricultural development in West Bandung Lembang Regency, this study aims to determine the effect of Relationship Marketing of tomato farmers on consumer loyalty. The process of analyzing the data from filling out the questionnaire using MicMac is to convert the weight of each variable into a matrix of direct influence (MDI) as presented in Figure 2.

The stages of MicMac analysis are based on two main stages [17]. The first stage is understanding the scope of the problem and the system to be studied. The flow of analysis using MicMac can be seen in Figure 2.

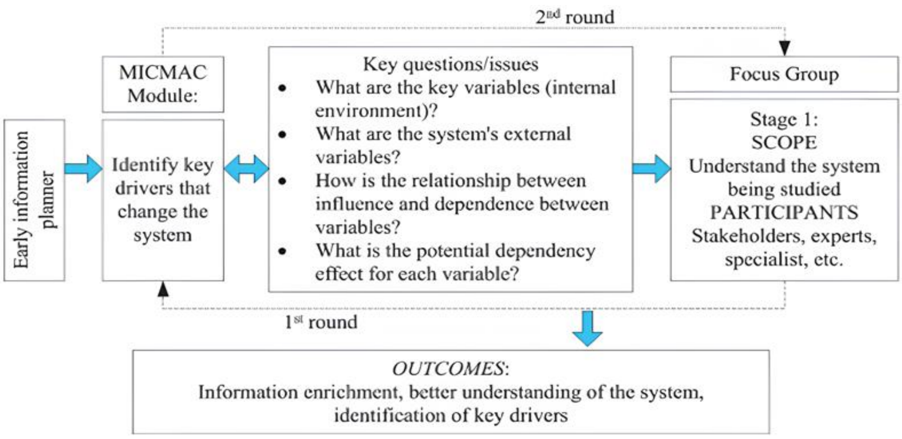


Figure 2. Framework of MicMac

Table 1. Identification of dimensions and variables of relationship marketing influence of tomato farmers

Dimensions	Variable/Attribution	
	Long Label	Short Label
	Members trust the services and programs provided	Member Trust (MT)
	Members believe that the services and promises offered are appropriate	Suitability of the promises (SP)
Trust	Consumers can be trusted in the collaboration they establish	Collaboration (Cb)
	The cooperative is honest and sincere in helping members	Honesty (Hn)
	Consumers pay attention to members by helping members	Attention (At)
	Member commitment to only be a member of one cooperative	Trusty (Ty)
	Members always receive the benefits of partnering with the cooperative	Advantage (Adv)
Commitment	Members accept the responsibilities given by the cooperative	Responsibilities (Rsp)
	Members are committed to selling their harvests to the cooperative	Yields (Y)
	Members will continue to collaborate as remaining members of the cooperative	Sustainability of cooperation (SoC)
	Consumers continuously provide the best information to members	Information (I)
Communication	The cooperative always welcomes suggestions and opinions	Receptive (R)
	Consumers can handle members' complaints and wishes	problem-solving (PS)
Satisfaction	Members are satisfied with the services provided by the cooperative	Service satisfaction (SS)
	Consumers always provide prices according to the agreement	Price suitability (PSty)

Based on the results of the distribution of questionnaires and FGDs, some variables have been determined, and quantified the relationship between variables that have been built so that a direct influence matrix is obtained as shown in Table 1. The MicMac application in Figure 3 in the form of a Matrix of Data Influence (MDI) is transformed into a variable map, which reflects or illustrates the position of the influence dependence chart into four sectors (quadrants).

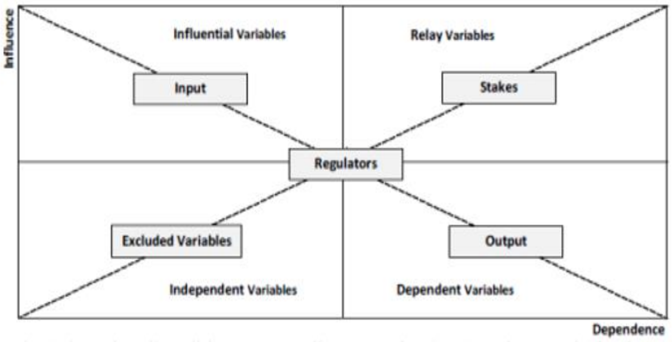


Figure 3. Illustration of MicMac analysis results [27]

2.3 Data analysis design

The categories of data collected are primary and secondary data. Four dimensions become a reference in building attributes or variables, namely trust, commitment, communication, satisfaction with loyalty. The attributes or variables used or built as a questionnaire are based on the results obtained directly from in-depth interviews, Focus Group Discussions (FGD), and direct observation. Extracting information through questionnaires was conducted on stakeholders and consumers around 230 people consisting of tomato distributors, dealers, and direct consumers. Implementation in filling out questionnaires that describe the direct relationship between variables is done by quantifying the use of a scale of 0 to 3 and P as illustrated by the study [27]: 0 = no relationship (non-existent), 1 = weak relationship (low direct influence), 2 = equal relationship (medium direct influence), 3 = strong relationship (high direct influence), P = potential influence.

3. RESULTS

3.1 Matrix of direct influence

Based on the results of field data analysis to see the loyalty of tomato farmers based on input data sourced from 4 subsystems of relationship marketing variables, among others: Trust, Commitment, Satisfaction, and Communication which in total consists of 15 variables. The 15 variables represent the dimensions of trust, commitment, satisfaction, and communication. For this analysis and based on the FGDs the 15 variables were grouped as listed in Figure 4. These variables were then included in the MicMac analysis. Each of these 15 elements was then evaluated through the matrix of direct influences (MDI). The results of testing the 15 variables that are considered important in developing consumer loyalty of tomato farmers show consistency and stability. This MDI matrix is listed in Figure 4 below.

The application of prospective analysis in the decision-making process that considers the position and intensity of influence of variables in the form of direct or indirect influence (and no causal relationship) has explained the validity and strength of the approach in determining the most desirable variable is the development of loyalty towards tomato farmers based on stake variables as key factors and at the same time will produce expected future benefits. An important component in looking at loyalty is the determination of key variables. The condition of the strength relationship between variables is depicted in the influence-dependence quadrant presented in Figure 5.

	1 : MT	2 : SP	3 : Cb	4 : Hn	5 : At	6 : Ty	7 : Adv	8 : Rsp	9 : Y	10 : SoC	11 : I	12 : R	13 : PS	14 : SS	15 : PSty
1 : MT	0	2	2	0	1	2	2	2	2	2	2	2	1	1	1
2 : SP	2	0	2	2	2	1	2	2	2	3	2	2	1	2	1
3 : Cb	2	2	0	2	2	2	1	1	2	2	1	1	1	1	2
4 : Hn	1	2	2	0	2	2	2	3	3	3	3	3	1	3	1
5 : At	1	2	2	2	0	2	2	2	3	2	3	3	2	2	2
6 : Ty	1	2	2	3	3	0	3	3	1	3	2	2	1	1	3
7 : Adv	2	1	1	3	3	3	0	3	2	2	2	1	1	1	2
8 : Rsp	2	2	1	2	3	3	3	0	2	2	2	2	1	1	2
9 : Y	1	2	2	3	1	1	2	2	0	2	2	3	3	2	3
10 : SoC	2	1	1	0	1	2	3	3	2	0	2	2	1	2	1
11 : I	2	3	3	3	0	2	3	3	3	3	0	2	1	2	1
12 : R	2	1	0	2	3	3	3	3	3	3	2	0	2	2	2
13 : PS	0	0	0	1	0	1	1	0	3	1	1	3	0	1	3
14 : SS	1	2	1	3	0	1	2	2	2	2	1	3	3	0	2
15 : PSty	0	1	0	2	0	1	1	1	3	1	2	2	2	2	0

Figure 4. Matrix of direct influence key variables of tomato farmer relationship marketing on consumer loyalty

Notes: Influences range from 0 to 3, with the possibility to identify potential influences: 0: No influence, 1: Weak, 2: Moderate influence, 3: Strong influence, P: Potential influence.

Figure 5. The position of a system variable in the direct influence-dependence map

Based on the results of the MicMac analysis in Figure 5, it is obtained that the variables in the first quadrant (determinant variables) are attention to members (At), services and promises offered are appropriate (SP), satisfaction with the services provided by consumers (SS) and choosing only one consumer (Ty). The characteristics of the first quadrant are variables that have a high level of influence and low dependence. The variables with high influence with high dependence, but unstable relationships between variables are in the second quadrant (key variables) are always giving the best information to members (I), Consumers are always honest sincerely and sincerely (Hn), accepting suggestions and opinions (R), accepting all responsibilities given by consumers (Rsp), selling crops to consumers (Y), receiving the benefits of partnering with consumers (Adv) and always establishing cooperation by remaining a member of consumers (SoC). Furthermore, the variables in quadrant three (result variables), namely variables that have low influence and high dependence, trust in the services and programs provided by consumers (Cb), consumers can be trusted in the cooperation established (MT). Quadrant four (Autonomous variables) is a variable, gives the price according to the agreement (PSty). Variables in quadrant four have low influence and dependence.

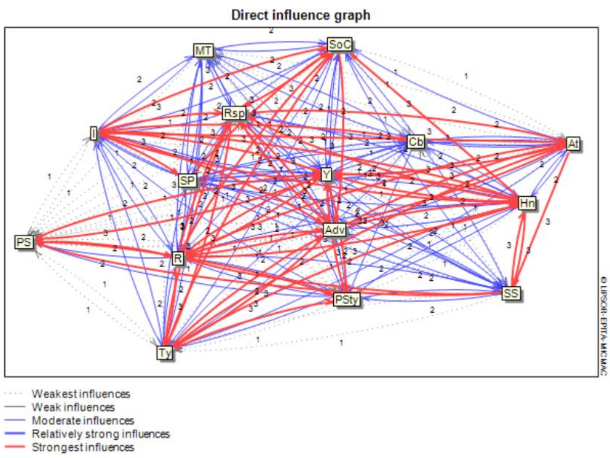


Figure 6. Graphic illustration of influence-dependence variables

Furthermore, it describes the form of the relationship between variables expressed in the graph shown in Figure 6. Based on Figure 6, the relationship expressed by the green line means Weak influences, the blue line means Moderate influences, the dark blue line means relatively strong influences, and the red line means Strongest influences. It can be seen that in determining consumer loyalty to tomato farmers in a row from all variables, namely selling crops to consumers (Y), giving prices according to the agreement (PSty), attention to consumer members (At), services and promises offered accordingly (SP), satisfaction with the services provided by consumers (SS) and choosing only one consumer (Ty) are variables that have a strong influence on Figure 6. While the lowest value is the variable for receiving suggestions and opinions from consumers (R). So, it can be concluded that the variable is a variable that determines the satisfaction of tomato farmers so that it automatically also increases the loyalty of tomato farmer consumers. It can also be explained that in addition to the above variables, the interaction between the market in this case consumers as customers and tomato farmers must be maintained well because it will increase customer satisfaction, and interactions that must be established can be through online [28, 29].

3.2 Matrix of indirect influence

Apart from being based on MDI, the position of variables in the influence-dependence chart quadrant is also based on MII (Matrix of indirect Influence) so that changes in their position can be seen through the displacement map. Based on MII, each system variable is reclassified into four sectors (quadrants) based on its position on the influence-dependence chart, as presented in Figure 7, it can be seen that there is no change in the position of the variables, this indicates that the variables specified are absolutely part of the consumer loyalty of tomato farmers.

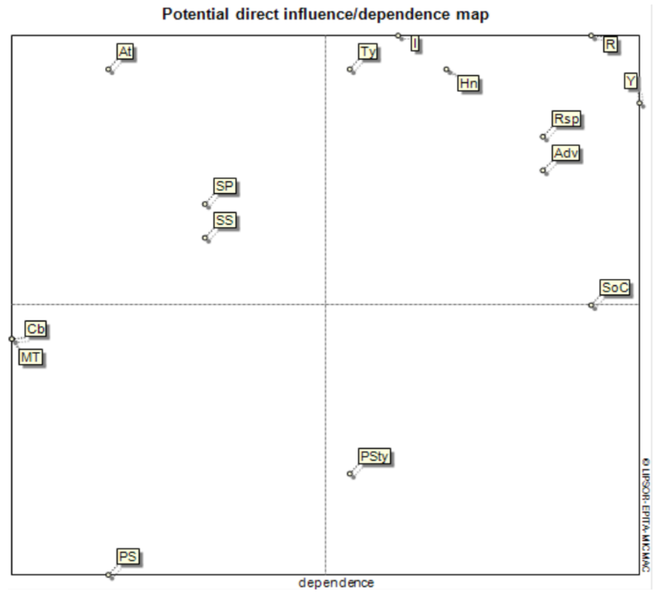


Figure 7. Matrix of indirect influence

Visually representing the complexity of interactions between system variables related to the level of influence and dependence indirectly (indirect influence) on other variables is shown in Figure 8 below. It can be seen from Figure 8 that the relationship marketing variable that is the main determinant of tomato farmer loyalty is the variable of selling crops to consumers (Y). In addition, it can also be seen that the price suitability variable and other variables that are colored red arrows indirectly become one of the determinants of consumer loyalty of tomato farmers. The number on each arrow indicates the degree or rating of influence obtained through matrix iteration. In contrast to direct influence, most variables have a very strong dependent influence on other variables (marked by the number of red lines).

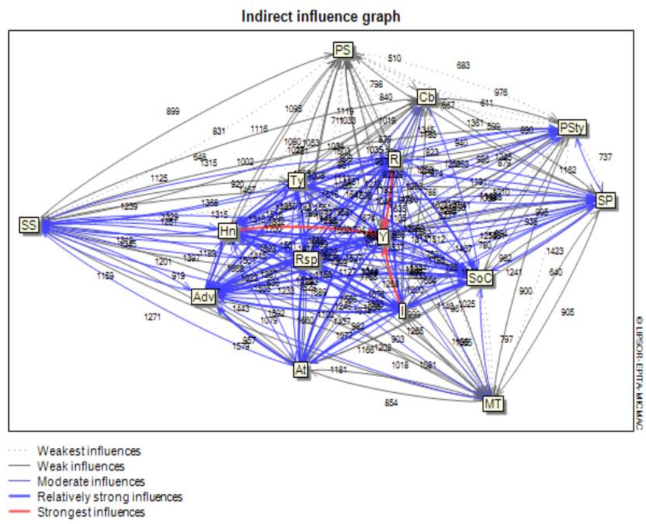


Figure 8. Potential indirect influence graph

3.3 Implementation of neuro fuzzy- ANFIS

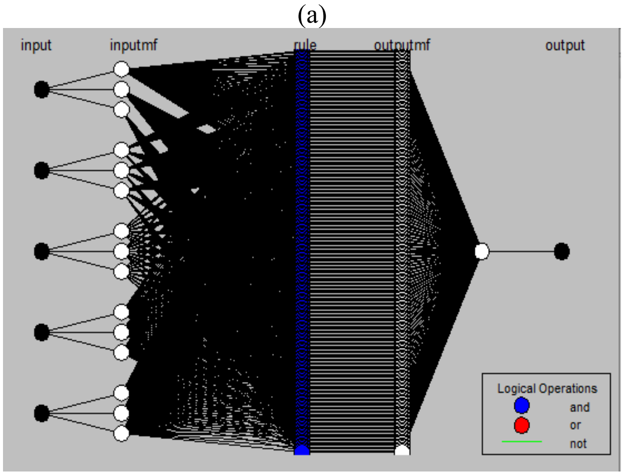
ANFIS analysis is developed based on sample data from respondents' questionnaires consisting of 5 input data as variables of trust, commitment, communication, satisfaction and loyalty to tomato farmer loyalty. Based on the input data, the ANFIS artificial neural network application automatically develops a data input model that forms a data input model for the basic rules as a reference in making predictions, as shown in Figure 9(a) and Figure 9(b) below.

```
>> fis=readfis('Loyalty.fis')

fis =

             name: 'Loyalty'
             type: 'sugeno'
        andMethod: 'prod'
         orMethod: 'probor'
    defuzzMethod: 'wtaver'
        impMethod: 'prod'
        aggMethod: 'sum'
            input: [1x4 struct]
           output: [1x1 struct]
             rule: [1x300 struct]
```

(a)



(b)

Figure 9. (a) Data input and (b) model building in neuro-fuzzy-ANFIS input

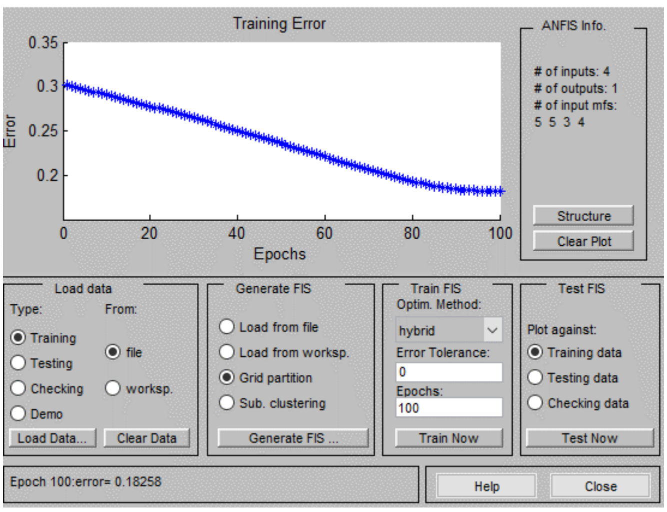


Figure 10. Training data and determination of ANFIS programming tolerance error

To see the suitability of the input data into the ANFIS application, testing needs to be done by determining the training error data on ANFIS. in determining the accuracy of the training data, it is necessary to determine the repetition of data training in the ANFIS application or what is commonly referred to as the epoch. in this study, the number of epochs used is 100. In addition, in determining the analysis, it is also necessary to first determine the Error Tolerance value of 0. In the results of the ANFIS analysis in the study, it can be seen that the error obtained on the main graph is 0.182 as seen in Figure 10. This shows that the input data will be read by the ANFIS program accurately.

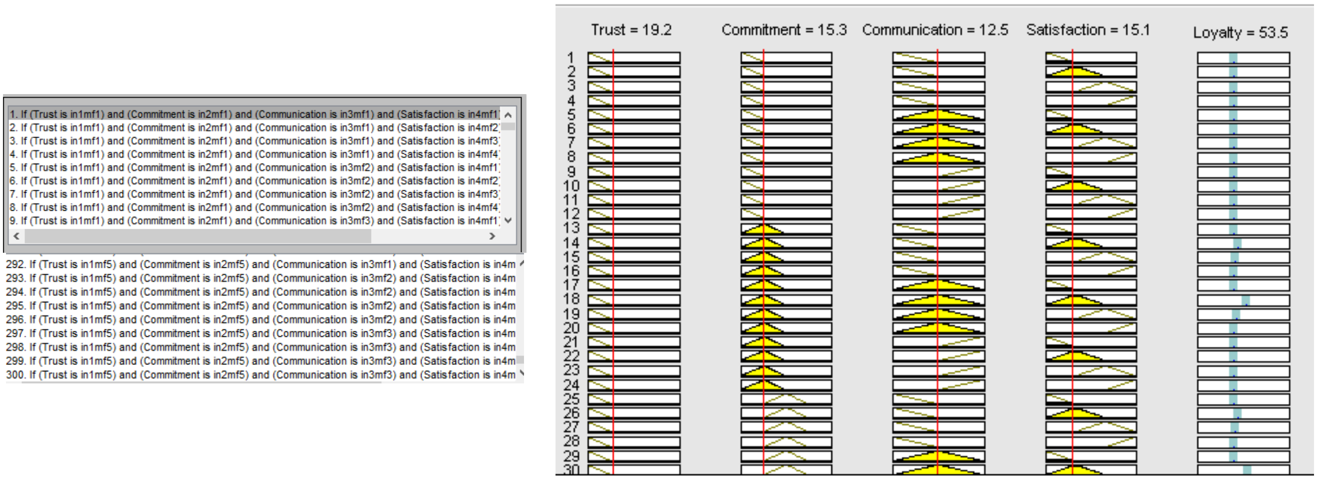
In visualizing the suitability of input data and ANFIS prediction data will display the accuracy on the ANFIS Editor graph. where the training data is symbolized by a blue circle on the ANFIS visualization, and a red star as the result of ANFIS training as seen in Figure 11. The accuracy of ANFIS predictions can be seen in the initial visualization with the provision of the location of the red star intersection with the blue circle, then the more precise the intersection, the higher the accuracy of the training data against the prediction. From Figure 11, it can be seen that the input training data has a very close intersection between the blue circle and the red star. This indicates that the input data from the variables of trust, commitment, communication, and satisfaction support the accurate tomato farmer loyalty prediction process.

Figure 11. Training data input ANFIS programming

From the input data of 4 variables to see the prediction of tomato farmer loyalty into the ANFIS program, a total of 300 rules were obtained which were formed by ANFIS (Figure 12(a)). Based on the rules built by the ANFIS rule viewer, we can see the variables that need to be maintained to get good loyalty output. From the 300 rules formed by ANFIS, one example of a rule in Figure 12(b) built by ANFIS is considered the best result with a loyalty value of 53.5.

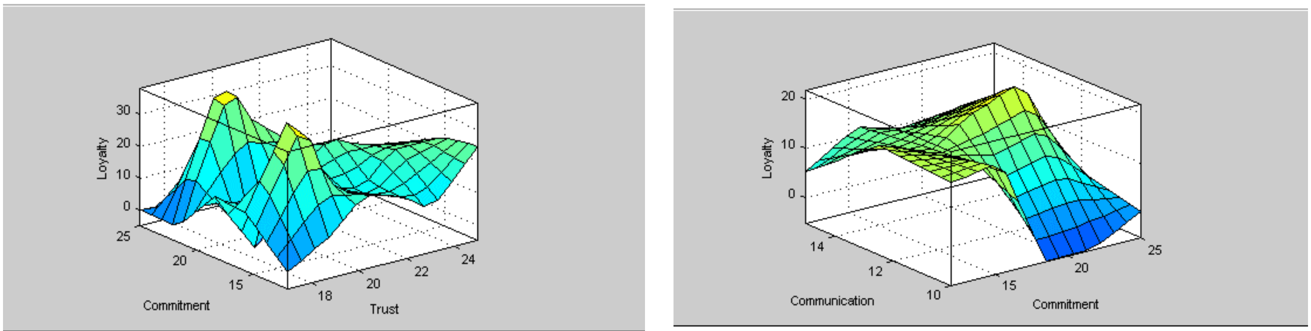
Figure 13 below is the result of the 3D surface visualization built by ANFIS programming. Figure 13(a) is a visualization of trust variables, and commitment to the loyalty of tomato farmers, from the surface visualization it can be seen that the value of commitment on a scale of 15-20 means moderate to good and trust on a scale of 15-20 means moderate to good can build the loyalty of tomato farmers which is quite high. Figure 13(b) is a visualization of communication variables, and commitment to the loyalty of tomato farmers, from the surface visualization it can be seen that the value of communication on a scale of 10-15 is poor to moderate, and commitment on a scale of 20-25 means good to very good can build the loyalty of tomato farmers which is quite high.

Based on the results of ANFIS in Figure 14, the comparison was made between real data and ANFIS prediction output data. In this study, an accuracy of 97.1% was obtained, indicating that the input data in the model can represent real data in the field. So, in making decisions to develop tomato farmer loyalty to consumers in the Lembang area, it can refer to the rules formed by ANFIS.



(a) (b)

Figure 12. (a) Rules built by ANFIS programming, (b) ANFIS rule viewer



(a) (b)

Figure 13. Visualization of surface images from ANFIS programming results (a) a visualization of trust variables, and commitment to tomato farmer loyalty, (b) a visualization of communication variables and commitment to tomato farmer loyalty

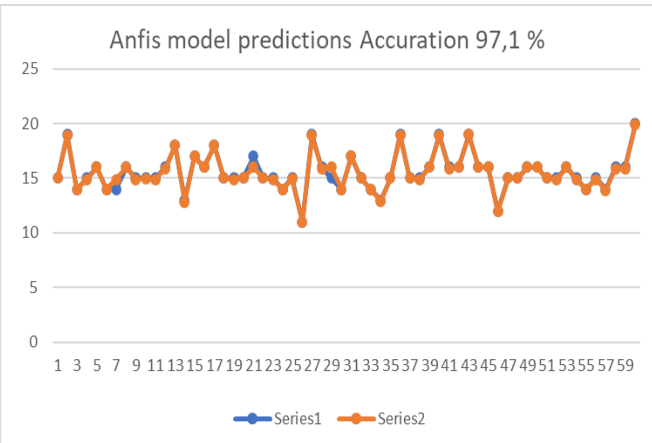


Figure 14. Prediction accuracy of ANFIS programming

4. DISCUSSION

Visualization of the MicMac analysis results shows that there are differences in the impact of each variable determined as a builder to determine the output of tomato farmer loyalty. Farmer loyalty can also be supported by an optimal logistics system with the quality consumers desire in the right amount, time, and place at an efficient cost [30]. Each variable of the analysis results in a row in influencing the loyalty of farmers is the suitability of prices, fixity in the sale of products, and the trust given by consumers to farmers so that these variables will be able to develop customer value based on consumer quality perceptions of tomato commodities [31]. Combined with the results shown by the rules built by ANFIS, it can be seen that one of the important variables in building predictions is commitment. In the commitment variable, of course, there are determining indicators such as suitability, market certainty, and consumer confidence and this has an impact on consumer loyalty as a central concept in the marketing process in the current era [32]. This condition also makes it clear that the sub-variables shown in the MicMac analysis can strengthen the predictions built by ANFIS. The product, in this case, tomatoes, will be repeatedly consumed by buying from the same farmer because they feel they are not disappointed with the tomatoes, so this is what is seen from consumer loyalty [33]. This can be emphasized that relational marketing has a strong relationship with consumer loyalty.

5. CONCLUSIONS

Relationship marketing is the main factor in building the loyalty of tomato farmers in Lembang region consumers as seen from the accuracy of predicting input data into ANFIS programming 97.1%. The variables that affect the loyalty of tomato farmers in consumers are price suitability, crop sales, and trust in consumers.

The implications of the results of this study can develop relational marketing by building the loyalty of tomato farmers and consumers so as to increase the sustainability of tomato production.

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