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Classification of restrictions on community activities level in the covid-19 pandemic using fuzzy logic

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Abstract

Indonesia is facing a second wave of Covid-19 cases in mid-2021. In that time, the increase reached 381 percent or almost 5 times. Therefore, the government announced the Enforcement of Restrictions on Community Activities. This is determined by the government for each city in Indonesia so it cannot be predicted by the general public. Actually, The Restrictions on Community Activities status level determines the risk of a region's economic activities. Therefore, we need a method that can help to categorize the level of PPKM in an area based on available daily data. Thus, this study aims to create a rule model based on Fuzzy Tsukamoto logic that can help determine the level of risk of an area. Based on data on Covid-19 patients in Malang District, East Java has formed 6 fuzzy variables, each of which has 4 fuzzy sets, and 15 rules that can be used as a classification model. From the results, we obtained an accuracy value of 80%. This shows that the generated rule can properly classify the daily Covid-19 data to then estimate the next restrictions level.

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1. Introduction

Indonesia is facing a second wave of spikes in Covid-19 cases in mid-2021. This condition is marked by an increase in coronavirus cases in the country in a week. Even the addition of daily cases on June 27 2021 yesterday recorded the highest record during the pandemic, namely 21,345 people. The Task Force for handling Covid-19 noted that the spike in cases this time was much higher than the peak of the first wave that occurred in January 2021[1]–[3]. As a result, the President announced the Imposition of Emergency Community Activity Restrictions or in Bahasa is called *Pemberlakuan Pembatasan Kegiatan Masyarakat* (PPKM) in Java-Bali. This is certainly done to prevent transmission[4]–[6]. However, since July 21, 2021, the government no longer uses the term Emergency Restrictions on Community Activities in the Java-Bali region. Now, the term has become PPKM Level 4. This is stated in the Instruction of the Minister of Home Affairs Number 22 of 2021 concerning PPKM Level 4 Covid-19 in the Java-Bali Region. In the instructions of the Minister of Home Affairs it was explained, PPKM Level is the imposition of restrictions on activities in Java and Bali and adjusted to the criteria for the level of a pandemic situation based on the results of an assessment [7].

PPKM level status determines the risk of a region's economic activity. Therefore, Micro, Small, and Medium Enterprises (MSME) actors often feel worried whether the area they live in can carry out economic activities or be restricted. The process of determining this level is influenced by the number of confirmed cases, death cases, and the percentage of bed occupancy rate (BOR) per unit of time. This determination is centralized by the government for each district/city in Indonesia and cannot be predicted by the general public. Therefore we need a method that can help categorize PPKM levels in an area based on existing daily data. Furthermore, solving the problem of categorizing a case can use classification techniques from data mining. The methods used also vary, for example: K-Nearest Neighbor[8], Machine Learning[9], Naïve Bayes Classifier[8], Fuzzy[10]–[12], etc. Therefore, in this study fuzzy will be used because it has advantages in processing balance and imbalance data[13]. Fuzzy is also often used to process medical data[14]–[19]. In research [10] a PPKM level policy classification has been carried out using the Fuzzy Rough Set method. However, this study only determines the classification at three decision levels, even though in the Inmendagri there are four levels of PPKM levels [7]. In this study it was also stated that the Fuzzy rule used could classify regions according to the government's decision, but the accuracy or performance of the rule had not been stated. Therefore, it is necessary to do other research in generating Fuzzy rules in determining the classification of PPKM levels in an area. Thus, this study aims to create a rule model based on Fuzzy Tsukamoto logic that can help determine the level of risk of an area. Fuzzy Tsukamoto was chosen because it has ease in the decision making process and provides tolerance for inaccurate data[11], [12]. Then, the rule model based on fuzzy logic can be used to determine the risk level of an area. This research is relatively new because previous studies only predicted active cases[20]–[23]. With this research, it is hoped that business actors can estimate economic activity for the next two weeks in the form of seeing business opportunities that will be carried out. For example, if the PPKM level is in a high-risk area, then business people can minimize the supply to be processed. Meanwhile, if the PPKM level in an area is low risk, then business people in that area can start to generate more supply and selling quantities for their business in the next two weeks where the new PPKM level is implemented.

2. Methods

In this study there are five main stages including data collection and preprocessing, formulating variables and fuzzy sets, generating fuzzy rules, testing data classification based on fuzzy rules, and evaluating the results. This is a classification process based on fuzzy logic. This stage is illustrated in Figure 1:

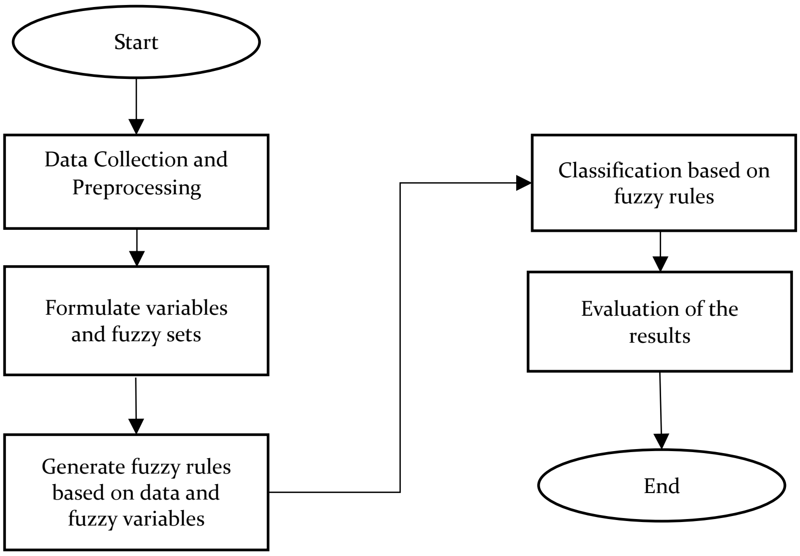


Figure 1. Stage of Research

Based on the Figure 1, the collect of data used in this study is data in the Malang District, East Java began at implementing PPKM untill December 2021. Then, it decided to two sets namely training data (July 21 2021 to. 31 December 2021) for determining fuzzy rule patterns and testing data (1 January 2022 s.d. 30 April 2022). The data taken is daily data which consists of: the number of confirmed cases, death cases, and BOR. Data on the number of confirmed cases, patient deaths, and BOR were taken from the Covid-19 task force page[24], while PPKM level status was obtained from mass media portals such as Kompas[25], Kontan[26], Tempo[27], CNN[28], Merdeka [29], and Liputan 6[30] which broadcast news from the PPKM status level announced by the central government. Then, the data is arranged in a table titled daily ases, BOR, death cases, and satatus. So that in determining the next level, we used the previous *n* data. The data is then arranged in tabular form as follows:

Tabel 1.
Data

	Daily cases	BOR	Death cases	Status
Day-1st				
Day-2nd				
...				
Day-n				
Next status				???

Changes in the PPKM level of an area sometimes occured for one or two weeks. If the PPKM period is one week, then 7 days data is used to determine the next level. However, if the PPKM validity period is two weeks, then 14 days data is used. All data collected is modeled as in Table 1 with *n* is following the number of days in a period. Evaluation of the classification results is done by calculating accuracy [31]–[35] with the following formula:

$$Accuracy = \frac{Negative + Positive - FP - FN}{Negative + Positive} x100\% \quad (1)$$

3. Results and discussion

3.1. Data

From the data that has been collected, on 21 July 2021 s.d. December 31, 2021 there were 15 PPKM level changes. The following is a display of data for 21 July 2021 s.d. August 2, 2021 in figure below:

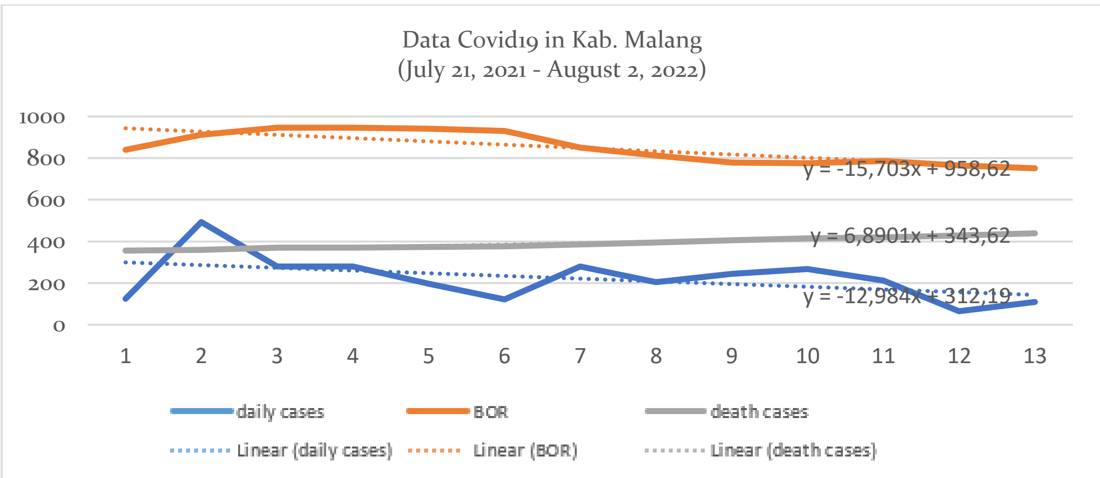


Figure 2. Graph of Patient Data in One PPKM Period

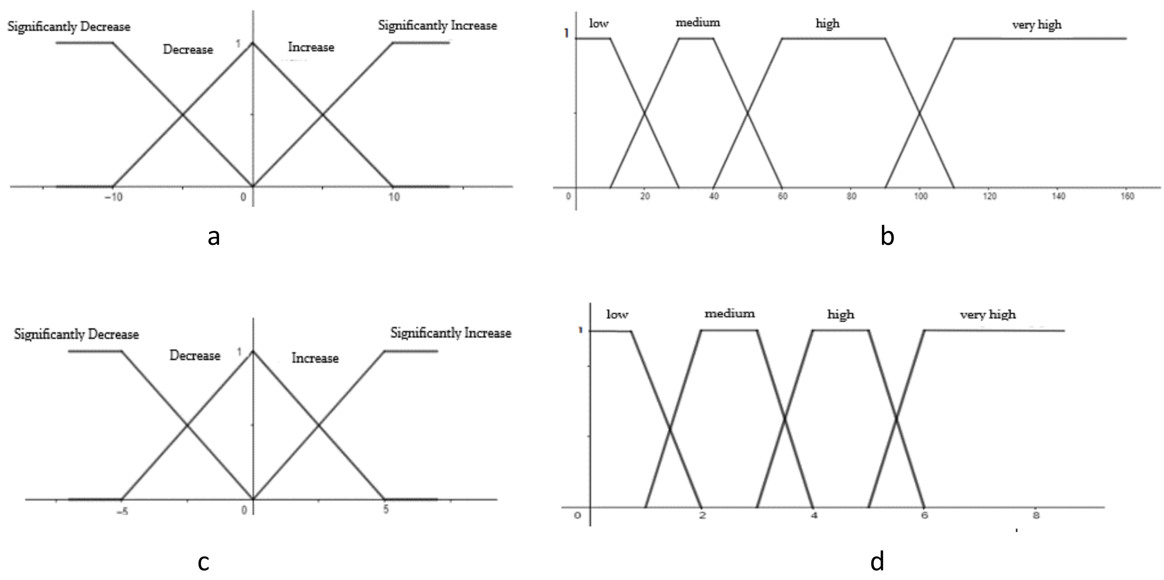
Figure 2 shows the data when PPKM was first applied. At that time the Malang District, is in level 3. Then on August 3, 2022 the area entered level 4. Judging from the fluctuations in the Covid-19 data as described above, it is not enough to determine the PPKM level only with real data in numerical form but also look at trend patterns. Does the data tend to go up or down. Thus the trend and constants will be used as fuzzy variables which are then used as the basis for data classification. This trend is taken from the slope value of the linear plot data or known as the regression coefficient while the real case value is taken from the regression constant[36]–[38].

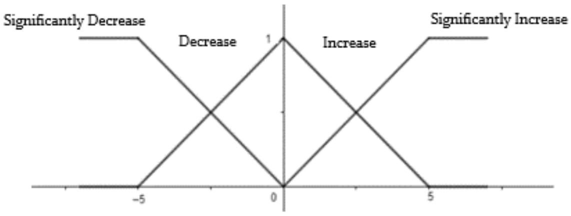
3.2. Variables and fuzzy sets

Based on the data that has been collected and based on the signs set forth in the Minister of Home Affairs Regulation Number 22 of 2021, there are 6 fuzzy variables, each of which has 4 fuzzy sets. The variables and fuzzy sets are as follows:

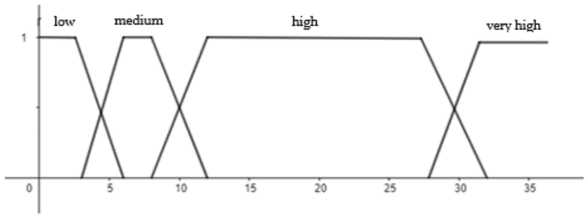
a. TREND OF DAILY CASES. This variable has 4 fuzzy sets, namely: SIGNIFICANTLY DECREASE=(-∞,0]; DECREASE =[-10,0]; INCREASE=[0,10]; and SIGNIFICANTLY INCREASE =[0,∞)
b. DAILY CASE CONSTANTS. This variable has 4 fuzzy sets, namely: LOW =[0.30]; MEDIUM =[10,60]; HIGH=[40,110]; and VERY HIGH=[100,∞)
c. TREND OF DEATH CASES. This variable has 4 fuzzy sets, namely: SIGNIFICANTLY DECREASE=(-∞,0]; DECREASE=[-5,0]; INCREASE=[0,5]; and SIGNIFICANTLY INCREASE =[0,∞)
d. DEATH CASES CONSTANT. This variable has 4 fuzzy sets, namely: LOW =[0,2]; MEDIUM=[1,4]; HIGH=[3,6]; and VERY HIGH =[5,∞)
e. TREND OF BOR OCCUPANCY. This variable has 4 fuzzy sets, namely: SIGNIFICANTLY DECREASE=(-∞,0]; DECREASE=[-5,0]; INCREASE=[0,5]; and SIGNIFICANTLY INCREASE =[0,∞)
f. BOR OCCUPANCY CONSTANT. This variable has 4 fuzzy sets, namely: LOW =[0,6]; MEDIUM =[3,12]; HIGH =[8,32]; and VERY HIGH =[28,∞)

Furthermore, from the variables above a membership function is created as follows as shown in Figure 3:





e



f

Figure 3. Membership Function (a) Trend of daily cases; (b) Daily case constants; (c) Trend of death cases; (d) Constant cases of death; (e) Trend of BOR occupancy; (f) BOR occupancy constant

Figure 3 shows the types of membership functions Figures. Figure 3a is a picture of daily cases trend, Figure 3b is picture of daily case constants; Figure 3c is a picture of death cases trend; Figure 3d is a picture of death Constant cases; Figure 3e is a picture of BOR occupancy trend; and Figure 3f is a picture of BOR occupancy constant. The differences between them is in fuzzy variables, fuzzy sets, and threshold. In fact, threshold is determined by looking at the data and trial and error which one is the best. On the trend chart, the fuzzy variables are significance decreased, decreased, increased, and significantly increased. Whereas, on the daily case chart, the fuzzy variables are low, medium, high, and very high. If the membership function in Figure 3 is translated into a mathematical formula, it can be written as follows:

a. Trend of daily positive cases

In this function we use threshold values of -10, 0, and 10 with the following categories:

$$\mu_{significantly\ decreased} = \begin{cases} 1, x < -10 \\ -\frac{x}{10}, -10 < x < 0 \\ 0, x > 0 \end{cases} ; \mu_{decreased} = \begin{cases} 0, x < -10 \\ \frac{x+10}{10}, -10 < x < 0 \end{cases}$$

$$\mu_{increased} = \begin{cases} 0, x > 10 \\ \frac{10-x}{10}, 0 < x < 10 \end{cases} ; \mu_{significantly\ increased} = \begin{cases} 1, x > 10 \\ \frac{x}{10}, 0 < x < 10 \\ 0, x < 0 \end{cases}$$

b. Daily positive case constants

In this function we use threshold values of 10, 30, 40, 60, 90, and 110 with the following categories:

$$\mu_{low} = \begin{cases} 1, x < 10 \\ \frac{30-x}{20}, 10 < x < 30 \\ 0, x > 30 \end{cases} ; \mu_{medium} = \begin{cases} 0, x < 10 \\ \frac{x-10}{20}, 10 < x < 30 \\ 1, 30 < x < 40 \\ \frac{60-x}{20}, 40 < x < 60 \\ 0, x > 60 \end{cases}$$

$$\mu_{high} = \begin{cases} 0, x < 40 \\ \frac{x-40}{20}, 40 < x < 60 \\ 1, 60 < x < 90 \\ \frac{110-x}{20}, 90 < x < 110 \\ 0, x > 110 \end{cases} ; \mu_{veryhigh} = \begin{cases} 1, x > 110 \\ \frac{x-90}{20}, 90 < x < 110 \\ 0, x < 90 \end{cases}$$

c. Tendency of cases of death
In this function we use threshold values of -5, 0, and 5 with the following categories:

$$\mu_{significantly\ decreased} = \begin{cases} 1, x < -5 \\ -\frac{x}{5}, -5 < x < 0 \\ 0, x > 0 \end{cases};\ \mu_{decreased} = \begin{cases} 0, x < -5 \\ \frac{x+5}{5}, -5 < x < 0 \end{cases}$$

$$\mu_{increased} = \begin{cases} 0, x > 5 \\ \frac{5-x}{5}, 0 < x < 5 \end{cases};\ \mu_{significantly\ increased} = \begin{cases} 1, x > 5 \\ \frac{x}{5}, 0 < x < 5 \\ 0, x < 0 \end{cases}$$

d. Constant cases of death
In this function we use threshold values of 1, 2, 3, 4, 5, and 6 with the following categories:

$$\mu_{low} = \begin{cases} 1, x < 1 \\ 1 - x, 1 < x < 2 \\ 0, x > 2 \end{cases};\ \mu_{medium} = \begin{cases} 0, x < 1 \\ x - 1, 1 < x < 2 \\ 1, 2 < x < 3 \\ 4 - x, 3 < x < 4 \\ 0, x > 4 \end{cases}$$

$$\mu_{high} = \begin{cases} 0, x < 3 \\ x - 1, 3 < x < 4 \\ 1, 4 < x < 5 \\ 6 - x, 5 < x < 6 \\ 0, x > 6 \end{cases};\ \mu_{veryhigh} = \begin{cases} 1, x > 6 \\ x - 5, 5 < x < 6 \\ 0, x < 5 \end{cases}$$

e. The trend of BOR filling
In this function we use threshold values of -5, 0, and 5 with the following categories:

$$\mu_{significantly\ decreased} = \begin{cases} 1, x < -5 \\ -\frac{x}{5}, -5 < x < 0 \\ 0, x > 0 \end{cases};\ \mu_{decreased} = \begin{cases} 0, x < -5 \\ \frac{x+5}{5}, -5 < x < 0 \end{cases}$$

$$\mu_{increased} = \begin{cases} 0, x > 5 \\ \frac{5-x}{5}, 0 < x < 5 \end{cases};\ \mu_{significantly\ increased} = \begin{cases} 1, x > 5 \\ \frac{x}{5}, 0 < x < 5 \\ 0, x < 0 \end{cases}$$

f. BOR load constant
In this function we use threshold values of 1,3,6,8, 12, 28, and 32 with the following categories:

$$\mu_{low} = \begin{cases} 1, x < 3 \\ \frac{6-x}{6}, 3 < x < 6 \\ 0, x > 6 \end{cases};\ \mu_{medium} = \begin{cases} 0, x < 3 \\ \frac{x-3}{3}, 3 < x < 6 \\ 1, 6 < x < 8 \\ \frac{12-x}{3}, 8 < x < 12 \\ 0, x > 12 \end{cases}$$

$$\mu_{high} = \begin{cases} 0, x < 8 \\ \frac{x-8}{4}, 8 < x < 12 \\ 1, 12 < x < 28 \\ \frac{32-x}{4}, 28 < x < 32 \\ 0, x > 32 \end{cases} ; \mu_{veryhigh} = \begin{cases} 1, x > 32 \\ \frac{x-28}{4}, 28 < x < 32 \\ 0, x < 28 \end{cases}$$

3.3. Generation of fuzzy rules

The next step is generating fuzzy rules with some treshold that will be used as inference engines[39], [40]. Of the 15 PPKM label change data in Malang District, the following rule patterns have been successfully generated:

a. **IF** The constant of daily positive cases is very high **AND** The trend of cases of death increases significantly **AND** The constant of cases of death is very high **AND** The BOR occupancy constant is very high **THEN** Level 4
b. **IF** The constant of daily positive cases is very high **AND** The trend of cases of death increases significantly **AND** The constant of cases of death is very high **AND** The trend of BOR occupancy increases significantly **OR** The BOR occupancy constant is high **THEN** Level 4
c. **IF** The daily positive case constant is very high **AND** The death case constant is very high **AND** The BOR occupancy constant is very high **THEN** Level 4
d. **IF** The tendency for daily cases to decrease **AND** The tendency for death cases to increase **AND** The tendency for BOR occupancy to fall significantly **THEN** Level 3
e. **IF** The trend of daily cases is decreasing **AND** The daily positive case constant is high **AND** The trend of fatal cases is decreasing significantly **AND** The number of fatalities is very high **AND** The tendency for BOR occupancy is to decrease significantly **AND** The BOR occupancy constant is very high **THEN** Level 3
f. **IF** The trend of daily cases is decreasing **AND** The daily positive case constant is moderate **AND** The trend of death cases is decreasing **AND** The constant number of fatalities is high **AND** The trend of BOR occupancy is decreasing **AND** The BOR occupancy constant is very high **THEN** Level 3
g. **IF** The trend of daily cases is decreasing **AND** The daily positive case constant is moderate **AND** The trend of fatal cases is decreasing **AND** The constant number of fatalities is low **AND** The tendency for BOR occupancy is to decrease significantly **AND** The BOR occupancy constant is very high **THEN** Level 3
h. **IF** The trend of daily cases is decreasing **AND** The daily positive case constant is moderate **AND** The trend of death cases is decreasing **AND** The constant number of fatalities is moderate **AND** The trend of BOR occupancy is significantly decreasing **AND** The BOR occupancy constant is very high **THEN** Level 3
i. **IF** The trend of daily cases is decreasing **AND** The daily positive case constant is low **AND** The trend of death cases is decreasing **AND** The casualty case constant is low **AND** The trend of BOR occupancy is decreasing **AND** The BOR occupancy constant is very high **THEN** Level 3
j. **IF** The daily positive case constant is very high **AND** The trend of death cases is down **AND** The death case constant is low **AND** The BOR occupancy constant is very high **THEN** Level 3
k. **IF** The trend of daily cases is decreasing **AND** The constant of positive daily cases is low **AND** The constant of cases of death is low **AND** The trend of BOR occupancy is decreasing **THEN** Level 2
l. **IF** The trend of daily cases is increasing **AND** The trend of fatal cases is increasing **AND** The constant of cases of death is low **AND** The trend of BOR occupancy is increasing **THEN** Level 2
m. **IF** The trend of daily cases is decreasing **AND** The daily positive case constant is low **AND** The trend of death cases is decreasing **AND** The casualty case constant is low **AND** The trend of BOR occupancy is increasing **THEN** Level 2

n. **IF** Low daily positive case constant **AND** Low fatality constant **AND** Moderate BOR occupancy constant **THEN** Level 1
o. **IF** Low daily positive case constant **AND** Low fatality constant **AND** Tendency for BOR occupancy to increase **THEN** Level 1

3.4. Testing and Evaluation

After generating fuzzy rules based on case data from 21 July 2021 to. 31 December 2021 then fuzzy rules will be used to classify PPKM levels from 1 January 2022 to.d. April 30, 2022. First, the test is carried out by inputting fuzzy variables obtained from weekly or bi-weekly Covid-19 data regression plots depending on the validity period of the PPKM. For example, in data testing January 4 2022 s.d. January 17, 2022 known Malang District is at level 2, so the classification is done to find out the decision for January 18th. From the plot data, the values of the coefficients and constants that describe the trend are calculated. The following is an example of the values used as input data for fuzzy rules taken on January 4, 2022 to. January 17, 2022:

Daily positive case trend = -0.0088
Daily positive case constant = 3.3516
The tendency of cases to die = -0.0242
Death case constant = 0.2527
BOR occupancy tendency = 0.178
Loading constant BOR = 11.451

After these parameters are obtained, fuzzification is performed by calculating the membership value ($\boldsymbol{\mu}$) based on the membership function in Figure 3. Next, the fuzzy rule is run as an inference and defuzzification engine. The following are the results of the data classification that has been carried out:

Table 2.
Classification Result

No	Target	Classification Result
1	Level 2	Level 2
2	Level 2	Level 2
3	Level 2	Level 2
4	Level 2	Level 2
5	Level 3	Level 4
6	Level 3	Level 3
7	Level 3	Level 0
8	Level 3	Level 3
9	Level 3	Level 3
10	Level 2	Level 2

Table 2 shows the accuracy results obtained in 80%. There are classification results that do not match the target. The level **0** value appears because the rule cannot read the pattern from the input data. While errors also occur when data should be classified at level 3 to level 4. After reviewing this, this is because the data has similarities with the rules which have implications for the conditions of the area at level 4.

4. Conclusion

This study aims to create a rule model based on Fuzzy Tsukamoto logic that can help determine the level of risk of an area. There are five main stages including data collection, formulating variables and fuzzy sets, generating fuzzy rules, testing data classification testing based on fuzzy rules, and evaluating classification results. Judging from the fluctuations in the Covid-19 data as described above, it is not enough to determine the PPKM level only with real data in numerical form but also look at trend patterns. Thus the trend and constants will be used as fuzzy variables which are then used as the basis for data classification. Based on data on Covid-19 patients in Malang District, East Java has formed 6 fuzzy variables, each of which has 4 fuzzy sets and 15 rules that can be used as a classification model. From the test results, an accuracy value of 80% was obtained. This shows that the generated rules can properly classify the daily Covid-19 data to then estimate the next PPKM level. Even though it has good accuracy, this rule is limited to the Malang District, East Java. Furthermore, the development of fuzzy rules like this can be used to classify data with other cases in the next research.

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