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Analysis of Gold Price Forecasts in Padang City Using Automatic Clustering Method and Fuzzy Logic Relationship

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ABSTRACT

Gold is often chosen as an investment due to its lucrative potential. To maximize profits and avoid losses, investors need to understand the volatile price movements of gold. This research aims to forecast the price of gold in the next period. In this research, the forecasting method used is Automatic Clustering and Fuzzy Logical Relationship (ACFLR). ACFLR is a method that uses the concept of fuzzy logic for modeling time series data. The forecasting process includes data sorting, cluster formation, interval determination, fuzzification, FLR and FLRG formation, and calculation of forecasting values. Based on this method, the result of the gold price forecast in Padang City for the next period, namely January 2024, using the ACFLR method, is IDR 978,796.9. With a MAPE value of 0.9%, this method is very good. For further research, it is hoped that other forecasting models can use the fuzzy time series method to obtain the most optimal method for forecasting gold prices.

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A. INTRODUCTION

The more advanced mindset of society wants to manage their income for future needs. Investment is a desire how to use some of the existing funds or resources owned to obtain large profits in the future. While according to Inayah (2020), Investment is a form of capital investment made by individuals or legal entities to increase or maintain the value of their assets, which can be in the form of equipment, cash, expertise, or intellectual property rights. There are three types of investments: long-term, medium-term, and short-term. Long-term investments include time deposits, property, mutual funds, and stocks. Medium-term investments are in the form of gold investments. While short-term investments are in the form of foreign exchange investments (Ramadhani et al., 2022). Gold is one type of investment that is in demand because it has several advantages such as security, profitability, high liquidity, low risk, and ease of self-management (Sitohang, 2018). The value of gold investment tends to increase, making it a profitable option with little risk (Nudia, 2022). However, gold prices do not always increase, for example, in Padang City.

Padang City has a long history in the gold trade in Indonesia. Many jewelry stores, financial institutions, and investors in the city are involved in gold trading. Therefore, forecasting analysis of gold prices in Padang City is important to understand local market behavior, manage investment risks, and make informed investment decisions.

Gold price fluctuations in Padang City attract investors to turn their money around for profit. Therefore, investors need accurate forecasting to predict future gold price movements. A method that can provide good forecasting accuracy to overcome the uncertainty of gold prices is Automatic Clustering and Fuzzy Logical Relationship (ACFLR).

ACFLR is a modified method of fuzzy time series that models time series data using an automatic clustering algorithm (Endaryati & Kurniawan, 2015). This algorithm forms intervals based on groups and the length of each interval. Automatic clustering aims to calculate the average difference and form clusters from the data used in forecasting (Pratama & Indriani, 2018). This method aims to understand the pattern of gold price fluctuations by clustering gold price data based on similar characteristics. Automatic clustering is effective in identifying patterns and trends in gold price fluctuations. The research of Ikhsanto et al. (2018), compares the accuracy of fuzzy time series forecasting models using automatic clustering and average-based for interval formation and defuzzification with the Markov chain concept, showing that automatic clustering is better at forming intervals. In addition, fuzzy logical relationships can identify relationships between data that have been clustered for forecasting, considering the uncertainty and complexity of the data. This method describes numerical data relationships flexibly, resulting in more accurate forecasting. As researched by Pratiwi et al. (2021), the method provides an accuracy rate calculated using MAPE (Mean Absolute Percentage Error) of 0.0496%, which shows that the fuzzy logic relationship method is very well used for forecasting.

This research aims to forecast gold prices in Padang City using automatic clustering as a determinant of interval length in fuzzy logical relationships. The difference between this research and previous research lies in using more specific methods to predict gold prices in Padang City. Previous studies generally focused more on other commodity prices or stocks on a global scale. For example, research by Putra & Rivandi (2018), entitled "The Effect of Income, Gold Prices, and Inflation Rates on Lending at Padang Branch Pawnshops," focuses more on analyzing the influence of economic factors, including gold prices, on the amount of credit disbursed by pawnshop institutions. The main focus of the study was on the economic relationship between gold prices, income, inflation, and lending, not on forecasting gold prices. Meanwhile, another study by Dewi et al. (2022) entitled "Analysis of Gold Price Forecasting in Indonesia during the Covid-19 Pandemic for Investment" using the Autoregressive Integrated Moving Average (ARIMA) method. The results showed that the ARIMA method is based on a linear model, so it is not optimal in capturing non-linear relationships in time series data. In contrast, fuzzy logic can capture uncertainty and non-linear relationships in data, often appearing in gold price fluctuations. This allows predictions to be more adaptive to patterns of price change. Other studies use the Automatic Clustering and Fuzzy Logic Relationship (ACFLR) method to forecast the population in Makassar in 2017-2021, with accurate forecasting results indicated by a MAPE value below 10%, namely 0.48% (Abdy et al., 2019). Therefore, this study is the first to use the ACFLR method to predict gold prices in Padang City.

B. RESEARCH METHOD

This type of research is applied research. Applied research aims to solve or provide solutions to a problem, which begins with analyzing theory, data collection, and its application to data. The type of data used in this research is secondary data, which is research data sourced from other parties or other existing agencies. This research data was obtained from the Central Bureau of Statistics (BPS). The data used is monthly data on gold prices in Padang City from January 2018 to December 2023. The official website used is https://padangkota.bps.go.id/. The work steps in this research are:

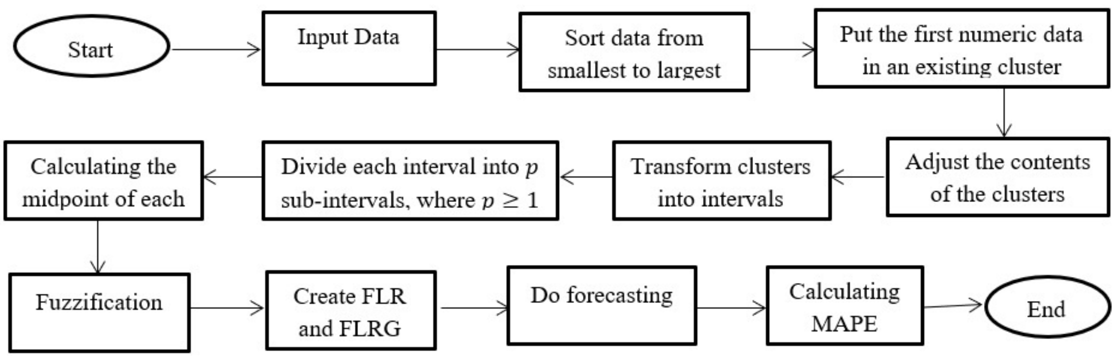

Figure 1. Research Steps

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1. An Automatic Clustering Algorithm

This section presents an automatic clustering algorithm for grouping numerical data into intervals. This algorithm is a modification of the work done by (Liu & Wang, 2015). The following is the presentation of the algorithm:

Step 1: Sort the numerical data in an ascending sequence having n different numerical data. Assume that the ascending data sequence without duplicate data is shown as follows:

$$d_1, d_2, d_3, \ldots, d_i, \ldots, d_n.$$

where d_1 indicates the first smallest data in ascending order, d_2 indicates the second smallest data in ascending order, and so on. Then, calculate the value of "$average\_diff$" as follow:

$$average\_diff = \frac{\sum_{i=1}^{n-1} (d_{i+1} - d_i)}{n-1} \tag{1}$$

where "$average\_diff$" denotes the average differences between every pair of data in the ascending data sequence.

Step 2: Put the first numerical datum (i.e., the smallest datum in the ascending sequence) into the current cluster. Based on the value of "*average_diff*" determine whether the numericadatum following the datum in the current cluster in the ascending data sequence can be put into the current cluster or needs to be put it into a new cluster based on the following principles:

Principle 1: Assume that the current cluster is the first cluster and there is only one datum d_1 in it and assume that d_2 is the adjacent datum following d_1, shown as follows:

$$\{d_1\}, d_2, d_3, \ldots, d_i, \ldots, d_n.$$

If $d_2 - d_1 \leq average\_diff$, then put d_2 into the current cluster, which d_1 belongs to. Otherwise, generate a new cluster for d_2 and let the newly generated cluster, which d_2 belongs to the current cluster.

Principle 2: Assume that the current cluster is not the first cluster and there is only one datum d_j in the current cluster. Assume that d_k is the adjacent datum next to d_j and assume that d_i is the largest datum in the cluster which is the antecedent cluster of the current cluster, shown as follows:

$$\{d_1\}, \ldots, \{\ldots, d_i\}, \{d_j\}, \ d_k, \ldots, d_n.$$

If $d_k - d_j \leq average\_diff$ and $d_k - d_j \leq d_j - d_i$, then put d_k into the current cluster, which d_j belongs to. Otherwise, generate a new cluster for d_k and let the newly generated cluster, which d_k belongs to the current cluster.

Principle 3: Assume that the current cluster is not the first cluster and has more than one datum in the current cluster. Assume that d_i is the largest datum in the current cluster and assume that d_j is the adjacent datum next to d_i, shown as follows:

$$\{d_1\}, \ldots, \{\ldots, d_i\}, d_j, \ldots, d_n.$$

If $d_j - d_i \leq average\_diff$ and $d_j - d_i \leq cluster\_diff$, then put d_j into the current cluster which d_i belongs to. Otherwise, generate a new cluster for d_j and let the new generated cluster that d_j belongs to be the current cluster, where "$cluster\_diff$" denotes the average difference of the distances between every pair of adjacent data in the cluster and the value of $cluster\_diff$, is calculated as follows:

$$cluster\_diff = \frac{\sum_{i=1}^{n-1} (c_{i+1} - c_i)}{n-1} \tag{2}$$

where $cluster\_diff$ is the average of the current cluster and $c_1, c_2, \ldots, c_n$ are the data in the current cluster.

Step 3: Based on the clustering results obtained in **Step 2**, adjust the contents of these clusters according to the following principles:

Principle 1: If a cluster has more than two data, we keep the smallest, keep the largest, and remove the others.

Principle 2: If a cluster has exactly two data, we leave it unchanged.

Principle 3: If a cluster only has one datum d_q, then we put the values of "$d\_q - average\_diff$" and "$d\_q + average\_diff$" into the cluster and remove d_q from this cluster. Moreover, if the following situations occur, the cluster needs to be adjusted again:

Situation 1: If the situation occurs in the first cluster, then we remove the value of "$d_q - average\_diff$" instead of d_q from this cluster.

Situation 2: If the situation occurs in the last cluster, then we remove the value of "$d_q + average\_diff$" instead of d_q from this cluster.

Situation 3: If the value of "$d_q - average\_diff$" is smaller than the smallest value in its antecedent cluster, then we undo all the action in **Principle 3**.

Step 4: Assume that the clustering results obtained in **Step 3** are shown as follows:

$$\{d_1, d_2\}, \{d_3, d_4\}, \{d_5, d_6\}, \ldots, \{d_r\}, \{d_s, d_t\}, \ldots, \{d_{n-1}, d_n\}.$$

Transform these clusters into contiguous intervals by the following sub-steps:

Step 4.1: Transform the first cluster $\{d_1, d_2\}$ into the interval $[d_1, d_2)$.

Step 4.2: If the current interval is $[d_i, d_j)$ and the current cluster is $\{d_k, d_l\}$, then

(1) If $d_j \geq d_k$, then transform the current cluster $\{d_k, d_l\}$ into the interval $[d_j, d_l)$. Let $[d_j, d_l)$ be the current interval and let the next cluster $\{d_m, d_n\}$ be the current cluster.

(2) If $d_j < d_k$, then transform $\{d_k, d_l\}$ into the interval $[d_k, d_l)$ and create a new interval $[d_j, d_k)$ between $[d_i, d_j)$ and $[d_k, d_l)$. Let $[d_k, d_l)$ be the current interval and let the next cluster $\{d_m, d_n\}$ be the current cluster. If the current interval is $[d_i, d_j)$ and the current cluster is $\{d_k\}$, then transform the current interval $[d_i, d_j)$ into $[d_i, d_k)$. Let $[d_i, d_k)$ be the current interval and let the next cluster be the current cluster.

Step 4.3: Repeatedly check the current interval and the current cluster until all the clusters have been transformed into intervals.

Step 5: For each interval obtained in **Step 4**, divide each obtained interval into p sub-intervals, where $p \geq 1$.

2. A New Method for Forecasting Based on Automatic Clustering Algorithm and Fuzzy Logical Relationships

In this section, we present a new method for forecasting gold prices based on the proposed automatic clustering algorithm and fuzzy logical relationships. The proposed method is now presented as follows:

Step 1: Apply the automatic clustering algorithm to group the historical gold price data into intervals and calculate the midpoint of each interval.

Step 2: Assume that there are n intervals $u_1,\ u_2,\ u_3, \ldots,\ u_n$, then define each fuzzy set A_i, where $1 \leq i \leq n$, as follows:

$$\begin{aligned}
A_1 &= 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + \ldots + 0/u_{n-1} + 0/u_n,\\
A_2 &= 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + \ldots + 0/u_{n-1} + 0/u_n,\\
A_3 &= 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + \ldots + 0/u_{n-1} + 0/u_n,\\
&\vdots \qquad\qquad\qquad \vdots\\
A_n &= 0/u_1 + 0/u_2 + 0/u_3 + 0/u_4 + \ldots + 0.5/u_{n-1} + 1/u_n.
\end{aligned}$$

Step 3: Fuzzify each datum in the historical enrollments into a fuzzy set. If the datum belongs to u_i, where $1 \leq i \leq n$, then the datum is fuzzified into A_i.

Step 4: Construct the fuzzy logical relationships based on the fuzzified historical enrollments obtained in **Step 3**. If the fuzzified enrollments of years t and $t+1$ are A_j and A_k, respectively, then construct the fuzzy logical relationship "$A_j \rightarrow A_k$", where A_j and A_k are called the current state and the next state of fuzzy logical relationship, respectively. According to the current states of fuzzy logical relationships, divide the fuzzy logical relationships into fuzzy logical relationship groups, where the fuzzy logical relationships having the same current state are put into the same fuzzy logical relationship group.

Step 5: Calculate the forecasted enrollment by the following principles:

Principle 1: If the fuzzified enrollment of year t is A_j and there is only one fuzzy logical relationship in the fuzzy logical relationship group whose current state is A_j, shown as follows:

$$A_j \rightarrow A_k \tag{3}$$

then the forecasted enrollment of year $t+1$ is m_k, where m_k is the midpoint of the interval u_k and the maximum membership value of the fuzzy set A_k occurs at the interval u_k.

Principle 2: If the fuzzified enrollment of year t is A_j and there are the following fuzzy logical relationships in the fuzzy logical relationship group whose current state is A_j, shown as follows:

$$A_j \rightarrow A_{k1}\left(x_1\right), A_{k2}\left(x_2\right), \ldots, A_{kp}(x_p) \tag{4}$$

then the forecasted enrollment of year $t+1$ is calculated as follows:

$$\frac{x_1 \times mk_1 + x_2 \times mk_2 + \ldots + x_p \times mk_p}{x_1 + x_2 + \ldots + x_p} \tag{5}$$

where x_i denotes the number of fuzzy logical relationships "$A_j \rightarrow A_k$" in the fuzzy logical relationship group, $1 \leq i \leq p$; $mk_1, mk_2, \ldots$, and mk_p are the midpoints of the intervals $u_{k1}, u_{k2}, \ldots$, and u_{kp}, respectively, and the maximum membership values of the fuzzy sets $A_{k1}, A_{k2}, \ldots$, and A_{kp} occur at the intervals $u_{k1}, u_{k2}, \ldots$, and u_{kp}, respectively.

Principle 3: If the fuzzified enrollment of year t is A_j and there is a fuzzy logical relationship in the fuzzy logical relationship group whose current state is A_j, shown as follows:

$$A_j \rightarrow \# \tag{6}$$

where the symbol "#" denotes an unknown value, then the forecasted enrollment of year $t+1$ is m_j, where m_j is the midpoint of the interval u_j and the maximum membership value of the fuzzy set A_j occurs at u_j.

3. Model Validation

Basically, forecasting is done by comparing the forecasting results with reality. The use of a forecasting technique that produces the smallest deviation/error is the best forecasting technique to use. In this study, using Mean Absolute Percentage Error (MAPE). MAPE is an evaluation calculation, and it is often used to measure how precise or accurate a prediction is (Kim & Kim, 2016).

MAPE is the average of the overall percentage error (difference) between actual data and forecasting data. The accuracy measure is matched with time series data and is shown in percentage. The MAPE used for accuracy measures is as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100 \tag{7}$$

Where n indicates the number of sample datasets, Y_i indicates the actual data value in period i, and $\hat{Y}_i$ indicates the predicted data value in period i. MAPE accuracy criteria according to Nabillah & Ranggadara (2020), can be seen in Table 1 below.

Table 1. MAPE Value Range

MAPE Range	Meaning
$< 10\%$	The ability of the prediction model is very good
$10\% - 20\%$	The ability of the prediction model is good
$20\% - 50\%$	The ability of a decent prediction model
$> 50\%$	Poor prediction model ability

C. RESULT AND DISCUSSION

The data to be analyzed in this study uses Gold price data in Padang City for the period January 2018 to December 2023. The total amount of data used is 72 data. The gold price data can be seen in Table 2.

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Table 2. Data on 24 Karat Gold Price Per Gram in Rupiah in Padang City

No.	Year	Month	Gold Price
1	2018	January	Rp507.131
2	2018	February	Rp507.132
3	2018	March	Rp507.133
4	2018	April	Rp507.134
⋮	⋮	⋮	⋮
69	2023	September	Rp907.331
70	2023	October	Rp922.635
71	2023	November	Rp955.600
72	2023	December	Rp980.512

Table 2 shows data on gold prices in Padang City. The full information can be found on the website: https://padangkota.bps.go.id/. The movement of gold prices in Padang City from January 2018 to December 2023 can be seen in Figure 2.

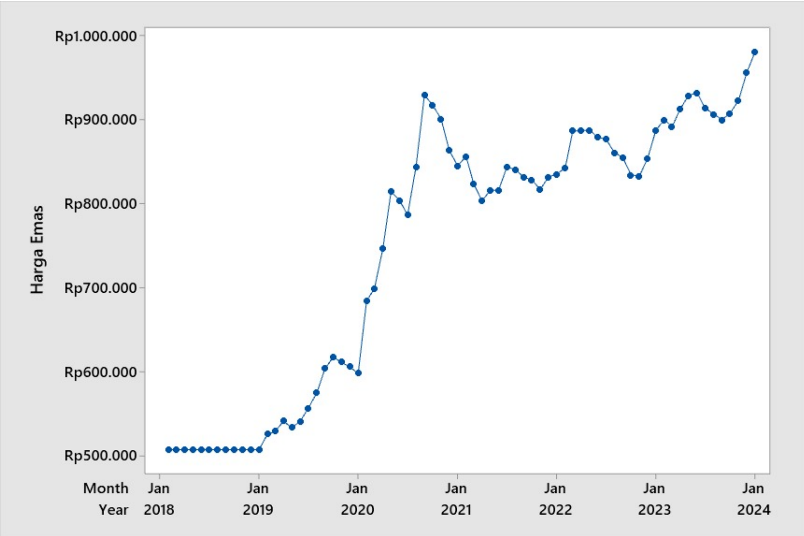

Figure 2. Plot of Monthly Data of 24 Karat Gold Price Per Gram in Rupiah in Padang City for 2018-2023

Based on Figure 2, it can be seen that the gold price data plot in Padang City experiences relatively stable fluctuations. The data pattern shows an upward trend. In 2020, the COVID-19 pandemic drove a significant increase in gold prices due to the high global demand for physical gold as a form of asset protection amid economic uncertainty. This condition led to an increase in gold prices as a market response to economic instability. Research by Setiyono et al. (2022) also shows that COVID-19 has a significant effect on gold prices in Indonesia.

The existing data can be grouped using the automatic clustering method to form an interval. Data can be clustered using automatic clustering methods because they can automatically identify patterns without requiring prior knowledge of the number of clusters. In the context of gold prices, this method can efficiently cluster data that is dynamic and complex, such as prices affected by inflation, exchange rates, and other economic factors. With automatic clustering, highly variable data can be organized based on similar characteristics, facilitating further analysis. The method also reduces bias in clustering and adaptively adjusts parameters to produce optimal clusters, making it an effective tool for simplifying and objectively clustering gold price data. The steps for applying the automatic clustering method are as follows.

Step 1: Sort the historical data in Table 2 in ascending order. The sorting results are shown in Table 3 below.

Table 3. Sorted Gold Price and No Double Data

No.	Year	Month	Gold Price
1	2018	January	Rp507.131
2	2018	February	Rp507.132
3	2018	March	Rp507.133

No.	Year	Month	Gold Price
4	2018	April	Rp507.134
⋮	⋮	⋮	⋮
67	2020	Agustus	Rp928.958
68	2023	May	Rp931.610
69	2023	November	Rp955.600
70	2023	December	Rp980.512

Table 3 shows the sorted gold prices, with only one data retained in the sorted data, if there is the same data. The initial 72 data has been reduced to 70 data. Based on Equation (1), we can calculate the value of $average\_diff$, where—

$$\begin{aligned} average\_diff &= \frac{(507.132-507.131)+(507.133-507.132)+\cdots+(980.512-955.600)}{70-1} \\ &= 6.860,594 \end{aligned}$$

Step 2: Based on the $average\_diff$ value and the three principles in **Step 2**, we can group the order of the data in ascending order so as to obtain the clustering result as follows:

Table 4. Clusters Formed

Cluster	Member	Cluster	Member	Cluster	Member
c_1	Rp507.131	c_{10}	Rp683.833	c_{19}	Rp860.369
	Rp507.132	c_{11}	Rp698.917		Rp863.333
	Rp507.133	c_{12}	Rp746.083	c_{20}	Rp876.333
	Rp507.134	c_{13}	Rp786.208		Rp878.581
	Rp507.135	c_{14}	Rp803.000	c_{21}	Rp886.367
	Rp507.136		Rp803.667		Rp887.167
	Rp507.137	c_{15}	Rp814.167	c_{22}	Rp887.267
	Rp507.138		Rp815.600	c_{23}	Rp891.050
	Rp507.139		Rp816.458	c_{24}	Rp899.507
	Rp507.140	c_{16}	Rp823.625		Rp899.565
	Rp507.141		Rp827.967		Rp900.708
	Rp507.142	c_{17}	Rp831.208		Rp906.181
c_2	Rp525.198		Rp831.458		Rp907.331
	Rp528.658		Rp832.458		Rp912.624
c_3	Rp533.424	c_{18}	Rp833.767		Rp913.027
c_4	Rp540.367		Rp834.800		Rp916.708
	Rp540.918		Rp840.467		Rp922.635
c_5	Rp556.126		Rp842.250		Rp928.330
c_6	Rp574.081		Rp843.208		Rp928.958
c_7	Rp597.650		Rp843.667		Rp931.610
	Rp603.172		Rp844.600	c_{25}	Rp955.600
	Rp605.643		Rp853.417	c_{26}	Rp980.512
c_8	Rp610.894	c_{19}	Rp854.583		
c_9	Rp617.279		Rp855.958		

Step 3: Based on the three principles in **Step 3**, we can adapt the clustering result from **Step 2** into the following form:

Table 5. Cluster Results After Adjusting the Conditions in Step 3

Cluster	Member	Cluster	Member	Cluster	Member
c_1	$\{507.131\,;507.142\}$	c_{10}	$\{676.972,4\,;690.693,6\}$	c_{19}	$\{853.417\,;863.333\}$
c_2	$\{525.198\,;528.658\}$	c_{11}	$\{692.056,4\,;705.777,6\}$	c_{20}	$\{876.333\,;878.581\}$
c_3	$\{526.563,4\,;540.284,6\}$	c_{12}	$\{739.222,4\,;752.943,6\}$	c_{21}	$\{886.367\,;887.167\}$
c_4	$\{540.367\,;540.918\}$	c_{13}	$\{779.347,4\,;793.068,6\}$	c_{22}	$\{887.267\}$
c_5	$\{549.265,4\,;562.986,6\}$	c_{14}	$\{803.000\,;803.667\}$	c_{23}	$\{891.050\}$
c_6	$\{567.220,4\,;580.941,6\}$	c_{15}	$\{814.167\,;816.458\}$	c_{24}	$\{899.507\,;931.610\}$
c_7	$\{597.650\,;605.643\}$	c_{16}	$\{823.625\,;827.967\}$	c_{25}	$\{948.739,4\,;962.460,6\}$
c_8	$\{604.033,4\,;617.754,6\}$	c_{17}	$\{831.208\,;832.458\}$	c_{26}	$\{973.651,4\,;980.512\}$
c_9	$\{610.418,8\,;624.139,6\}$	c_{18}	$\{833.767\,;844.600\}$		

Step 4: By repeating the sub-steps in **Step 4** repeatedly, we can get the following intervals:

Table 6. The Result of The Intervals Formed

u_i	Interval Class	u_i	Interval Class
u_1	[507.131 ; 507.142)	u_{23}	[793.068, 6 ; 803.000]
u_2	[507.142 ; 525.198)	u_{24}	[803.000 ; 803.667)
u_3	[525.198 ; 528.658)	u_{25}	[803.667 ; 814.167)
u_4	[528.658 ; 540.284, 6)	u_{26}	[814.167 ; 816.458)
u_5	[540.284, 6 ; 540.367)	u_{27}	[816.458 ; 823.625)
u_6	[540.367 ; 540.918)	u_{28}	[823.625 ; 827.967)
u_7	[540.918 ; 549.265, 4)	u_{29}	[827.967 ; 831.208)
u_8	[549.265, 4 ; 562.986, 6)	u_{30}	[831.208 ; 832.458)
u_9	[562.986, 6 ; 567.220, 4)	u_{31}	[832.458 ; 833.767)
u_{10}	[567.220, 4 ; 580.941, 6)	u_{32}	[833.767 ; 844.600)
u_{11}	[580.941, 6 ; 597.650)	u_{33}	[844.600 ; 853.417)
u_{12}	[597.650 ; 605.643)	u_{34}	[853.417 ; 863.333)
u_{13}	[605.643 ; 617.754, 6)	u_{35}	[863.333 ; 876.333)
u_{14}	[617.754, 6 ; 624.139, 6)	u_{36}	[876.333 ; 878.581)
u_{15}	[624.139, 6 ; 676.972, 4)	u_{37}	[878.581 ; 886.367)
u_{16}	[676.972, 4 ; 690.693, 6)	u_{38}	[886.367 ; 891.050)
u_{17}	[690.693, 6 ; 692.056, 4)	u_{39}	[891.050 ; 899.507)
u_{18}	[692.056, 4 ; 705.777, 6)	u_{40}	[899.507 ; 931.610)
u_{19}	[705.777, 6 ; 739.222, 4)	u_{41}	[931.610 ; 948.739, 4)
u_{20}	[739.222, 4 ; 752.943, 6)	u_{42}	[948.739, 4 ; 962.460, 6)
u_{21}	[752.943, 6 ; 779.347, 4)	u_{43}	[962.460, 6 ; 973.651, 4)
u_{22}	[779.347, 4 ; 793.068, 6)	u_{44}	[973.651, 4 ; 980.512)

Step 5: If $p = 2$, then each interval obtained in **Step 4** is divided into 2 sub-intervals. The result is as follows:

Table 7. Intervals are Divided Into $p = 2$

u_i	Interval $p = 2$	u_i	Interval $p = 2$	u_i	Interval $p = 2$
u_1	[507.131 , 507.136, 5)	u_{31}	[676.972, 4 ; 683.833)	u_{61}	[832.458 ; 833.112, 5)
u_2	[507.136, 5 ; 507.142)	u_{32}	[683.833 ; 690.693, 6)	u_{62}	[833.112, 5 ; 833.767)
u_3	[507.142 ; 516.170)	u_{33}	[690.693, 6 ; 691.375)	u_{63}	[833.767 ; 839.183, 5)
u_4	[516.170 ; 525.198)	u_{34}	[691.375 ; 692.056, 4)	u_{64}	[839.183, 5 ; 844.600)
u_5	[525.198 ; 526.928)	u_{35}	[692.056, 4 ; 698.917)	u_{65}	[844.600 ; 849.008, 5)
u_6	[526.928 ; 528.658)	u_{36}	[698.917 ; 705.777, 6)	u_{66}	[849.008, 5 ; 853.417)
u_7	[534.471, 3 ; 540.284, 6)	u_{37}	[705.777, 6 ; 722.500)	u_{67}	[853.417 ; 858.375)
u_8	[528.658 ; 534.471, 3)	u_{38}	[722.500 ; 739.222, 4)	u_{68}	[858.375 ; 863.333)
u_9	[540.284, 6 ; 540.325, 8)	u_{39}	[739.222, 4 ; 746.083)	u_{69}	[863.333 ; 869.833)
u_{10}	[540.325, 8 ; 540.367)	u_{40}	[746.083 ; 752.943, 6)	u_{70}	[869.833 ; 876.333)
u_{11}	[540.367 ; 540.642, 5)	u_{41}	[752.943, 6 ; 766.145.5)	u_{71}	[876.333 ; 877.457)
u_{12}	[540.642, 5 ; 540.918)	u_{42}	[766.145.5 ; 779.347, 4)	u_{72}	[877.457 ; 878.581)
u_{13}	[540.918 ; 545.091, 7)	u_{43}	[779.347, 4 ; 786.208)	u_{73}	[878.581 ; 882.474)
u_{14}	[545.091, 7 ; 549.265, 4)	u_{44}	[786.208 ; 793.068, 6)	u_{74}	[882.474 ; 886.367)
u_{15}	[549.265, 4 ; 556.126)	u_{45}	[793.068, 6 ; 798.034, 3)	u_{75}	[886.367 ; 888.708, 5)
u_{16}	[556.126 ; 562.986, 6)	u_{46}	[798.034, 3 ; 803.000)	u_{76}	[888.708, 5 ; 891.050)
u_{17}	[562.986, 6 ; 565.103, 5)	u_{47}	[803.000 ; 803.333, 5)	u_{77}	[891.050 ; 895.278, 5)
u_{18}	[565.103, 5 ; 567.220, 4)	u_{48}	[803.333, 5 ; 803.667)	u_{78}	[895.278, 5 ; 899.507)
u_{19}	[567.220, 4 ; 574.081)	u_{49}	[803.667 ; 808.917)	u_{79}	[899.507 ; 915.558, 5)
u_{20}	[574.081 ; 580.941, 6)	u_{50}	[808.917 ; 814.167)	u_{80}	[915.558, 5 ; 931.610)
u_{21}	[580.941, 6 ; 589.295, 8)	u_{51}	[814.167 ; 815.312, 5)	u_{81}	[931.610 ; 940.174, 7)
u_{22}	[589.295, 8 ; 597.650)	u_{52}	[815.312, 5 ; 816.458)	u_{82}	[940.174, 7 ; 948.739, 4)
u_{23}	[597.650 ; 601.646, 5]	u_{53}	[816.458 ; 820.041, 5)	u_{83}	[948.739, 4 ; 955.600)
u_{24}	[601.646, 5 ; 605.643)	u_{54}	[820.041, 5 ; 823.625)	u_{84}	[955.600 ; 962.460, 6)
u_{25}	[605.643 ; 611.698, 8)	u_{55}	[823.625 ; 825.796)	u_{85}	[962.460, 6 ; 968.056)
u_{26}	[611.698, 8 ; 617.754, 6)	u_{56}	[825.796 ; 827.967)	u_{86}	[968.056 ; 973.651, 4)
u_{27}	[617.754, 6 ; 620.947, 1)	u_{57}	[827.967 ; 829.587, 5)	u_{87}	[973.651, 4 ; 977.081, 7)
u_{28}	[620.947, 1 ; 624.139, 6)	u_{58}	[829.587, 5 ; 831.208)	u_{88}	[977.081, 7 ; 980.512)

u_i	Interval $p = 2$	u_i	Interval $p = 2$	u_i	Interval $p = 2$
u_{29}	$[624.139,6\,;650.556)$	u_{59}	$[831.208\,;831.833)$		
u_{30}	$[650.556\,;676.972,4)$	u_{60}	$[831.833\,;832.458)$		

Furthermore, the application of forecasting using automatic clustering and fuzzy logic relationship methods, is carried out with the following steps:

Step 1: Clustering historical data using automatic clustering with a value of p=2. The results can be seen in Table 7. Next, calculate the center value m_i with $1 \leq i \leq 88$, the results are obtained as follows:

Table 8. Midpoint of Each Intervals

m_i, where $1 \leq i \leq 88$							
m_1	507.133,8	m_{23}	599.648,2	m_{45}	795.551,4	m_{67}	855.896
m_2	507.139,2	m_{24}	603.644,8	m_{46}	800.517.1	m_{68}	860.854
m_3	511.656	m_{25}	608.670,9	m_{47}	803.166,8	m_{69}	866.583
m_4	520.684	m_{26}	614.726,7	m_{48}	803.500,2	m_{70}	873.083
m_5	526.063	m_{27}	619.350,8	m_{49}	806.292	m_{71}	876.895
m_6	527.793	m_{28}	622.543,3	m_{50}	811.542	m_{72}	878.019
m_7	531.564,6	m_{29}	637.347,8	m_{51}	814.739,8	m_{73}	880.527,5
m_8	537.377,9	m_{30}	663.764,2	m_{52}	815.885,2	m_{74}	884.420,5
m_9	540.305,2	m_{31}	680.402,7	m_{53}	818.249,8	m_{75}	887.537,8
m_{10}	540.346,4	m_{32}	687.263,3	m_{54}	821.833,2	m_{76}	889.879,2
m_{11}	540.504,8	m_{33}	691.034,3	m_{55}	824.710,5	m_{77}	893.164,2
m_{12}	540.780,2	m_{34}	691.715,7	m_{56}	826.881,5	m_{78}	897.392,8
m_{13}	543.004,9	m_{35}	695.486,7	m_{57}	828.777,2	m_{79}	907.532,8
m_{14}	547.178,6	m_{36}	702.347,3	m_{58}	830.397,8	m_{80}	923.584,2
m_{15}	552.695,7	m_{37}	714.138,8	m_{59}	831.520,5	m_{81}	935.892,4
m_{16}	559.556,3	m_{38}	730.861,2	m_{60}	832.145,5	m_{82}	944.457,1
m_{17}	564.045	m_{39}	742.652,7	m_{61}	832.785,2	m_{83}	952.169,7
m_{18}	566.162	m_{40}	749.513,3	m_{62}	833.439,8	m_{84}	959.030,3
m_{19}	570.650,7	m_{41}	759.544,5	m_{63}	836.475,2	m_{85}	965.258,3
m_{20}	577.511,3	m_{42}	772.746,5	m_{64}	841.891,8	m_{86}	970.853,7
m_{21}	585.118,7	m_{43}	782.777,7	m_{65}	846.804,2	m_{87}	975.366,6
m_{22}	593.472,9	m_{44}	789.638,3	m_{66}	851.212,8	m_{88}	978.796,9

Step 2: Based on Table 2, the data can be fuzzified, and the fuzzification results can be seen in Table 9. For example, take the eighth data, which is the August 2018 period with a value of 507.138. For that period, the data is in the interval $u_2 = [507.136,5\,;507.142)$, so the data in the August 2018 period is fuzzified into A_2.

Table 9. Fuzzification Result

No.	Year	Month	Gold Price	Fuzzification
1	2018	January	Rp507.131	A_1
2	2018	February	Rp507.132	A_1
3	2018	March	Rp507.133	A_1
4	2018	April	Rp507.134	A_1
⋮	⋮	⋮	⋮	⋮
69	2023	September	Rp907.331	A_{79}
70	2023	October	Rp922.635	A_{80}
71	2023	November	Rp955.600	A_{84}
72	2023	December	Rp980.512	A_{88}

Step 3: Based on Table 9, form a fuzzy logic relationship. For example, take 69$^{\text{th}}$ data and 70$^{\text{th}}$ data, whose fuzzification results are A_{79} and A_{80}. Then, the fuzzy logic relationship formed is $A_{79} \rightarrow A_{80}$, with A_{79} as the current state and A_{80} as the next state. For other data, it can be seen in Table 10 below.

Table 10. Fuzzification Result

No.	Year	Month	Gold Price	Current State	Next State
1	2018	January	Rp507.131	A_1	A_1
2	2018	February	Rp507.132	A_1	A_1
3	2018	March	Rp507.133	A_1	A_1
4	2018	April	Rp507.134	A_1	A_1
⋮	⋮	⋮	⋮	⋮	⋮
69	2023	September	Rp907.331	A_{79}	A_{80}
70	2023	October	Rp922.635	A_{80}	A_{84}
71	2023	November	Rp955.600	A_{84}	A_{88}
72	2023	December	Rp980.512	A_{88}	0

Step 4: Based on Table 10, the fuzzy logic relationship results are divided into groups, which are presented in Table 11 below.

Table 11. Forecasting Results

Group	FLRG	Group	FLRG
Group 1	: $A_1 \to A_1(5),\ A_2(1)$	Group 22	: $A_{53} \to A_{59}(1)$
Group 2	: $A_2 \to A_2\,(4)\,,\ A_3(1)$	Group 23	: $A_{55} \to A_{47}(1)$
Group 3	: $A_3 \to A_5(1)$	Group 24	: $A_{57} \to A_{53}(1)$
Group 4	: $A_5 \to A_7(1)$	Group 25	: $A_{59} \to A_{57}\,(1)\,,\ A_{63}(1)$
Group 5	: $A_7 \to A_{11}\,(1)\,,\ A_{13}(1)$	Group 26	: $A_{61} \to A_{67}(1)$
Group 6	: $A_{11} \to A_{16}(1)$	Group 27	: Group 26 : $A_{61} \to A_{67}(1)$
Group 7	: $A_{13} \to A_7(1)$	Group 28	: $A_{64} \to A_{59}\,(1)\,,\ A_{64(1)}\,,\ A_{75}\,(1)\,,\ A_{80}(1)$
Group 8	: $A_{16} \to A_{20}(1)$	Group 29	: $A_{65} \to A_{67}(1)$
Group 9	: $A_{20} \to A_{24}(1)$	Group 30	: $A_{66} \to A_{55}(1)$
Group 10	: $A_{23} \to A_{32}(1)$	Group 31	: $A_{67} \to A_{63}\,(1)\,,\ A_{75}(1)$
Group 11	: $A_{24} \to A_{26}(1)$	Group 32	: $A_{68} \to A_{67}(1)$
Group 12	: $A_{25} \to A_{23}(1),\ A_{25}(1)$	Group 33	: $A_{69} \to A_{65}(1)$
Group 13	: $A_{26} \to A_{25}(1)$	Group 34	: $A_{71} \to A_{68}(1)$
Group 14	: $A_{32} \to A_{36}(1)$	Group 35	: $A_{73} \to A_{71}(1)$
Group 15	: $A_{36} \to A_{40}(1)$	Group 36	: $A_{75} \to A_{73}\,(1)\,,\ A_{75}\,(2)\,,\ A_{79}(1)$
Group 16	$A_{40} \to A_{51}(1)$	Group 37	: $A_{77} \to A_{79}(1)$
Group 17	: $A_{44} \to A_{64}(1)$	Group 38	: $A_{79} \to A_{69}\,(1)\,,\ A_{77}\,(1)\,,\ A_{79}\,(3)\,,\ A_{80}(2)$
Group 18	: $A_{47} \to A_{51}(1)$	Group 39	: $A_{80} \to A_{79}\,(1)\,,\ A_{80}\,(1)\,,\ A_{81}\,(1)\,,\ A_{84}(1)$
Group 19	: $A_{49} \to A_{44}(1)$	Group 40	: $A_{81} \to A_{79}(1)$
Group 20	: $A_{51} \to A_{49}(1)$	Group 41	: $A_{84} \to A_{88}(1)$
Group 21	: $A_{52} \to A_{52}\,(1)\,,\ A_{64}(1)$	Group 42	: : $A_{88} \to \#$

Step 5: In this section, forecasting is performed according to the principles in **Step 5**. For example, to perform forecasting in the February 2018 period, we look at the previous period, January 2018. Based on Table 9, the fuzzification value in the January 2018 period is A_1. From Table 10, the fuzzy logic relationship is "$A_1 \to A_1$" in group 1. Then, the forecasting result can be calculated using Equation (5) as follows:

$$\frac{507.133,8\,(5) + 507.139(1)}{5+1} = 507.134,7$$

So, the result of gold price forecasting for the February 2018 period is 507.134,7Forecasting results for other periods can be done in the same way. Table 12 shows the results of gold price forecasting in Padang City from January 2018 to December 2023.

Table 12. Forecasting Results

No.	Year	Month	Gold Price	Forecasting
1	2018	January	Rp507.131	-
2	2018	February	Rp507.132	507.134,7
3	2018	March	Rp507.133	507.134,7
4	2018	April	Rp507.134	507.134,7
⋮	⋮	⋮	⋮	⋮
69	2023	September	Rp907.331	904.216,3

No.	Year	Month	Gold Price	Forecasting
70	2023	October	Rp922.635	904.216,3
71	2023	November	Rp955.600	931.509,9
72	2023	December	Rp980.512	978.796,9

The comparison plot of actual data and gold price forecasting in Padang City for January 2018-December 2023 using automatic clustering and fuzzy logic relationship methods is shown in Figure 3.

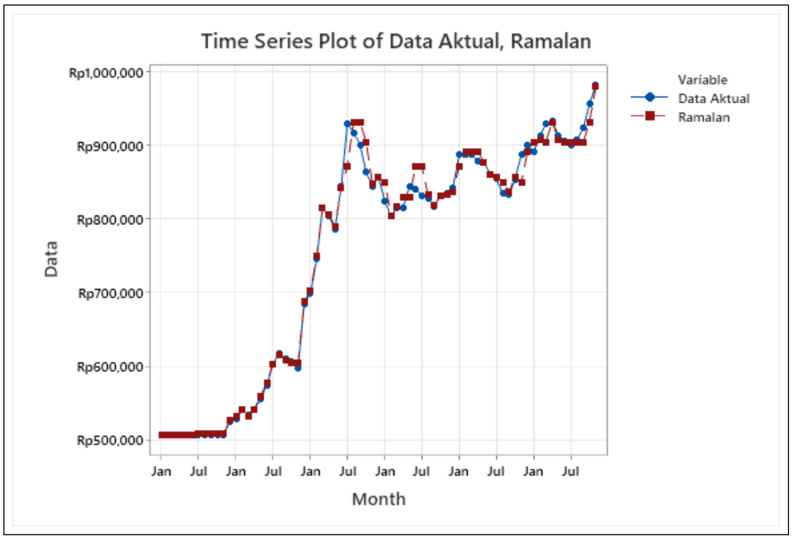

Figure 3. Data Plot of Actual and Forecast Data Comparison

Figure 3 shows the results of using automatic clustering and fuzzy logic relationship methods to forecast gold prices in Padang City. The graph does not show a significant difference between the original data and the forecasting data, which indicates that the forecasting model is accurate in describing the pattern of gold price movements.

Model Validation

The model validation used in this research uses the MAPE (Mean Absolute Percentage Error) value to measure the level of accuracy of the model on gold price data in Padang City. MAPE measures the percentage error of the prediction results obtained. Based on the rules in Equation (7), the MAPE value can be calculated as follows.

$$\begin{aligned} MAPE &= \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i-\hat{Y}_i}{Y_i}\right| \times 100 \\ &= \frac{\left(5{,}32406\times10^{-6}\right)+\left(3{,}35218\times10^{-6}\right)+\cdots+0{,}001749188}{72-1} \times 100 \\ &= 0.9078\% \end{aligned}$$

From the calculation results using MAPE, the forecasting error value obtained by the Automatic Clustering and Fuzzy Logic Relationship method is 0.9%. The MAPE value of less than 10% indicates that this method is very good at forecasting gold prices. Meanwhile, in another study predicting gold prices in Indonesia in 2014-2019 using the ARIMA Box-Jenkins method by John & Latupeirissa (2021). The forecasting results produced an MAPE value of 19.78%, which shows that the ACFLR method is superior to the ARIMA method in forecasting gold prices.

D. CONCLUSION AND SUGGESTION

Based on the results and discussion on the analysis of gold price forecasting in Padang City for the period January 2018-December 2023 that has been carried out, the conclusion obtained in this study is the value of gold price forecasting in Padang City using automatic clustering and fuzzy logic relationship has a MAPE value of 0.9% which means the method is very good. And for the results of the gold price forecast in Padang City for the next period using the automatic clustering and fuzzy logic relationship method, namely the January 2024 period, it was obtained at IDR 978,796.9.

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AUTHOR CONTIBUTION

All authors contributed to this manuscript, from exploring ideas to writing this article.

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COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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