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Implementation of fuzzy mamdani method in predicting cayenne chili prices in Tegal Regency

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ABSTRACT

This study investigates the application of Fuzzy Mamdani's method in predicting the price of cayenne pepper in Tegal Regency, one of the important agricultural commodities that has significant economic implications. This study aims to develop an accurate and reliable cayenne pepper price prediction model in Tegal Regency using the fuzzy Mamdani method. Research methods include collecting historical data on cayenne pepper prices, cayenne pepper production, and rainfall, as well as the implementation of the Mamdani fuzzy method consisting of fuzzification, inference, and defuzzification using Python programming language computing. The results showed that the fuzzy Mamdani method can predict the price of cayenne pepper with a good level of accuracy, with an average prediction error of 16.653285% and a prediction correctness rate of 83.346715%. This finding has implications for improving production planning capabilities and marketing strategies for cayenne pepper farmers in Tegal District, as well as contributing to the scientific literature in the application of fuzzy methods in agriculture.

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Introduction

Indonesia, as an agricultural country, is very dependent on the agricultural sector to meet the food needs of its population(Duffy et al., 2021). In this context, cayenne pepper is one of the important commodities that has a strategic role in the national economy and food sustainability(Zou & Zou, 2021). Tegal Regency, known as one of Indonesia's cayenne pepper producing regions(Dewi, 2023), experiences significant price fluctuations, affecting farmers' economies and local market stability(Puji et al., 2022). This price variability raises the urgent need to develop efficient and accurate predictive methods, to assist farmers and stakeholders in production planning and marketing.

The main problem faced is the uncertainty of cayenne pepper prices which can have an impact on farmers' production decisions and local economic stability(Muflikh et al., 2021). Price fluctuations are often caused by various factors, including cayenne pepper production, weather conditions, market demand, and market dynamics (Lukas et al., 2023). Without a clear understanding of price trends, farmers can incur losses or miss opportunities to maximize profits (Benyam et al., 2021). Unstable cayenne pepper prices lead to unpredictable incomes for farmers, making it difficult for them to plan their finances and investments.

This research was conducted to overcome the problem of price uncertainty by developing an accurate and reliable cayenne pepper price prediction model(Achour et al., 2021). This study is important to assist farmers in planning production and marketing strategies, as well as to improve food security and local economic stability, to overcome this problem, propose the application of the fuzzy Mamdani method, known for its ability to handle uncertainty and incomplete information(Steenkamp et al., 2021) (Küçüktopçu et al., 2023). This study aims to explore how Mamdani's fuzzy method can be applied in predicting cayenne pepper prices in Tegal District, fill gaps in the existing literature, and provide practical guidance for farmers and stakeholders(Song & Dong, 2021) (Ingram et al., 2020).

The state of the art in this study includes previous studies that have applied fuzzy methods in predicting agricultural commodity prices, highlighting the advantages and limitations that exist(Lezoche et al., 2020). The innovation proposed through this research is the development of predictive models that are more adaptive and responsive to local market dynamics(Belhadi et al., 2024).

In this study will use historical data on cayenne pepper prices, factors influencing them, and expert knowledge to develop and validate Mamdani's fuzzy model(Benyezza et al., 2021) (Machala et al., 2022). The new contribution of this research lies in developing a more localized and adaptive predictive model for cayenne pepper prices in Tegal Regency, incorporating region-specific variables and expert knowledge to enhance accuracy. This model can handle unique local market dynamics better than existing models, offering practical tools for farmers and stakeholders.

This research improves farmer welfare and local market stability by providing an accurate price prediction tool for cayenne pepper. With reliable predictions, farmers can make more informed decisions about planting, harvesting, and marketing, reduce planning, plan production better, optimize resources, and get better market prices. This increases productivity, income and economic stability of farmers and society.

The practical application of this research involves using the predictive model to guide farmers' production and marketing decisions, helping them anticipate price fluctuations and plan accordingly. By providing accurate price forecasts, the model can improve production planning, optimize marketing strategies, and enhance overall economic stability for cayenne pepper farmers in Tegal Regency and potentially other similar agricultural regions.Cayenne pepper farmers in Tegal Regency face challenges such as bad weather, plant diseases and market access. The expected result of this study is a price prediction model that can provide accurate estimates and be useful for decision-making in the field, as well as contributing to the scientific literature on the application of fuzzy methods in agriculture (Poldrack et al., 2020; Visentin et al., 2020).

Research into fuzzy methods in agricultural commodity price prediction has shown significant progress in the past decade, highlighting the huge potential in supporting decisions in the agricultural sector(Zhai et al., 2020). In research(Akhter & Sofi, 2022), Although the main focus is not on prices, the methodology used is relevant for addressing uncertainty and data variability in the agricultural sector, the study could provide insight into how to combine fuzzy techniques with machine learning tools to improve prediction accuracy. Further Research(Khoury et al., 2022), Although the commodity and geographical context are different, this approach can provide insight into how to apply similar methods to predict cayenne pepper prices, emphasizing the importance of temporal analysis in price modeling. Next Research(Jamroen et al., 2020), Although the techniques and data used differ, methodology provides examples of practical applications of fuzzy logic in price prediction, which can be adapted and optimized for cayenne pepper price cases. In another study(Liu et al., 2021), Although the focus is on financial markets, the principles and techniques used can be adapted for price prediction in agriculture, demonstrating the flexibility and usefulness of fuzzy methods in various prediction domains. Then Research(Abioye et al., 2020), mamdani's fuzzy model can adapt to various factors affecting rice prices, provide an adoptable and customizable framework for cayenne pepper price studies, underscoring the applicability of this method in different geographical and commodity contexts.

Method

Research Flow

The research flow depicted in this flow chart aims to investigate and analyze historical data using the fuzzy method contained in figure 1.

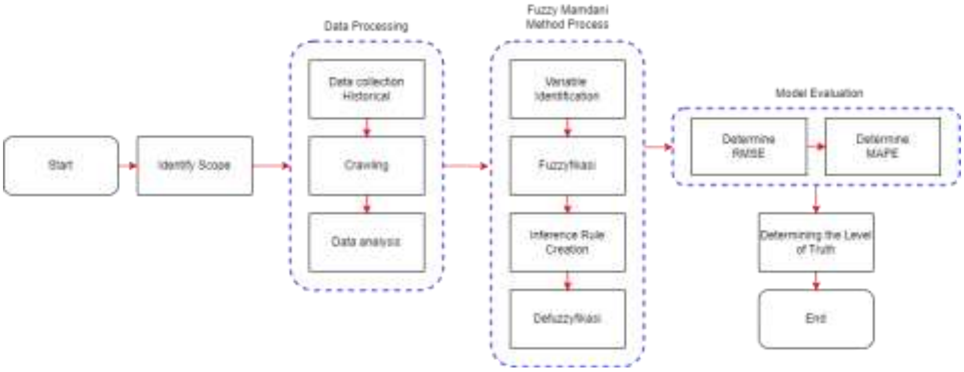

Figure 1. Research Flow

The methodology of this study follows a structured path as illustrated in Figure 1. The process begins by identifying the problem to be resolved, then continues with the collection and processing of relevant data. Furthermore, the data is processed using the fuzzy Mamdani method which includes crawling historical data, data analysis, variable fuzzification, forming inference rules, and defuzzification to produce predictions. The next stage is to evaluate the performance of the prediction model by calculating the error rate using MAPE and RMSE metrics. Finally, the prediction results and the accuracy level of the model are determined based on these evaluations.

Scope Identification

In this study, the scope of research includes the process of collecting and processing data related to variables that have the potential to affect the price of cayenne pepper in Tegal Regency(Haqqoni & Pramana, 2022). The data is then used to build a prediction model based on a fuzzy system by applying the Mamdani method. After the model is formed, the next stage is to evaluate the model's performance in predicting cayenne pepper prices in the region through measuring the level of prediction accuracy.

Data Processing

Data collection is taken by scrawling method on the internet on several official Indonesian websites. Historical data and variables that have the potential to affect cayenne pepper prices (cayenne pepper production, and rainfall data) are collected from a variety of reliable sources, including government agricultural databases, market reports, and academic publications (Central Bureau of Statistics, and BMKG Online Data). Data collection period January 2018 - December 2022. Once the data is collected, it is analyzed with the necessary data cleaning, normalization, and data transformation to ensure that the data is ready for analysis by the fuzzy mamdani method. This includes handling missing values, detecting outliers, and converting data formats to fit the needs of methods with 60 data ready quantities. The following can be seen in table 1.

Table 1. Results of Data Processing

No	Month/Year	Cayenne Chili Price (Rp)	Cayenne Chili Production (Ton)	Precipitation (mm)
1	January/18	73667	71940.16	258
2	February/18	71750	222672.76	40
3	Maret/18	72708	6314.9	74
4	April/18	77375	7812.58	303
5	From / 18	63600	1750.49	235

⋮	⋮	⋮	⋮	⋮
58	October/22	46389	2374.39	376
59	November/22	46806	88104.85	526
60	Dec/22	47778	14860.35	321

Table 1 displays monthly historical data from January 2018 to December 2022 which includes cayenne pepper prices (in Rupiah), cayenne pepper production (in tons), and rainfall (in millimeters) in Tegal Regency as inputs to build a cayenne pepper price prediction model using the fuzzy Mamdani method.

Mamdani Fuzzy Method Process

The Fuzzy Mamdani method will be implemented using the python programming language computing software, starting with identifying relevant variables, such as cayenne pepper production and rainfall. Each of these variables is then processed through the Fuzzification stage, where real values are converted into fuzzy values using the corresponding membership function. In general, it is written (1).

$$\mu A(x) = max(min(\frac{x-a}{b-a}, \frac{c-x}{c-b}),0) \quad (1)$$

Where a, b, and c are parameters that define the angular angle points of the triangle on the horizontal axis. Furthermore, Inference Rule Making is done based on expert knowledge and analysis of historical data. These rules are usually in the format "If conditions A and B, then C", where A and B are fuzzy labels for input variables and C are fuzzy labels for output variables. These rules are then evaluated in the Inference stage, where fuzzy logic is applied to determine fuzzy output based on the fuzzy input provided. Finally, the inference results are converted back into real values through the Defuzzification process with the centroid method where a firm solution is obtained by taking the center point of the fuzzy area, the centroid method in defuzzification in general is as follows (2).

$$y^* = \frac{\int_x x \ . \ \mu_{agregate}(x)dx}{\int_x \ \mu_{agregate}(x)dx} \quad (2)$$

Where $\boldsymbol{y^*}$ is the crisp output value produced by the defuzzification process, $\boldsymbol{x}$ is an output variable, $\boldsymbol{\mu_{agregate}(x)}$ is an aggregate membership function obtained from the aggregation process of fuzzy rules that have been applied. This function shows the degree of fuzzy output membership in each value $\boldsymbol{x}$.

Model Evaluation

Model Evaluation is implemented using Python programming language computing software, to measure the level of prediction accuracy and identify how much error is generated by the model. In the study, two main metrics were used to evaluate model performance, namely Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). MAPE is used to measure the average absolute percentage of error between the predicted value and the actual value. Mathematically, MAPE is calculated by the formula (3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2} \quad (3)$$

Where $\boldsymbol{n}$ is the total number of observations or data points, $\boldsymbol{A_i}$ is the i-th actual value, $\boldsymbol{F_i}$ is the i-th predicted value, $\boldsymbol{(A_i - F_i)^2}$ is the square of the difference between the actual value and the predicted value. Meanwhile, MAPE is used to measure the square mean root of the difference between the predicted value and the actual value. MAPE is calculated by the formul (4).

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right|\right) x\ 100\% \tag{4}$$

Where $\boldsymbol{n}$ is the total number of observations or data points, $\boldsymbol{A_i}$ is the i-th actual value, $\boldsymbol{F_i}$ is the i-th predicted value, $\left|\frac{A_i-F_i}{A_i}\right|$ is the absolute value of the error percentage for each data point. Evaluate this
It is very important to ensure that how well the developed Mamdani fuzzy method can produce cayenne pepper price predictions in Tegal Regency.

Results and Discussions

In this study, the initial stage is to identify relevant variables to be used as inputs and outputs in prediction models. The three main variables chosen, namely cayenne pepper production, rainfall, and cayenne pepper price, will be processed through a series of processes in the fuzzy Mamdani method. The process includes fuzzification, where the values of input variables are converted into fuzzy sets, the establishment of inference rules based on expert knowledge and analysis of historical data, and defuzzification to produce output values that are predictions of cayenne pepper prices. The implementation of this method is done using the computing programming language Python. The input and output variables used in this study can be seen in table 2.

Table 2. Input and Output Variable Data

No	Function	Input		Output
	Month/Year	Cayenne Chili Production (Ton)	Precipitation (mm)	Cayenne Chili Price (Rp)
1	January/18	71940.16	258	73667
2	February/18	222672.76	40	71750
3	Maret/18	6314.9	74	72708
4	April/18	7812.58	303	77375
5	Mei / 18	1750.49	235	63600
⋮	⋮	⋮	⋮	⋮
58	October/22	2374.39	376	46389
59	November/22	88104.85	526	46806
60	Dec/22	14860.35	321	47778

Table 2 presents several examples of data rows that show input variables in the form of cayenne pepper production in tons and rainfall in millimeters, as well as output variables in the form of cayenne pepper prices in rupiah which are used to build a cayenne pepper price prediction model using the fuzzy Mamdani method. After identifying input variables (cayenne pepper production and rainfall) and output variables (cayenne pepper price), the data was processed using the fuzzy Mamdani method implemented with the Python programming language. This process involves three main stages. First, fuzzification converts the crisp values of the input variable into fuzzy sets. Second, the establishment of fuzzy inference rules based on expert knowledge and analysis of historical data. Finally, defuzzification to convert the fuzzy values of inference into crisp values as a prediction of cayenne pepper prices.

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl
import matplotlib.pyplot as plt
import pandas as pd
# Load data from the previously uploaded file
data = pd.read_excel('C:/Users/bango/Documents/Document Pekuliahan STMIK YMI TEGAL/TUGAS KULIAH/TUGAS KULIAH SMTR 6/PKL/DATAANALISIS_GPT.xlsx')
# Initialize variables
```

```
produksi = ctrl.Antecedent(np.arange(0, 300000, 1000), 'produksi')
curah_hujan = ctrl.Antecedent(np.arange(0, 500, 5), 'curah_hujan')
harga = ctrl.Consequent(np.arange(20000, 100000, 500), 'harga')
# Fuzzification
produksi.automf(3, names=['rendah', 'sedang', 'tinggi'])
curah_hujan.automf(3, names=['rendah', 'sedang', 'tinggi'])
harga.automf(3, names=['rendah', 'sedang', 'tinggi'])
# Defining rules
rule1 = ctrl.Rule(produksi['rendah'] & curah_hujan['tinggi'], harga['tinggi'])
rule2 = ctrl.Rule(produksi['tinggi'] & curah_hujan['rendah'], harga['rendah'])
rule3 = ctrl.Rule(produksi['sedang'] & curah_hujan['sedang'], harga['sedang'])
# Additional rules
rule4 = ctrl.Rule(produksi['sedang'] & curah_hujan['tinggi'], harga['tinggi'])
rule5 = ctrl.Rule(produksi['rendah'] & curah_hujan['sedang'], harga['sedang'])
# Control system
harga_ctrl = ctrl.ControlSystem([rule1, rule2, rule3, rule4, rule5])
harga_sim = ctrl.ControlSystemSimulation(harga_ctrl)
# Prepare the predicted_price column
data['predicted_price'] = 0.0
# Simulate for each row and collect results
for index, row in data.iterrows():
  harga_sim.input['produksi'] = row['Produksi Cabai Rawit (Ton)']
  harga_sim.input['curah_hujan'] = row['Curah Hujan (mm)']
  try:
    harga_sim.compute()
    data.at[index, 'predicted_price'] = harga_sim.output['harga']
  except ValueError as e:
    data.at[index, 'predicted_price'] = np.nan  # Set default or handle error
    print(f"Defuzzifikasi gagal untuk baris {index}: {e}")
...
```

Figure 2. Source code of Fuzzy Mamdai Prediction Process

In figure 2 the source code in Python programming language used to perform the cayenne pepper price prediction process using the Fuzzy Mamdani method, which consists of importing the necessary libraries, loading data from Excel files, initializing fuzzy antecedent and consequent variables, fuzzifying by creating automatic membership functions, defining fuzzy inference rules, creating fuzzy control systems and fuzzy control simulation systems, Initialize columns to store prediction results, as well as simulate for each row of data by entering cayenne pepper production and rainfall values into the fuzzy control simulation system, then calculating and storing cayenne pepper price prediction values. The process will produce cayenne pepper price predictions based on chili production and rainfall using the fuzzy mamdani method which can be seen in table 3.

Table 3. Fuzzy Mamdani Prediction Results

No	Year	Cayenne Chili Price (Rp)	Fuzzy Mamdani Price Prediction (Rp)
1	2018	Rp57,292	Rp66,833
2	2019	Rp67,708	Rp64,704
3	2020	Rp55,556	Rp62,195
4	2021	Rp51,333	Rp59,750
5	2022	Rp51,222	Rp59,750

Table 3 presents the actual cayenne pepper price and the price predicted by the fuzzy Mamdani method for each year from 2018 to 2022, which allows evaluation of the model's performance in predicting cayenne pepper prices in Tegal Regency. Can be seen easily using the line graph image that can be seen in the figure 3.

Figure 3. Fuzzy Mamdani Prediction Results Chart

The line graph shown in figure 3. is a comparison of actual cayenne pepper prices with predicted prices from January 2019 to December 2022. In the line chart, the continuous blue line shows the actual price of cayenne pepper recorded each month, while the dotted red line represents the price predicted by the fuzzy mamdani method.

To evaluate the accuracy of the cayenne pepper price prediction model using the fuzzy Mamdani method, the prediction error rate was calculated using the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. This calculation is implemented with Python programming language in figure 4 to get a quantitative value of prediction error compared to actual data on cayenne pepper price. RMSE measures the root mean squared of the difference between prediction and actual values, while MAPE expresses the average of the absolute percentage of error between prediction and actual.

```
import pandas as pd
import numpy as np
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
# Load the data from the Excel file
data_path = "C:/Users/bango/Documents/Document Pekuliahan STMIK YMI TEGAL/TUGAS KULIAH/TUGAS KULIAH SMTR 6/PKL/DATAHASIL.xlsx"
data = pd.read_excel(data_path)
# Clean up currency formatting and convert to floats
data['Harga Aktual'] = data['Harga Aktual'].replace('[Rp\.]', '', regex=True).astype(float)
data['Harga Prediksi'] = data['Harga Prediksi'].replace('[Rp\.]', '', regex=True).astype(float)
# Extract year from 'Tahun' column if necessary or ensure it's already year format
data['Year'] = pd.to_datetime(data['Tahun'], format='%Y').dt.year  # Adjust the format if necessary
# Initialize a DataFrame to store results per year
results = pd.DataFrame()
# Calculate metrics per year
for year in data['Year'].unique():
    year_data = data[data['Year'] == year].copy()  # Ensure you work with a copy to avoid SettingWithCopyWarning
    rmse = np.sqrt(mean_squared_error(year_data['Harga Aktual'], year_data['Harga Prediksi']))
    rmse_percentage = (rmse / year_data['Harga Aktual'].mean()) * 100
    mape = np.mean(np.abs((year_data['Harga Aktual'] - year_data['Harga Prediksi']) / year_data['Harga Aktual'])) * 100
    # Calculate percentage errors for the year
    year_data.loc[:, 'Percentage Error'] = np.abs((year_data['Harga Aktual'] - year_data['Harga Prediksi']) / year_data['Harga Aktual']) * 100
    avg_percentage_error = year_data['Percentage Error'].mean()
...
```

Figure 4. RMSE and MAPE source code

In figure 4 Python source code used to calculate RMSE and MAPE evaluation metrics in assessing the performance of cayenne pepper price prediction model with the Fuzzy Mamdani method, by loading data from Excel files, cleaning the data, extracting years, looping per year to calculate RMSE, RMSE percentage, MAPE, and error percentage per row of data, and storing the results in a DataFrame. The results of the calculation above, produce RMSE and MAPE which can be seen in table 4.

Table 4. Model Evaluation Results with RMSE and MAPE

No	Tahun	RMSE	MAPE
1	2018	9541.0	16.653285
2	2019	3004.0	4.436699
3	2020	6639.0	11.950104
4	2021	8417.0	16.396860
5	2022	8528.0	16.649096

Table 4 presents the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) values for each year from 2018 to 2022, which are used to evaluate the accuracy of Mamdani's fuzzy model in predicting cayenne pepper prices compared to its actual price data. After generating the percentage of error, then calculate to determine the level of truth of the Fuzzy Mamdani model, namely $100\% - 16.653285 = 83.346715\,\%$. This research makes a new contribution by applying a model specifically to predict the price of cayenne pepper in Tegal Regency by taking into account local market dynamics and other factors which previously had no research like this in the Tegal Regency area. These results fill existing gaps in the literature and provide practical guidance for farmers and stakeholders in the Tegal district area.

Conclusions

This research concludes that the Mamdani fuzzy method is able to predict the price of cayenne pepper in Tegal Regency with good accuracy, with an average prediction error of 16.653285% and a correctness level of 83.346715%. MAPE values between 10%-30% indicate good performance(Fan et al., 2021). However, this research is limited to the fuzzy Mamdani method, the Tegal Regency sample, one cayenne pepper commodity, and a certain time context. Data quality and completeness also affect model accuracy. To improve generalization, it is recommended to use more complex methods, expand data coverage, extend the time period, and improve data quality.These findings provide practical benefits for farmers, policy makers and other stakeholders. For farmers, accurate price prediction models can help better plan production and marketing strategies to maximize profits. For policy makers, these findings can be a basis for developing policies that support price stability and farmer welfare, such as market regulations, incentives, or price protection programs. The research results also have implications for farmers' production and marketing decisions, as well as providing policy recommendations such as price information systems. However, the dataset still has shortcomings. For future research, it is recommended to expand the scope of the data by including other factors that might influence prices, expanding geographic coverage, and including other agricultural commodities.

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