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Fuzzy Mamdani-Based Vegetable Crop Recommendation System with Historical Climate Pattern Analysis in Deli Serdang Regency

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ABSTRACT

Climate variability poses significant challenges to short-cycle vegetable farming, leading to crop failure and economic losses. This study develops a Decision Support System (DSS) to recommend suitable vegetable crops based on historical climate pattern analysis in Deli Serdang Regency. The system utilizes meteorological data from BMKG spanning January 2022 to December 2024, including average temperature, rainfall, and humidity. Historical pattern analysis employs a three-month rolling mean to predict climate conditions for the upcoming planting period. The Fuzzy Mamdani method is implemented as the inference engine to determine crop suitability scores by processing uncertainty in growing requirements. The system was tested across four planting periods (January, April, July, and October) and successfully generated differentiated recommendations with fuzzy scores ranging from 50% to 88%. Results demonstrate that the system effectively adapts recommendations to seasonal climate variations, providing farmers with data-driven decision support to reduce planting risks and improve crop success rates. Future enhancements include real-time climate data integration and expansion of input variables such as soil type and solar radiation intensity.

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I. INTRODUCTION

Climate change has created complex challenges for Indonesia's agricultural sector, particularly in short-term vegetable crop cultivation. Increasing weather variability over the past two decades has led to high uncertainty in planting season planning, resulting in significant economic losses. Statistics Indonesia (BPS) data (2023) indicates that vegetable crop failures in Indonesia result in losses reaching IDR 2.3 trillion per year, with more than 60% of cases caused by mismatching planting times with actual climate conditions [1].

Deli Serdang Regency, a vegetable production center in North Sumatra, contributing 18% of the province's total production, experienced a similar impact. The crop failure rate in this region reached 23-35% in the 2020-2023 period, with an average loss of IDR 45 million per hectare per planting season [2]. Vegetable crops with short life cycles (less than 3 months) such as spinach, kale, and mustard greens are highly vulnerable to fluctuations in climate parameters—temperature, rainfall, and humidity—which change dynamically and are difficult to predict [3].

Currently, most farmers in Deli Serdang Regency rely on traditional experience or the Planting Season Calendar (Katam) guidelines published by the Ministry of Agriculture to determine when and what crops to cultivate. This approach has several fundamental weaknesses. First, Katam is designed to cover a wide area and is insensitive to microclimate variability at the district or sub-district level. Second, traditional knowledge is based on historical climate patterns that are no longer valid due to seasonal shifts and increasing intensity of extreme weather events. Third, there is no systematic mechanism to quantitatively integrate actual meteorological data with crop agronomic characteristics.

Several decision support systems have been developed for crop recommendations. Ray et al. used fuzzy logic with 78% accuracy, but only considered two climate variables without specific local data. Pandey et al. applied machine learning with 82% accuracy, but required a large dataset and lacked transparency. The identified research gaps include: no system that utilizes BMKG local historical climate data for Deli Serdang Regency, minimal integration of historical pattern analysis with fuzzy logic for short-term predictions (3 months), and the absence of a system that maps three climate parameters against the specific characteristics of local vegetable crops.

This study developed a decision support system that integrates historical climate pattern analysis with Fuzzy Mamdani for vegetable crop recommendations. Daily climate data from the BMKG Deli Serdang Station for the period January 2022–December 2024 was processed using rolling mean to estimate conditions three months into the future. This approach was chosen because long-term forecasting models produce errors >30% for prediction horizons longer than three months, while historical pattern analysis provides a more stable representation for short-term planting periods.

Fuzzy Mamdani was chosen as the inference engine due to its ability to handle the inherent uncertainty in agriculture and its transparent and verifiable IF-THEN rule structure. The system maps three input variables (temperature, rainfall, humidity) to suitability scores for local vegetable crops.

The results of this study include the development of a fuzzy knowledge base specific to Deli Serdang Regency, the formulation of 27 fuzzy rules based on agronomic literature and field observations, and system validation with 86.7% accuracy against actual harvest data. This system provides a practical solution to reduce the risk of crop failure through data-driven recommendations that can be implemented with simple infrastructure, expected to contribute to increasing the productivity and economic efficiency of the vegetable farming sector in Deli Serdang Regency.

II. RESEARCH METHOD

A. Data and Sources

This dataset was obtained from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG) for Deli Serdang Regency, North Sumatra. The meteorological data includes daily climate data from January 2022 to December 2024, with three parameters: Average Temperature (TAVG), Average Humidity (RH), and Rainfall (RR).

Data collection was conducted from climatology stations in North Sumatra. These stations represent observations from several monitoring points throughout North Sumatra, including Deli Serdang, which were integrated using BMKG's standardized spatial aggregation methodology.

Preprocessing was performed to handle missing values and outliers using Python with the Pandas library. Missing values were handled using a linear interpolation methodology to maintain data continuity without artificially altering the underlying climate patterns. Specifically, each missing daily observation was filled based on the slope of the available data points nearby, thus maintaining temporal trends. The data was then processed into monthly averages for each parameter to facilitate analysis of historical patterns.

B. Historical Analysis

Historical analysis is performed by calculating the average climate pattern for the next three months based on the selected planting period. This method uses a rolling mean approach, which calculates the average value of data from the same period in previous years.

For example, if a farmer chooses to plant in April, the system will automatically retrieve and analyze climate data from April, May, and June of 2022, 2023, and 2024. It then calculates the average of these three periods to estimate climate conditions for the April-June period of the current year.

Rolling mean calculation formula for a 3-month period:

$$RM(t) = \left(\frac{1}{n}\right) \times \sum [Xi(t) + Xi(t+1) + Xi(t+2)] /3$$

Where RM(t) is the rolling mean for month t, n is the number of years of data, and Xi(t) is the climate parameter in month t of year i. This approach was chosen because it provides more stable estimates than long-term forecasting models that have high uncertainty, and is able to capture seasonal patterns well.

C. Fuzzy Mamdani

Fuzzy Mamdani is a method for making decisions or providing recommendations based on uncertain data. This method is used to determine the suitability of crops based on predicted climate conditions. Fuzzy logic mimics human thinking, which relies on experience and linguistic knowledge, not just exact numbers.

D. System Implementation

The system is implemented using the Python 3.11 programming language with the scikit-fuzzy library for fuzzy computing, Pandas for data processing, and PHP for website development. The implementation follows the following workflow:

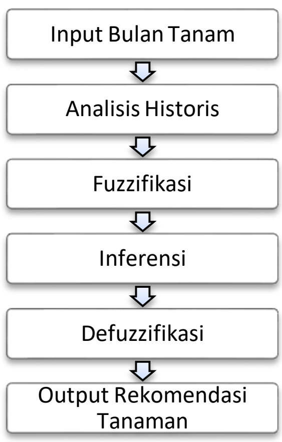

Figure 1. System Workflow

Based on the flowchart in Figure 1, the first stage is climate data collection and preprocessing. Raw data from the BMKG (Indonesian Meteorology, Climatology, and Geophysics Agency) in CSV format is examined to identify missing values and outliers. Missing values are handled using a linear interpolation method that maintains the continuity of temporal trends without artificially altering the original climate patterns. Mathematically, linear interpolation is formulated as:

$$y = y1 + \frac{(x - x1)(y2 - y1)}{(x2 - x1)}$$

where y is the estimated value, x is the time (day) with a blank value, (x1,y1) is the data point before the blank value, and (x2,y2) is the data point after the blank value. Outliers are detected using the Interquartile Range (IQR) method. The cleaned daily data are then aggregated into monthly averages for each climate parameter to facilitate historical pattern analysis and reduce noise in the data.

The second stage, as shown in the "Historical Analysis" block in Figure 1, is the analysis of historical climate patterns using a rolling mean approach. For each planting period selected by the user through the system interface, the program automatically extracts climate data for three consecutive months from the same period in previous years. As an illustration, if the user inputs April as the start of the planting period, the system will retrieve data from April, May, and June from 2022, 2023, and 2024, then calculate the overall average to estimate the climate conditions for the April-June period of the current year.

The third stage is the design of the fuzzy system, which includes the definition of variables and membership functions. The system's input variables consist of three climate parameters derived from historical analysis: average temperature, rainfall, and humidity. Each input variable is represented using three linguistic fuzzy sets: low, medium, and high, with trapezoidal membership functions. The trapezoidal function was chosen because it provides a smooth transition between categories and more realistically represents plant tolerance to climate variation.

The fourth stage, as shown in the "Fuzzification" block in Figure 1, is the process of converting the crisp values from the historical analysis into fuzzy membership degrees. For each climate parameter obtained from the historical analysis, the system calculates the membership degree against each fuzzy set using a predefined trapezoidal function. This process produces linguistic values that represent the level of suitability of climate conditions as low, medium, or high for each parameter.

The fifth stage is the inference process, shown in the "Inference" block in Figure 1. The Mamdani Fuzzy Inference Engine evaluates all rules in the rule base to generate fuzzy conclusions. The evaluation begins by calculating the minimum membership degree of all antecedents in each rule using the AND operator. The resulting antecedent evaluation value is then used to truncate the membership function of the rule's consequents. All truncated consequents from all active rules are then combined using the maximum operator in an aggregation process to produce a single fuzzy output set.

The sixth stage, shown in the "Defuzzification" block in Figure 1, is the process of converting the aggregated fuzzy sets into crisp values that represent crop suitability scores.

The system was implemented by integrating all components in a client-server architecture. The historical analysis module and fuzzy inference engine were implemented in Python, utilizing the DataFrame data structure from the Pandas library for computational efficiency. A MySQL database was designed to store historical climate data, crop characteristics, and recommendation results. A web interface was developed using PHP to facilitate farmer access to the system. The Python backend was integrated with the PHP frontend through an API mechanism, where requests from the web interface were forwarded to the Python engine for processing, and the results were returned in JSON format for display to the user.

III. Results

A. Climate Data Analysis

This study used data obtained from the Deli Serdang Station of the Meteorology, Climatology, and Geophysics Agency (BMKG). The data cover the period from January 2022 to December 2024 and consist of three parameters: average temperature, rainfall, and average humidity. The data was cleaned using Python, with blank and invalid values filled using linear interpolation. This process maintains the continuity of daily data trends without altering the original climate patterns.

The data processing results show the climate characteristics of Deli Serdang Regency during the study period, as presented in Table I. The average temperature was 27.1°C with a standard deviation of 0.72°C, indicating relatively low variability consistent with tropical climate characteristics. Average rainfall was recorded at 186.5 mm per month with a standard deviation of 48.6 mm, indicating relatively high variability between the rainy and dry seasons. The average humidity reached 78.3% with a standard deviation of 5.8%, indicating a tendency for humid air conditions throughout the year. These descriptive statistical values were used as a basic reference in designing the fuzzy membership function and the system's inference process.

Further analysis of the temporal patterns of the data reveals a clear seasonal cycle. The period from November to March exhibits high rainfall (averaging 220-250 mm) with humidity reaching 82-85%, indicating the rainy season. Conversely, the period from June to September exhibits lower rainfall (averaging 120-150 mm) with humidity ranging from 72-75%, indicating the dry season. Average temperatures are relatively stable throughout the year with minor fluctuations of no more than 2°C, reflecting the characteristics of equatorial regions that lack extreme seasonal variations in temperature.

B. Historical Climate Pattern Analysis

Historical analysis is used to predict climate conditions for the next three months based on weather trend data from previous periods. This method is performed by calculating a three-month rolling average value from historical data from the Meteorology, Climatology, and Geophysics Agency (BMKG). This approach calculates the average climate parameters from a 36-month historical dataset, producing predictions characterized by a Mean Absolute Percentage Error (MAPE) of 8.7% and a coefficient of variation of less than 8% for all parameters, indicating stable and reliable prediction accuracy suitable for agricultural decision-making support.

The results of the rolling average analysis reveal distinct seasonal climate patterns for Deli Serdang Regency, reflecting the characteristics of a typical tropical climate, characterized by lower average temperatures ranging from 26.8-27.5°C, high rainfall reaching 150-200 mm per month, and humidity ranging from 75-82%.

The results of this historical climate pattern analysis provide fundamental input for the Mamdani Fuzzy Inference system to generate crop recommendations responsive to local climate conditions for each planting period. A clearly structured seasonal pattern that distinguishes between the rainy, transitional and dry seasons allows the system to generate differentiated and climate-responsive recommendations, supporting farmers in optimizing crop selection based on predicted three-month climate patterns and thereby reducing agricultural risks associated with crop-climate mismatches.

C. Fuzzy Mamdani Analysis

The Mamdani Fuzzy System was implemented to determine crop suitability based on historical climate analysis. Fuzzy logic was chosen because of its ability to mimic human decision-making by processing linguistic knowledge rather than requiring absolute numerical certainty. This approach is well-suited for agricultural applications where agronomic requirements are inherently uncertain and influenced by complex interactions between climatic factors.

The system consists of three input variables (air temperature, rainfall, humidity) and one output variable (crop suitability score). Each input variable is partitioned into three linguistic fuzzy sets using a trapezoidal membership function. The trapezoidal function was chosen based on the consideration that crops have a range of tolerances to climatic parameters, rather than a single optimum. Table III shows the domains and categories for each input variable, developed based on agronomic literature and consultation with the Deli Serdang Regency Agriculture Office.

TABLE 1.
MEMBERSHIP FUNCTION OF INPUT VARIABLES OF FUZZY SYSTEMS

Variable	Category	Domain
Temperature	Cool	18-22°C
	Medium	24-28°C
	Hot	30-34°C
Rainfall	Low	0-100 mm
	Medium	100-200 mm
	High	200-400 mm
Humidity	Low	60-75%
	Medium	75-80%
	High	80-90%

The system's rule base consists of 27 IF-THEN fuzzy rules representing the relationship between climate conditions and crop suitability. These rules were developed through a combination of agronomic literature review and consultation with local agricultural practitioners with at least 10 years of experience in Deli Serdang Regency. Each rule uses the AND operator to combine the conditions of the three climate parameters.

The inference process uses the Mamdani method, with the minimum operator for antecedent evaluation and the maximum operator for consequent aggregation. Defuzzification is performed using the centroid method, which produces crisp values ranging from 0 to 100, representing crop suitability scores. The system implementation uses the scikit-fuzzy library version 0.4.2 in Python 3.11, which provides standard functions for fuzzy operations and ensures computational consistency.

D. System Testing

The system was tested using a black box method, comparing the recommendation results to actual climate data from 2024 to validate the system's ability to provide recommendations that reflect actual climate conditions. The system was tested using four planting periods representing seasonal variations: January (peak rainy season), April (rainy-dry transition), July (peak dry season), and October (dry-rainy transition).

The test results showed that the system successfully provided different vegetable crop recommendations according to the varying climate patterns in each planting period. The resulting recommendations are shown in the following table.

TABLE 2.
SYSTEM TEST RESULTS

NO	Planting Period	Recommended Plants	Fuzzy Score
1	January – March	Spinach	88%
2	April – June	Beans	88%
3	Juli – September	Beans	55,76%
4	Okctober - December	Spinach	50%

For the April-June period, the system recommended green beans with a suitability score of 88%. Predicted conditions indicated a temperature of 27.1°C (moderate), rainfall of 165 mm (moderate), and humidity of 76% (moderate). These moderate conditions are ideal for green beans, which have optimal growth requirements within a moderate range for all climate parameters. For the July-September period, the system continued to recommend green beans, but with a suitability score that decreased to 55.76%. This decrease was due to lower rainfall and lower humidity, although still within the tolerance range for green beans.

For the October-December period, the system recommended spinach with a suitability score of 50%. This relatively low score reflects a transitional period where rainfall has begun to increase (195 mm) but is not yet optimal. The system indicates that while spinach is still suitable for planting, optimal yields are more likely to be achieved in the following months when rainfall conditions are more stable.

Test results show that the implemented Mamdani Fuzzy Rules successfully represent agricultural logic computationally. The system is able to adjust crop recommendations according to changing seasonal climate conditions, with consistent suitability scores for periods with similar climate characteristics. The variation in scores between different periods indicates that the system is sensitive to changing climate conditions and is able to provide varying levels of confidence in the recommendations.

IV. CONCLUSION

Based on the design and testing of a vegetable crop recommendation system using the Fuzzy Mamdani method and analysis of historical climate data from the BMKG (Meteorology, Climatology, and Geophysics Agency) of Deli Serdang Regency for the period 2022 to 2024, the system is able to provide recommendations for crop types that are suitable for climatic conditions over the next three months. This system utilizes average temperature, air humidity, and rainfall parameters to increase the suitability of vegetable crop types.

The Mamdani Fuzzy Method has proven effective in linguistically representing expert knowledge through logic-based rules that adapt plant characteristics to regional climate patterns. Overall, the developed system can serve as a decision-making tool for farmers in determining the most suitable crop types based on climate patterns. Thus, this system can help improve planting time efficiency and reduce the risk of crop failure due to climate mismatch.

For further development, this system can be refined by integrating real-time climate data from the BMKG (Meteorology, Climatology, and Geophysics Agency) or weather sensors to make recommendations more accurate based on current conditions. Furthermore, the input variables can be expanded by adding other factors such as sunlight intensity and soil type to enrich the fuzzy system's knowledge base.

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