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Application of fuzzy tsukamoto method in forecasting weather

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ABSTRACT

In today's information age, accurate weather prediction is essential given its far-reaching impact on various aspects of life and economic activity. This study aimed to test the effectiveness of Fuzzy Tsukamoto's method in predicting important weather variables such as temperature, humidity, and precipitation. This research method uses a combination design that includes experimental methods for model development, quantitative analysis of historical weather data, and model validation using separate data. The results showed that the Fuzzy Tsukamoto method was able to increase the accuracy of weather predictions compared to conventional methods, with a significant decrease in the value of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). In conclusion, this study successfully demonstrates that Fuzzy Tsukamoto's method can be a more accurate alternative in weather prediction, making a significant contribution to the field of meteorology and its practical application in decision-making in various sectors that depend on weather prediction.

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1. INTRODUCTION

In today's information age, accurate weather predictions are crucial, given their far-reaching implications for various aspects of life and economic activity (Kumar et al., 2021). Technological developments have enabled improvements in weather prediction methodologies, but there are still significant challenges in achieving the desired level of accuracy (Fathi et al., 2022) . Uncertainties in meteorological phenomena and limitations of conventional predictive models give rise to the need for more adaptive and sensitive methods to the nuances of weather data (Han et al., 2024).

The underlying problem with the study is the persistent inaccuracies in weather prediction, which can result in economic losses, safety risks, and planning failures (Guo et al., 2020). Therefore, an approach is needed that can reduce this predictive gap, allowing for more reliable and accurate predictions (Wang et al., 2020). Tsukamoto's Fuzzy method, with its advantages in managing uncertainty and providing a more graded output, offers a potential solution to this problem.

This study aims to apply Fuzzy Tsukamoto's method in predicting the weather, testing its ability to improve prediction accuracy (Yudhana, 2023). With a focus on integrating these fuzzy techniques, the research is expected to address the weaknesses of existing prediction methodologies, providing a stronger foundation for reliable and precise weather prediction (AlHaddad et al., 2023).

The significance of this research lies in its potential to change the paradigm of weather prediction, introducing methods that are more responsive to the complexity of weather data (Ren et al., 2021). Success in this research is expected to not only advance the field of meteorology but also provide more effective tools for decision-making in various sectors that rely on weather prediction (Meque et al., 2021).

By adopting Fuzzy Tsukamoto's method, the study aims to fill gaps in the current literature, offering new insights and practical improvements in weather prediction (Michailidis et al., 2023). The integration of Fuzzy Tsukamoto's method in weather prediction models can pave the way for interdisciplinary applications, linking meteorology with sectors such as agriculture, transportation, and disaster management (Berawi et al., 2021). This holistic approach not only enhances the robustness of weather prediction but also facilitates proactive measures in mitigating adverse weather impacts (Singh & Goyal, 2023). By leveraging advanced fuzzy logic techniques, this research aspires to set a new benchmark in predictive accuracy, fostering resilience and preparedness in communities and industries affected by weather variability (Giannakidou et al., 2024). It is hoped that the output of this research will enrich scientific understanding and practice in the field, making a meaningful contribution to improving the accuracy and reliability of future weather predictions (Barasa et al., 2021).

The Tsukamoto Fuzzy method is chosen as a potential approach to improve weather prediction accuracy due to its ability to handle uncertainty and provide more nuanced outputs compared to other fuzzy methods. The specific advantages of this method lie in its capability to manage uncertainty by converting numerical inputs into fuzzy values through the fuzzification process and then producing more defined outputs through fuzzy inference and defuzzification processes. The Tsukamoto Fuzzy method also allows for the creation of more intuitive and comprehensible rules, such as "if-then" statements, which can accommodate various weather variables more flexibly. Additionally, this method has been proven effective in specific case studies to enhance weather prediction accuracy by significantly reducing Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values. Therefore, it offers a more adaptive and responsive solution to changing weather conditions, making it a superior choice compared to conventional prediction methods.

Previous research examining the use of fuzzy logic systems in improving the accuracy of weather predictions by utilizing historical weather data and applying fuzzy systems to model uncertainty in meteorological data (Silver et al., 2020). Later research exploring the application of fuzzy logic to meteorological data analysis focusing on grouping and processing uncertain data showed that fuzzy logic can provide better results than traditional methods (Muhammad et al., 2021). Furthermore, research comparing various fuzzy inference systems in weather prediction includes several fuzzy methods and evaluates their performance based on historical weather datasets (Khodayar et al., 2022). In a study that examines hybrid models that combine fuzzy logic with other techniques such as artificial neural networks to improve the accuracy of weather predictions (Zhang et al., 2022). And research focusing on applying fuzzy logic to short-term weather prediction shows that fuzzy logic can improve the accuracy of short-term predictions over conventional statistical methods (Anđelković & Bajatović, 2020).

Some researchers have focused on using fuzzy logic systems to improve the accuracy of weather predictions by leveraging historical data and addressing uncertainties in meteorological data. However, there is limited research relating to the development of hybrid models that combine fuzzy logic with other techniques, such as artificial neural networks, to further improve the accuracy of weather predictions. Therefore, this research intends to develop a hybrid model of fuzzy logic and artificial neural networks to accurately predict short-term weather conditions by utilizing historical weather data. The goal is to evaluate the performance of hybrid models, compare them with fuzzy logic methods, artificial neural networks, and conventional statistics, and identify factors that affect prediction accuracy.

One of the main challenges in weather prediction today is the inherent uncertainty and complexity of meteorological phenomena, which are often difficult to predict accurately. The inaccuracy of weather predictions can significantly impact various sectors. In agriculture, inaccurate forecasts can lead to substantial crop losses as farmers are unable to plan planting and harvesting activities appropriately. In the transportation sector, especially aviation and shipping, unexpected weather conditions can cause delays, disruptions, and even accidents, leading to economic losses and safety risks. Furthermore, in disaster management, inaccurate weather predictions can hinder mitigation efforts and emergency responses to natural disasters such as floods and storms, thereby increasing the risk of property damage and loss of life. Therefore, improving the accuracy of weather predictions is crucial to minimizing these negative impacts and enhancing planning and preparedness across different sectors.

This research contributes to the literature on hybrid models combining fuzzy logic with artificial neural networks (ANNs) by demonstrating the effectiveness of the Fuzzy Tsukamoto method in improving weather prediction accuracy. The study highlights the strengths of fuzzy logic in handling uncertainty and reducing prediction errors, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These findings provide a foundation for future research integrating fuzzy logic with ANNs, potentially leading to more robust and accurate hybrid models for various complex and uncertain environments.

2. RESEARCH METHOD

Research Objectives

This study aimed to test the effectiveness of Fuzzy Tsukamoto's method in predicting important weather variables such as temperature, humidity, and precipitation. Through quantitative approaches and combination research designs, this study proposes the development and validation of weather prediction models (Chhetri et al., 2020).

Research Design

This diagram includes important steps such as data collection, data processing, fuzzy set modeling, fuzzification, fuzzy inference, defuzzification, and evaluation and analysis of results.

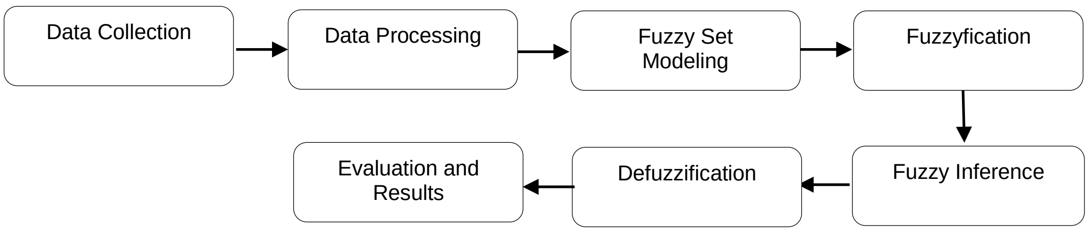

Figure 1. Research flow

The process begins with the collection of data from relevant sources. After that, the collected data is processed (Data Processing) to ensure the quality and readiness of the data for further analysis. The next step is fuzzy set modeling, where the variables used in predictions are converted into fuzzy sets through the fuzzification process. Then, fuzzy inference is performed to process fuzzy data and produce relevant fuzzy output. The results of this inference process are then defuzzified to convert them back into interpretable values. Finally, the prediction results are evaluated and analyzed (Evaluation and Results) to assess the accuracy and effectiveness of the prediction model that has been made. The diagram shows a systematic workflow that helps in ensuring that each stage is done meticulously to get accurate weather predictions.

This study used a combination design that included experimental methods for model development, quantitative analysis of historical weather data, and model validation using separate data. This design allows a comprehensive evaluation of the performance of the proposed prediction model.

Data Collection

The data used in the study comes from historical weather records for 2023 that include average, maximum, and minimum daily temperatures, humidity, precipitation, wind speed, and wind direction. This data was obtained from the Tegal Meteorology, Climatology and Geophysics Agency (BMKG).

Table 1. Weather data 2023

Date	Tn	Tx	Tavg	RH_avg	RR	180180	ff_x	ddd_x	ff_avg	ddd_car
01-01-2023	24,2	29,1	26,6	86	10,2	0	7	300	3	270
02-01-2023	25	31,2	27,8	82	0,4	1,6	9	300	4	315
03-01-2023	25,6	31	27,1	85	0	6,7	10	310	2	270
04-01-2023	25,2	32,2	27,8	82	0,2	2	6	350	2	270
⋮					⋮					⋮
⋮					⋮					⋮

Date	Tn	Tx	Tavg	RH_avg	RR	180180	ff_x	ddd_x	ff_avg	ddd_car
28 – 10 – 2023	26	34	29,2	72	0	9,4	6	60	3	180

Data Processing

The selection of variables is based on correlation analysis to determine the variables that most influence weather prediction including Temperature, Air Humidity and Wind Speed. Model optimization involves adjusting Fuzzy Tsukamoto's parameters to achieve optimal predictions based on established evaluation criteria (Bin et al., 2023).

Fuzzy Set Modeling

A fuzzy set is a representation of a specific condition on a fuzzy variable. Linguistic values are associated with fuzzy sets, where each value has a predefined membership function. In this study, a fuzzy set was used with two linguistic values, namely "low", "medium" and "high". The formation of fuzzy sets is adjusted to the input data used to predict rainfall (Burda & Štěpnička, 2022).

Table 2. Input himpunan fuzzy

	Fuzzy Set	
Input Criteria	Linguistic Value	Range of Values
Tavg	Low	20 – 28
	Medium	24 – 32
	High	28 – 36
RH_avg	Low	50 – 70
	Medium	60 – 80
	High	70 – 90
RR	Low	0 – 10
	Medium	5 – 20
	High	10 – 30

Fuzzification

Fuzzy Tsukamoto's algorithm was implemented to develop weather prediction models. This implementation uses computing software to automate calculations and simulations of weather conditions. Fuzzification is the process of converting crisp values into fuzzy values. This process involves several steps, including determining the degree of membership of a value in a fuzzy set (Kontogiannis et al., 2021).

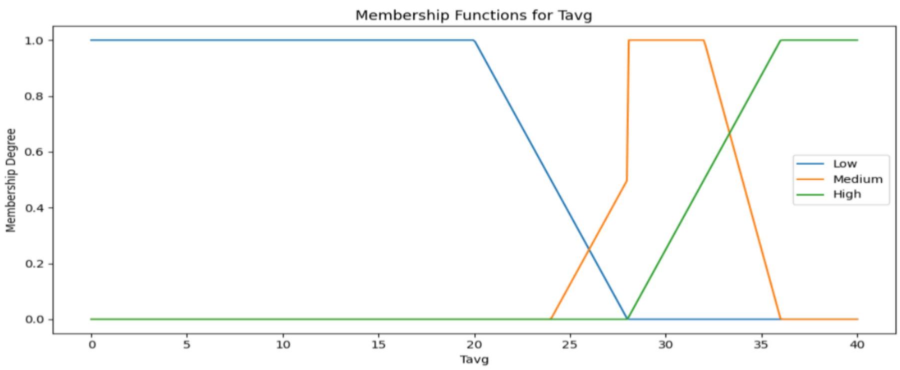

Figure 2. Tavg input membership function

Low membership function:

$$\mu low[x] = \begin{cases} 1; & x \leq 20 \\ \dfrac{(x-20)}{(28-20)}; & 20 \leq x \leq 28 \\ 0; & x \geq 28 \end{cases}$$

Medium membership functions:

$$\mu medium[x] = \begin{cases} 0; \; x \leq 24 \\ \dfrac{(24 - x)}{(32 - 24)} : 24 \leq \mathrm{x} \leq 32 \\ \dfrac{(24 - x)}{(36 - 32)} : 32 \leq \mathrm{x} \leq 36 \\ 0; \; x \geq 36 \end{cases}$$

High membership function:

$$\mu high[x] = \begin{cases} 1; \; x \leq 28 \\ \dfrac{(28 - x)}{(36 - 28)} : 28 \leq \mathrm{x} \leq 36 \\ 0; \; x \geq 36 \end{cases}$$

Fuzzification of temperature variables helps in handling the uncertainty of climate data by converting numerical values into degrees of membership in fuzzy sets. This allows for a more flexible and adaptive analysis to changing environmental conditions. Figure 2. It shows how the degree of membership changes according to the average temperature value. The "Low" category decreased from 1 to 0 in the range of 20 to 28, the "Medium" category increased from 0 to 1 in the range of 24 to 28 and then remained from 1 between 28 to 32, then decreased from 1 to 0 between 32 and 36 while the "High" category increased from 0 to 1 in the range of 28 to 36.

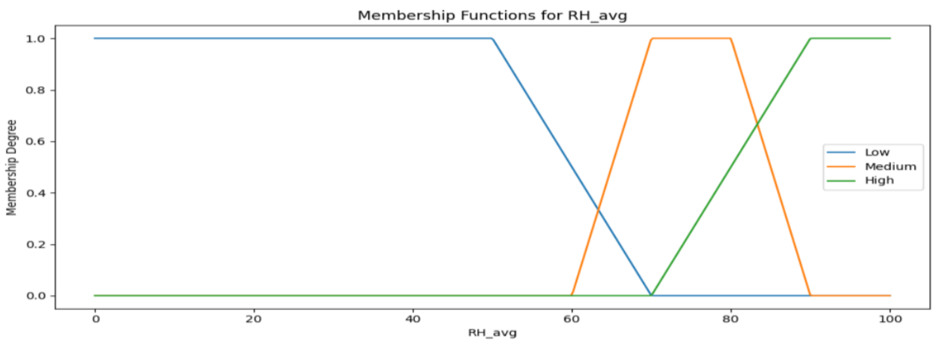

Figure 3. Input membership function RH avg

Low Membership function:

$$\mu low[x] = \begin{cases} 1; \; x \leq 50 \\ \dfrac{(x - 50)}{(70 - 50)} : 50 \leq \mathrm{x} \leq 70 \\ 0; \; x \geq 70 \end{cases}$$

Medium Membership function:

$$\mu medium[x] = \begin{cases} 0; \; x \leq 60 \\ \dfrac{(x - 60)}{(70 - 60)} : 60 \leq \mathrm{x} \leq 70 \\ \dfrac{(90 - x)}{(90 - 80)} : 80 \leq \mathrm{x} \leq 90 \\ 0; \; x \geq 90 \end{cases}$$

High Membership function:

$$\mu high[x] = \begin{cases} 1; \; x \leq 70 \\ \dfrac{(x - 70)}{(90 - 70)} : 70 \leq \mathrm{x} \leq 90 \\ 0; \; x \geq 90 \end{cases}$$

Variable fuzzification of humidity helps in handling the uncertainty of climate data by converting numerical values into degrees of membership in fuzzy sets. This allows for a more flexible and adaptive analysis to changing environmental conditions. Figure 3. It shows how the degree of membership changes according to the average humidity value. The "Low" category decreased from 1 to 0 in the range of 50 to 70, the "Medium" category increased from 0 to 1 in the range of 60 to 70, remained 1 between 70 and 80, then decreased from 1 to 0 between 80 and 90 while the "High" category increased from 0 to 1 in the range of 70 to 90.

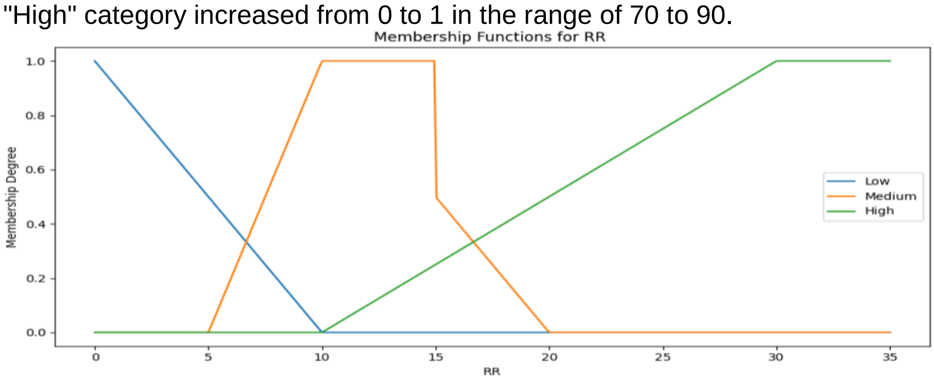

Figure 4. RR input membership function

Low Membership function:

$$\mu low[x] = \begin{cases} 1; & x \le 0 \\ \dfrac{(x-10)}{(10-0)}: & 0 \le x \le 10 \\ 0; & x \ge 10 \end{cases}$$

Medium Membership function:

$$\mu medium[x] = \begin{cases} 0; & x \le 5 \\ \dfrac{(x-5)}{(10-x)}: & 5 \le x \le 10 \\ \dfrac{(20-x)}{(20-10)}: & 10 \le x \le 20 \\ 0; & x \ge 20 \end{cases}$$

High Membership function:

$$\mu high[x] = \begin{cases} 1; & x \le 10 \\ \dfrac{(x-10)}{(30-10)}: & 10 \le x \le 30 \\ 0; & x \ge 30 \end{cases}$$

Fuzzification of precipitation variables helps in handling the uncertainty of climate data by converting numerical values into degrees of membership in fuzzy sets. This allows for a more flexible and adaptive analysis to changing environmental conditions. Figure 4. It shows how the degree of membership changes according to the rainfall value. The "Low" category decreased from 1 to 0 in the range of 0 to 10, the "Medium" category increased from 0 to 1 in the range of 5 to 10, remained 1 between 10 and 15, then decreased from 1 to 0 between 15 and 20 while the "High" category increased from 0 to 1 in the range of 10 to 30.

Fuzzy Inference

Fuzzy Inference System (FIS) is a system that performs computations based on fuzzy set theory, fuzzy logic, and fuzzy rules. FIS has input in the form of crisp values which are then calculated using predetermined rules, resulting in fuzzy quantities through the fuzzification process. Tsukamoto's FIS method forms the basis of rules in the form of "if-then" or "causation" (Aliev et al., 2024). The first step in the calculation of Tsukamoto's FIS method is to draw up a rule or rule base. Furthermore, the degree of membership is calculated according to the rules that have been made. After knowing the membership degree value of each fuzzy rule, the next step can be done.

Table 3. Rule basic

Tavg	RH_avg	RR	Output Fuzzy
Low	Low	Low	Low
Low	Low	Medium	Low
Low	Low	High	Low
⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮
High	High	Medium	High
High	High	High	High

Table 2. Helps in determining the output produced based on the combination of input values of temperature, humidity, and precipitation. Using fuzzy logic, these tables allow us to deal with uncertainty and variability in climate data, thus enabling more flexible and adaptive analysis to changing environmental conditions. The output generated from these tables can be used for a variety of analysis and decision-making purposes in the context of climate and weather, such as weather prediction, water resources management, and agricultural planning.

Table 4. Implementasi rule base database

Moon	Tavg e-mail	Category Tavg	War-war RH_avg	Category RH_avg	Average RR	RR Category	Rata-rata Output Fuzzy	Output Category
January	27.58	Medium	83.13	High	8.41	Medium	2.015	Medium
February	27.03	Medium	85.68	High	9.18	Medium	2.000	Medium
Maret	27.80	Medium	82.26	High	5.85	Medium	2.067	Medium
April	28.56	High	80.57	High	4.13	Low	2.186	Medium
From	28.62	High	77.03	Medium	1.83	Low	2.067	Medium
June	28.22	High	78.47	Medium	3.14	Low	2.000	Medium
July	27.43	Medium	74.10	Medium	1.05	Low	1.000	Low
August	27.23	Medium	73.84	Medium	0.11	Low	1.000	Low
September	27.90	Medium	69.33	Medium	0.00	Low	1.000	Low
October	28.92	High	73.68	Medium	0.06	Low	NaN	High

Table 4. above describes the fuzzy inference results using datasets listed with output category results if output 1.5 is "low", and if output between 1.5 to 2.5 is in the "medium" category and if output 2.5 is included in the "high" category and NaN code indicates the data in the dataset is invalid.

Defuzification

Defuzzification is the process of converting fuzzy output into definite numerical values. The results of this defuzzification are used for decision making or action based on fuzzy analysis (Chi & Chien, 2023). The formulation of defuzzification is found in equation (1).

$$Z = \frac{\sum(\mu i \cdot xi)}{\sum \mu i} \tag{1}$$

Algorithm Configuration and Model Evaluation

Algorithm configuration involves tuning parameters such as fuzzy membership functions and inference rules. Model evaluation uses metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to measure the accuracy of predictions against actual data. The formula Mean Absolute Error (MAE) can be written in the equation (2).

$$MAE = \left(\frac{1}{n}\right) * \sum |i = 1|^{\wedge} n |y^i - \hat{y}^i| \tag{2}$$

Where n is the number of samples in the data, $y^i$is actual and $\hat{y}^i$is the predicted value. The Root Mean Square Error (RMSE) formula can be written in the equation (2)

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

Where n is the number of samples in the data, y^i is actual and $\acute{y}^i$ is the predicted value

3. RESULTS AND DISCUSSIONS

This study applied Tsukamoto's fuzzy method to conduct weather forecasts in Tegal. The data used include average temperature (Tavg), average humidity (RH_avg), and monthly rainfall (RR) from January to October. Fuzzy inference is done by applying predefined fuzzy rules. These rules are designed based on domain knowledge and expert experience in meteorology, so as to produce accurate fuzzy output. The final stage of this process is defuzzification, which uses the centroid method to convert the fuzzy output into crisp values that represent the weather conditions each month. This crisp value provides a more understandable interpretation of the weather, such as whether a particular month is likely to have high (hot or intense rain), moderate (normal conditions), or low (cooler or light rain).

Table 5. Defuzzification results

Moon	Low Output	Medium Output	High Output	Centroid Crisp Value	Weather Interpretation
January	0.0	0.0	2.015	3.0	High weather, may be hot or intense rain
February	0.0	2.000	0.0	2.0	Moderate weather, normal conditions
Maret	0.0	0.0	2.067	3.0	High weather, may be hot or intense rain
April	0.0	2.186	0.0	2.0	Moderate weather, normal conditions
From	0.0	0.0	2.067	3.0	High weather, may be hot or intense rain
June	0.0	2.000	0.0	2.0	Moderate weather, normal conditions
July	1.000	0.0	0.0	1.0	Low weather, possibly colder or light rain
Agustus	1.000	0.0	0.0	1.0	Low weather, possibly colder or light rain
September	1.000	0.0	0.0	1.0	Low weather, possibly colder or light rain
October	In	In	In	In	Data is unavailable or invalid

Based on Table 5. January, March, and May show a centroid crisp value of 3.0, which is interpreted as high weather, the possibility of heat or intense rain. February, April, and June have a crisp centroid value of 2.0, which is interpreted as moderate weather or normal conditions. The months of July, August, and September show a centroid crisp value of 1.0, which is interpreted as low weather, a chance of cooler or light rain. October has no valid or available data.

The results of the study from the 2023 data show significant variations in weather conditions based on analysis using the Fuzzy Tsukamoto method. In January, the fuzzy output shows a centroid crisp value of 3.0, which is interpreted as high weather, the possibility of intense heat or rain. The average temperature was recorded at 27.58°C with 83.13% humidity and 8.41 mm rainfall, indicating cloudy weather conditions. In February, a crisp centroid value of 2.0 indicates moderate weather or normal conditions with an average temperature of 27.03°C, humidity of 85.68%, and rainfall of 9.18 mm. March also shows a crisp centroid value of 3.0, which is interpreted as high weather with an average temperature of 27.80°C, humidity of 82.26%, and rainfall of 5.85 mm. In April, the temperature increases to 28.56°C with 80.57% humidity and rainfall decreases to 4.13 mm, resulting in a crisp centroid value of 2.0 indicating moderate or sunny weather conditions. This sunny weather continues into June with an average temperature of 28.22°C, humidity of 78.47%, and rainfall of 3.14 mm, with a crisp centroid value of 2.0. In July, a centroid crisp value of 1.0 indicates low weather, possibly colder or light rain, with an average temperature of 27.43°C, humidity of 74.10%, and rainfall of 1.05 mm. August and September also show crisp centroid values of 1.0, with average temperatures of 27.23°C and 27.90°C, humidity of

73.84% and 69.33%, and rainfall of 0.11 mm and 0.00 mm respectively, indicating low or cloudy to sunny weather conditions. Entering October, the data shows the NaN value, which indicates that the data is not available or valid for analysis in that month.

These data show significant fluctuations in meteorological conditions throughout the year and confirm the effectiveness of Fuzzy Tsukamoto's method in producing accurate weather predictions. This research has a high value for planning and decision-making in various sectors affected by weather conditions, such as agriculture, transportation, and disaster management. By utilizing the Fuzzy Tsukamoto method, you can gain a deeper understanding of weather patterns and prepare appropriate mitigation measures in the face of changing dynamic weather conditions.

The results that have been obtained after applying Fuzzy Tsukamoto, then evaluated the model using RMSE and MAE.

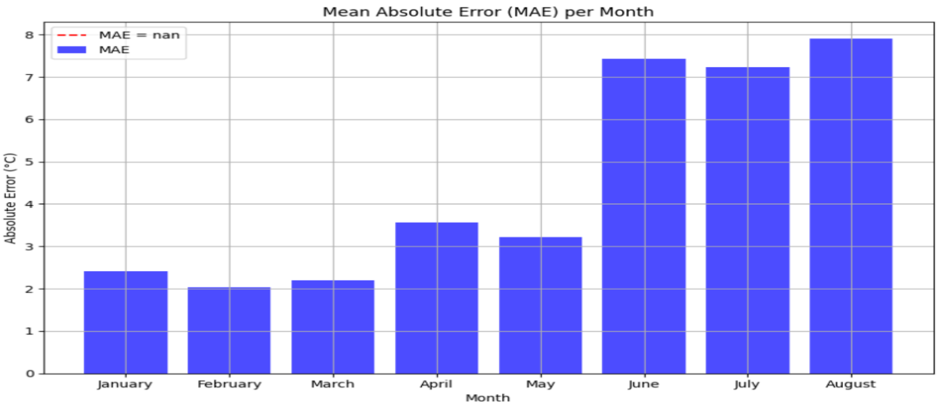

Figure 5. MAE graphic

The Mean Absolute Error (MAE) graph shows the variation in average absolute error between actual and predicted values for each month from January to August. From January to March, the MAE was relatively consistent around 2°C, indicating a fairly accurate prediction. However, starting in April, the MAE increased to around 3°C and peaked in June at around 6°C, indicating a significant prediction error. July and August have the highest MAE, around 7°C to 8°C, which indicates a huge prediction error in these months. This graph indicates the need to adjust and refine prediction models, especially in months with high MAE, to improve the accuracy of future weather predictions.

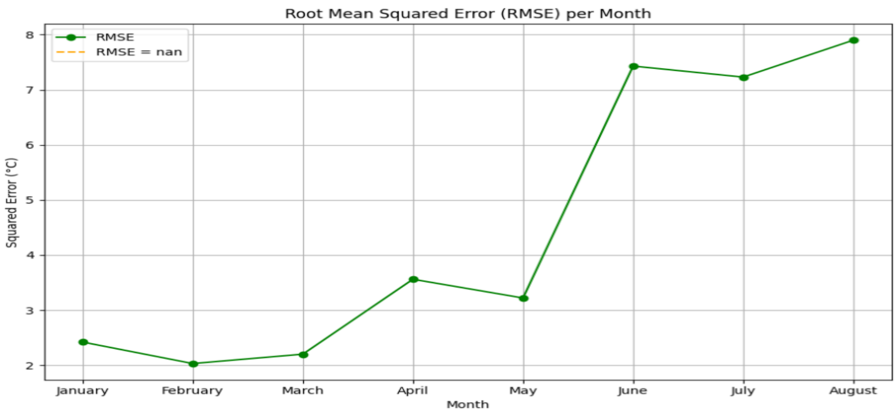

Figure 6. RMSE graphics

The Root Mean Squared Error (RMSE) graph shows the variation in mean squared error between actual and predicted values for each month from January to August. In January to March, the RMSE hovered around 2°C, showing relatively small errors. However, starting in April, the RMSE increased to around 3°C and peaked in June at around 7°C, indicating a significant prediction error. July and August show high RMSE values, around 6°C to 8°C, which indicates a huge prediction error in these months. This graph indicates that the prediction model has a larger error in certain months, especially in the summer, so refinement of the model is needed to improve the accuracy of future weather predictions.

4. CONCLUSION

This research demonstrates that Fuzzy Tsukamoto's method effectively handles uncertainty, improving weather prediction accuracy. The MAE and RMSE values (4.50°C and 5.10°C) indicate a good predictive model. Refining the model further could enhance accuracy, particularly in high-error months. These results have practical implications for sectors like agriculture, transportation, and disaster management. Accurate weather predictions can help farmers optimize schedules, enhance safety and efficiency in transportation by reducing delays, and improve disaster preparedness and response, potentially saving lives and reducing property damage. Thus, the study provides significant academic and practical benefits.

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