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Prediction of Precipitation Using a Fuzzy Rule System in India

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Abstract:

Warm and humid conditions characterize India's tropical climate. Predicting precipitation is essential for the everyday operations and choices of nations that rely on agriculture. Predicting precipitation is difficult due to the dynamic nature of tropical meteorological characteristics such as Temperature, humidity, air pressure, dew point, and wind speed. These criteria were utilized in this investigation. The precipitation forecasts are compared and examined. Fuzzy Logic and Fuzzy Inference System can handle the uncertainty that frequently occurs in meteorological forecasting; it can be combined with expert knowledge and empirical research. This work will assess the dependability of the Fuzzy Logic method to rainfall prediction within the specified approximation of rainfall rate, investigate the application of Fuzzy Logic, and create a fuzzy model for rainfall forecast. the suggested Fuzzy Inference System model achieves 92 percent accuracy.

Keywords **—**Expert system, Fuzzy inference system, Rain prediction, Rainfall forecast, Soft computing, Tropical climate

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1. INTRODUCTION

Climate change has increased the frequency of erratic precipitation patterns, which frequently result in widespread floods. Any technology that can forecast precipitation rates in advance might be used to anticipate floods before a rain storm. The need for precise local rainfall forecasting is apparent when one considers the numerous benefits such data would bring for river management, reservoir operations, forestry interests, flash flood monitoring, and agricultural requirements. Data fusion offers new prospects for precipitation and flood forecasting. This is essential in tropical settings with localized rainfall and frequent flash flooding. Fusion of sensor-collected local environmental data, such as Temperature, humidity, atmospheric pressure, air pressure, dew point, solar radiation, clouds, wind direction, and wind speed, might be utilized to generate more precise local forecasts.[1]

This work aims to identify the rules and models for predicting rainfall using Fuzzy Logic (FL). The guidelines will be used to forecast the precipitation in India. The inference rules are determined using fundamental environmental factors like Temperature, humidity, air pressure, dew point, and wind speed. FL is one of the critical approaches of soft computing, to use decision-tolerance making for imprecision, uncertainty, ambiguity, and vagueness.[2]

In engineering and research, the application of soft computing can address issues that have historically been intractable to analytical approaches. The necessary data to make such forecasts has been readily accessible for quite some time. Using standard computer analysis has frequently proven challenging due to the complexities and changes in data linkages and their influence on likelihood. The use of soft computing techniques to learn rather than analyze these complicated interactions has shown significant promise in achieving the objective of forecasting both the chance and amount of rainfall in a small region. Soft computing approaches include knowledge processing and flexible knowledge acquisition through data-driven learning to address non-linear problems. The research indicates that FL may obtain a 92 percent accuracy rate in data mining performance comparison. The performance outcomes are evaluated by evaluating the error amount and measuring the correlation between the observed and predicted values. The results show that accurate projections may be made one hour in advance. The results demonstrate that Fuzzy Inference System models can accurately predict precipitation.

2. LITERATURE REVIEW

Numerous uses of FL-based soft computing in precipitation forecasting exist. Fuzzy Rule-Based Systems (FBS) and Fuzzy Inference systems (FIS) have been used experimentally to anticipate meteorological occurrences such as rain, fog, tornado, thunderstorm, and clear conditions. Fuzzy Time Series (FTS) was proposed as a time-invariant and variant model for dealing with forecasting issues. If the yearly precipitation data spans more than ten years, the FTS model may be employed as an appropriate rainfall forecasting method. Design and development of rules based on three primary sources: expert opinion, literature review, and automated rule creation. Commonly, the rule base is derived from expert opinion; however, Handoyo and Marji recommended that the rule base be developed based on the relationship between input and output pairs, and then each rule is optimized using the ordinary least square (OLS) approach. Agboola et al. predict precipitation using the FIS method. Two relevant components comprise the system: the knowledge base and the fuzzy reasoning unit. The FL model was subjected to two operations: fuzzification and defuzzification.[1] Asklany et al. predict precipitation usingapproximation reasoning based on FL, the IF-THEN principles.

Using the fundamentals of fuzzy logic, the fuzzy inference engine employs these fuzzy IF-THEN rules to produce a mapping between the fuzzy input sets and the output fuzzy sets. The fuzzy sets in the proposed model comprise the following five environmental variables: humidity, cloud, wind direction, Temperature, and air surface pressure. These parameters are the variable inputs. Each fuzzy set comprises three membership functions, each with a single output. In fuzzy set theory, characteristics of a fuzzy set are translated to a universe of membership values utilizing a function theoretic form belonging to the closed interval 0 to 1. Hasan et al. created a model for predicting rainfall by selecting fuzzy variables depending on the degree of correlation between various elements. The correlation between wind speed, Temperature, and precipitation was positive, although the suggested model's performance was improved by adding humidity threshold values. Cristina et al. have proposed an architecture incorporating reasoning approaches in environmental investigation using fuzzy reasoning. The list of precipitation prediction models created using the FL methodology is incomplete. The model's development and research may be found. These situations are only a few illustrations of the potential and future direction of the FL-based rainfall forecasting model.[2]

3. STUDY AREA

Officially known as the Republic of India, India (Hindi: Bharat) is a nation in South Asia.[3] It is the world's most populous democracy and the seventhlargest country by area. India shares land boundaries with Pakistan to the west, China, Nepal, and Bhutan to the north, and Bangladesh and Myanmar to the east. It is bordered to the south by the Indian Ocean, to the southwest by the Arabian Sea, and to the southeast by the Bay of Bengal. India lies close to Sri Lanka and the Maldives in the Indian Ocean, and is Andaman and Nicobar Islands share a maritime border with Thailand, Myanmar, and Indonesia.[3]

India is a vast country in geographical terms, with various regions experiencing very different climatic conditions. This is also reflected in the distribution of rainfall in India. Some regions experience very high rainfall, and others receive very scanty rainfall. India's recorded highest and lowest rainfall is approximately 1178 cm.[3]

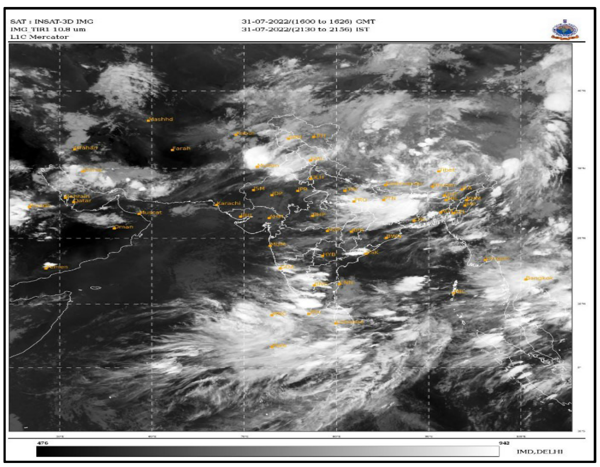


Figure 1. Satellite images of India's weather

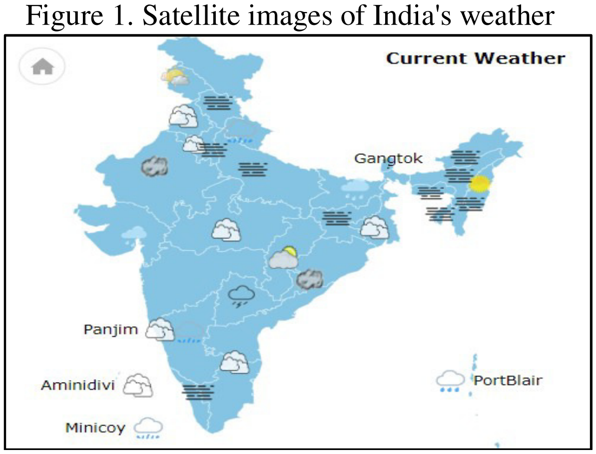


Figure 2. Current weather in India

4. METHOD

Fuzzy logic

We attempt to predict when it will rain using fuzzy logic and approximate reasoning. The fuzzy rule basis for this procedure is a collection of fuzzy IF-THEN rules based on the notion of a pure fuzzy logic system. An inference engine employs IF-THEN rules derived from the fuzzy input world to produce a logical mapping between those worlds based on fuzzy logic principles. Each of the five input variables (relative humidity, total cloud cover; wind direction; Temperature; surface pressure) has three membership functions with a single output (rain event %) that we constructed for our model.[4]

Elements of a fuzzy set are translated to a universe of membership values using a function-theoretic form belonging to the closed interval 0 to 1 according to the fuzzy set theory. Fuzzy logic is beneficial for modeling complicated and imprecise systems. Fuzzy set theory is a potent instrument whose applications have rapidly risen as its value has been established in several scientific fields. Any system with nebulous and confusing input variables may contribute to the outcome. Some believe that the fuzzy logic possibilities and their degree of influence owing to unclear input variables are formed in the human mind and are frequently referred to as expert knowledge. Therefore, decision-making processes may be seen as fuzzy expressions experienced by the expert.

A fuzzy Inference System(FIS) is designed to operate with the settings provided. The system determines the output rule based on the input provided by the user. MATLAB's fuzzy logic toolbox will be utilized during the design phase for the fuzzy model. The Figure depicts the fuzzy model with five input factors (humidity, Temperature, pressure, wind speed, and dew point) and one output parameter (Rainfall Rate).[1]

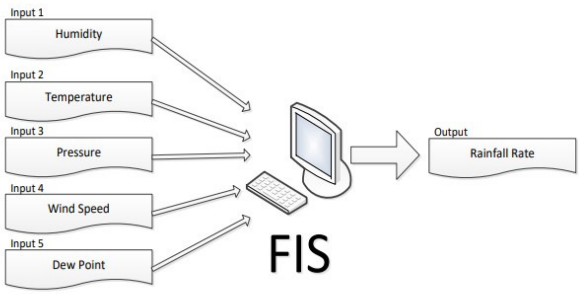


Figure 3. Schematic illustration of the rainfall rate fuzzy model[1]

Two or more membership functions (MF) are defined for each given input and output variable, typically three, although more qualitative categories can be used for each. The projected FIS will employ four MFs, whereas the output will employ five MFS. The shape of these functions can vary, although they typically take the form of triangles. Once the input and output variables and MF have been established, the rule-base or decision matrix of the fuzzy knowledge-base consisting of expert IF-THEN rules must be designed. These rules translate the input data into an output that indicates the rainfall rate likelihood. MF must also be used to specify the output variables, which are typically low, standard, and high. The rule-based system can define a greater or lesser probability of rain depending on the number of MF for the input and output variables. The greater the number of variables, the greater the number of rules that may be established, and the greater the reliability of the inference rules. Once the realistic rules are developed based on expert knowledge and gathered weather data, these rules will constitute the knowledge foundation of each prediction model. However, it is not required to convert all knowledge into rules; specific rules may be superfluous or removed. This research utilizes the FIS Mamdani Model[2].

Similar to the Sugeno and Tsukamoto model, the Mamdani fuzzy model consists of a series of inputs, each of which has its own MFs. The Mamdani model is distinct from others because the output has membership functions. The output of the Sugeno model is a function of the input MF, but the output of the Tsukamoto model is a linear function of the input.

MATLAB CODE

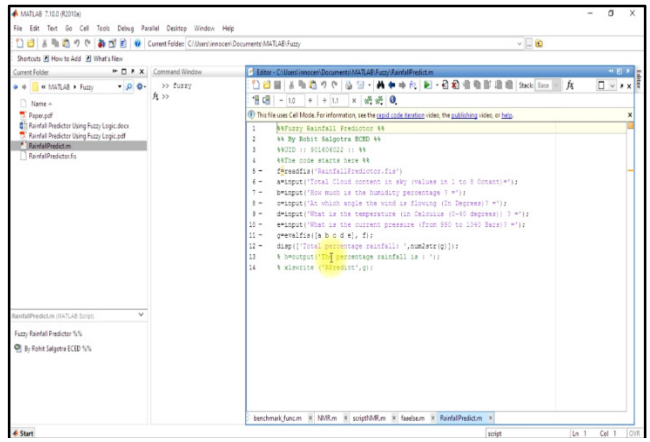


Figure 4. MATLAB Editor Window

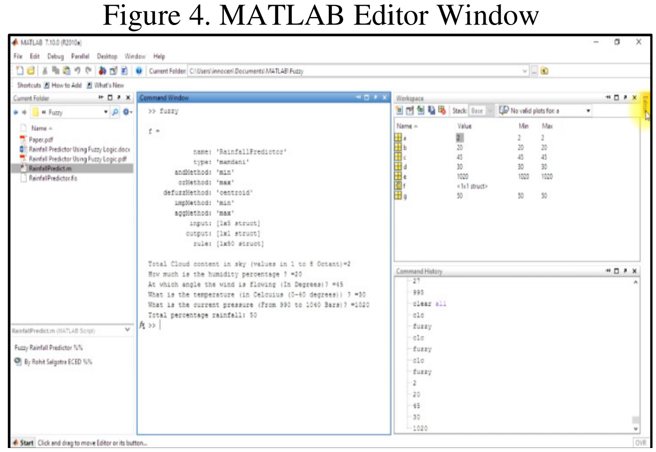


Figure 5. MATLAB Command Window

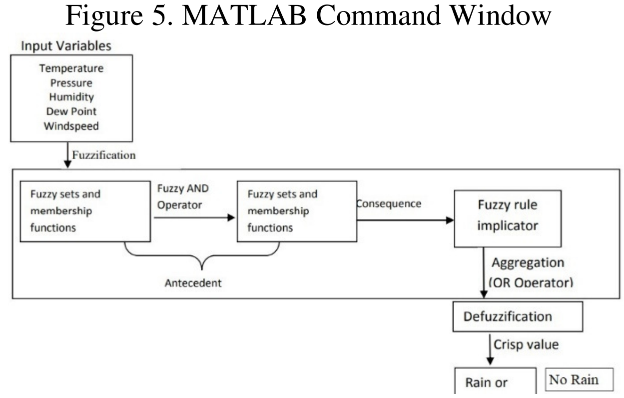


Figure 6. Model of rainfall fuzzy inference procedure[2]

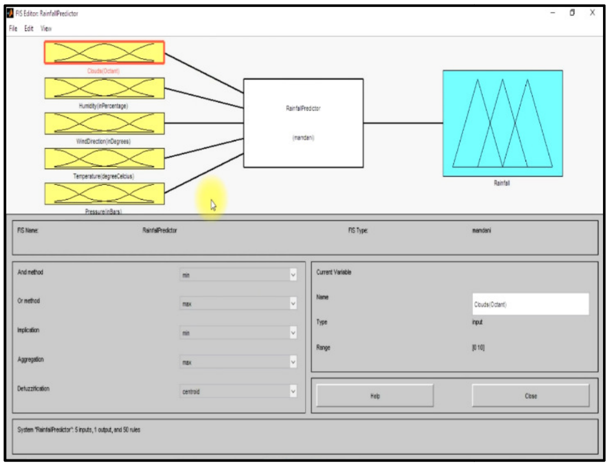


Figure 7. Rainfall fuzzy inference

Rules based on basic IF-THEN rules can be used to develop elementary types of Prediction, particularly for strongly interdependent circumstances. Developing rules involves determining which combination of phrases in the rule antecedent best identifies a class term. Moreover, OR are the most frequent logical operator used to implement the combination rules. Initial research aimed to determine the relationship between environmental elements and precipitation conditions.[4]

Using Cumulative Distribution Function (CDF) curves, the most relevant factors for predicting whether or not it would rain were identified. The CDF of each parameter is compared between episodes with and without precipitation. The Figure displays the humidity curves. When it was raining, the relative humidity ranged from 68% to 100%. Thus, the following rule is formulated: IF Relative Humidity Is Less Than 70 Percent, THEN 'No Rain' Based on the Temperature's CDF, the rule developed is IF Temperature > 33° Celsius THEN 'No Rain.'

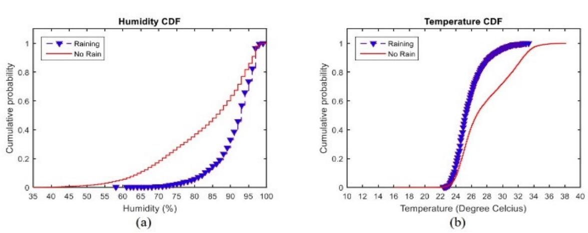


Figure 8. (a) CDF for Humidity, (b) CDF for Temperature[1]

Input Parameters	Unit	Fuzzy Variables			
Humidity	%	Poor	Low	Medium	High
Temperature	℃	Poor	Low	Medium	High
Pressure	Minibar	Poor	Low	Medium	High
Wind Speed	Km/h	Poor	Low	Medium	High
Dew Point	℃	Poor	Low	Medium	High

Table 1. List of Input Parameters[1]

A fuzzy set contains elements that have varying degrees of MF in the set of ordered pairs given by:

$$A = \{(x, \mu A(x)) | \forall x \epsilon X\}$$

Where X is a universal set and $\mu A\ (x)$ (usually $0 \leq \mu A\ (x) \leq 1$) is the grade of MF of the object x in A, a membership function $\mu A\ (x)$is characterized by μA: $X \rightarrow (0,1)$ where X is the universe of discourse; x is a natural number describing an object or its attribute, and each element of X is mapped to a value between 0 to 1, MFs can be graphically represented as a fuzzy set in the form of a triangular, trapezoidal, or bell shape (Gaussian). Every input is fuzzified by constructing the MF. The proposed model used triangular membership functions to describe input and output variables. Triangular membership has been used because of its simplicity and computational efficiency. The triangular MFs are shown in Figure where a, b and c are the parameters of the linguistic value, and the x axis is a value input parameter's series.

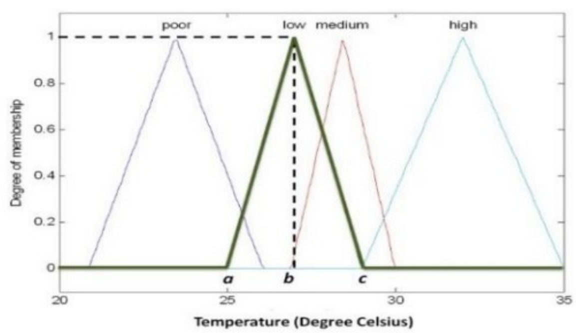


Figure 9. Triangular MF[1]

Let A=(a,b,c) with a<b<c, be a fuzzy set on R = (-α,α). It is called a triangular fuzzy number; if its MF is

$$\mu A(x) = \begin{cases} \dfrac{x - a}{x - b}, if\ a \le x \le b \\ \dfrac{c - x}{c - b}, if\ b \le x \le c \\ 0, otherwise \end{cases}$$

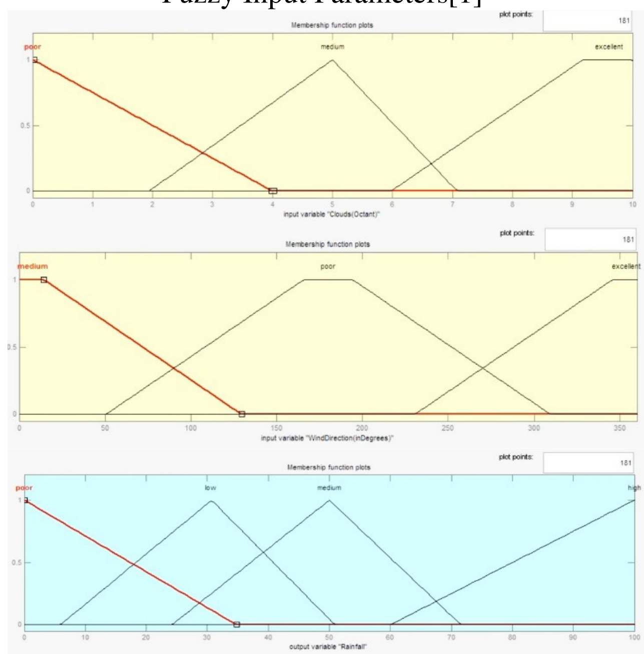
The MFs have been defined and built using weather parameters; the fuzzy output is rainfall rate. All membership function types were selected based on a statistical study of training data and a synoptic and climatological study of the area. However, most of the decisions rely on knowledge and statistical analysis. The MFs linguistic variables for the output were adopted from the Mamdani model. To make the inference rules reliable, the rainfall rate has been classified into five linguistic labels; Poor, Low, Medium, High, and Very High. A composition method of fuzzy relations for output has been identified using the fuzzy c-means (FCM) clustering method. In FCM, each data belongs to a cluster specified by a membership group. FCM algorithm uses the reciprocal of distances to decide the cluster centers. FCM uses a weight that minimizes the total weighted mean-square error. The FCM permits each feature vector to belong to every cluster with a fuzzy value. The approach allocates a feature vector to a cluster based on the feature vector's most excellent weight across all clusters. Table 1 and Table 2 show the MF input and output. The Figure is a fuzzy representation based on the input-output MFs for Temperature.

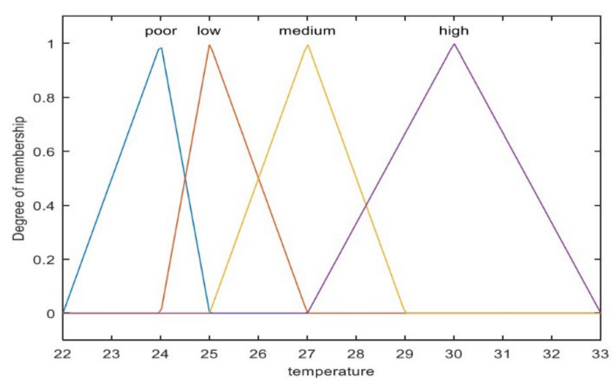
Fuzzy Variable	Rainfall Rate
Poor	0.01 – 3.09
Low	2.94 – 10.56
Medium	10.05 – 24.11
High	22.93 – 46.20
Very High	43.95 – 63.18

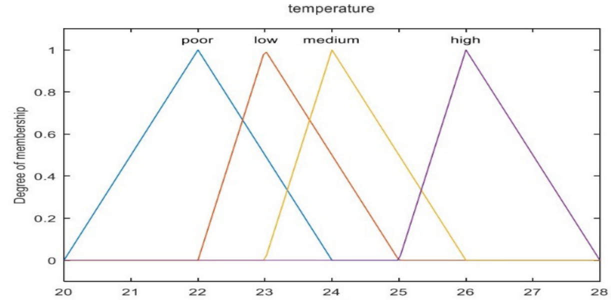
Table 2. Membership Function Interval Values for Fuzzy Output Parameter[1]

	Humidity	Temperature	Pressure	Wind Speed	Dew Point
Poor	70.1 – 82.6	22.4 – 25.3	1001 – 1010	0.07 – 0.49	20.9 – 24.0
Low	78.6 – 90.1	24.0 – 27.0	1005 – 1012	0.47 – 1.23	22.8 – 25.0
Medium	86.3 – 96.4	25.7 – 29.4	1007 – 1014	1.17 – 2.14	23.8 – 26.3
High	91.7 – 100.6	27.9 – 30.8	1009 - 1016	2.04 - 4.41	25.0 – 26.8

Table 3. Membership Function Interval Values for Fuzzy Input Parameters[1]







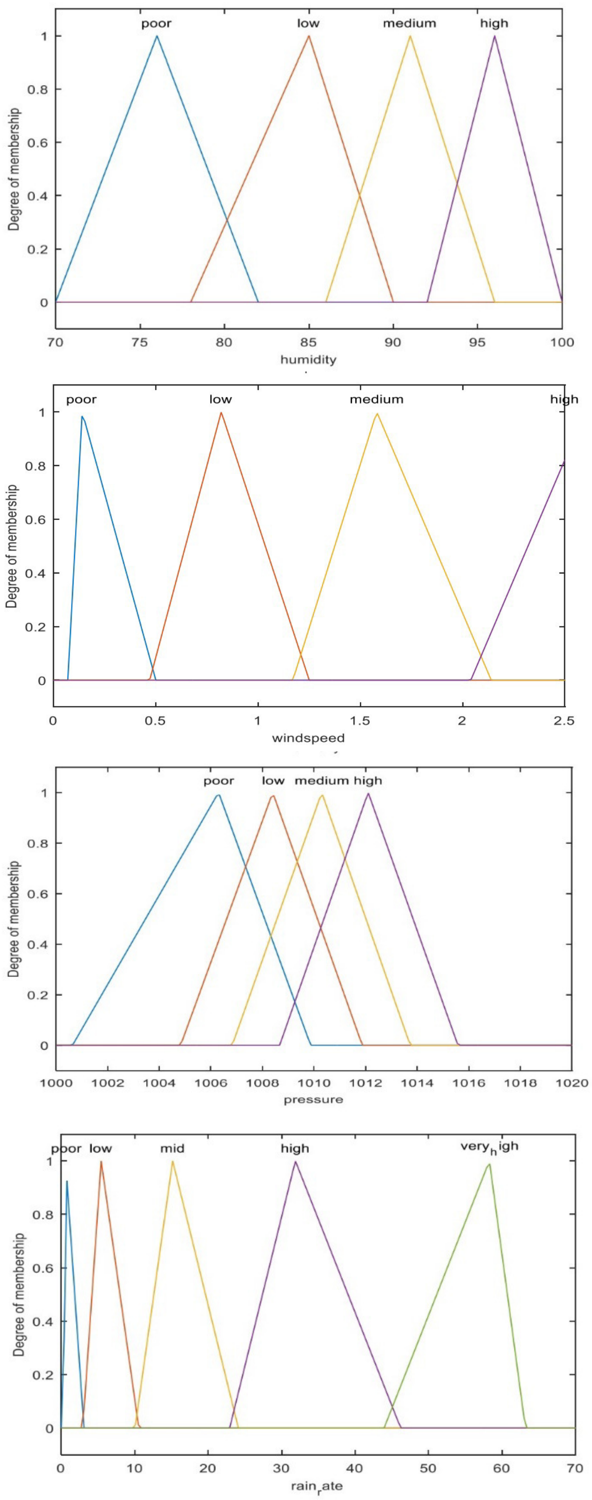


Figure 10. Input and output variables in Fuzzy representation[1], [2]

The most straightforward method for constructing rules from a fuzzy set is to enumerate every conceivable combination of the MF of the input parameter. Listing every potential combination makes the system excessively particular, wastes system memory, and increases the likelihood of total failure. Some regulations might never be applied. A thorough categorization approach is required to identify classes and their attributes to eliminate these issues. The decision learning tree approach is utilized to accomplish this goal. Quinlan suggested the decision tree. It is a projection model that maps input interpretations to the desired output. Introducing the criteria that determine the proper rainfall rate is interactive. Each process introduces a new node (environmental parameter MF). A node creates some sub-nodes until all of the tree's branches have the same class (rainfall rate). The diagram depicts the decision tree process, beginning with the root (Humidity is High).

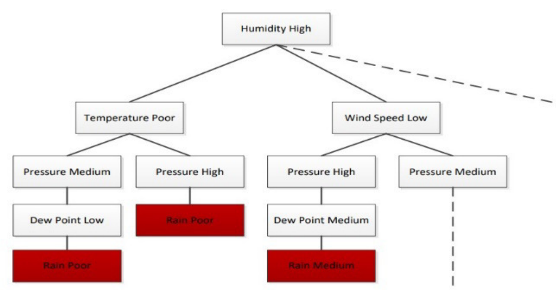


Figure 11. The fuzzy decision tree[1]

According to the empirical analysis of the association between the fuzzy input and fuzzy output mapping and the aggregation process of the output, 37 inference rules are generated. Some of the inference rules, as shown in Table 3

	Humidity	Temperature	Pressure	Wind Speed	Dew Point	Rain Rate Prediction
Rule 1	HIGH	POOR	MEDIUM	POOR	LOW	POOR
Rule	HIGH	POOR	MEDIUM	POOR	MEDIUM	POOR

7						
Rule 11	HIGH	LOW	MEDIUM	LOW	MEDIUM	POOR
Rule 18	MEDIUM	LOW	MEDIUM	LOW	HIGH	POOR
Rule 19	HIGH	POOR	HIGH	NONE	HIGH	LOW
Rule 29	MEDIUM	POOR	HIGH	NONE	LOW	LOW
Rule 30	MEDIUM	LOW	HIGH	NONE	LOW	LOW
Rule 31	HIGH	POOR	HIGH	LOW	MEDIUM	MEDIUM
Rule 36	MEDIUM	LOW	HIGH	MEDIUM	MEDIUM	HIGH
Rule 37	MEDIUM	NONE	MEDIUM	MEDIUM	MEDIUM	VERY HIGH

Table 4. Some of the Inference Rules[1]

Figure 12. MATLAB Inference Rules

5. RESULT FROM DISCUSSION

Temperature, humidity, dew point, wind speed, and pressure are all used to predict rainfall. To create a single record, the values of these parameters were separated by commas. These data were further normalized and fuzzified so the fuzzy logic system could utilize them to build the prediction rules. Table 4 summarises the fuzzy logic system's output. In this table, the firing strength for a good rule, the total records column, and the adequately classified record column indicate how many of the total records were successfully categorized and the prediction error of the classification.

Firing strength (rule threshold value)	Total records (unclassified records)	Correctly classified records	Prediction Error (PE) %
40.0	8204	4021	52.13
50.0	8204	5221	34.17
60.0	8204	5802	29.28
70.0	8204	4217	48.60
80.0	8204	4771	41.85
90.0	8204	3886	52.88

Table 5: Fuzzy logic result summary[2]

From Table 4, It is evident that the firing strength of 60.0 has the minimum prediction error.

Finally, the observed data and predicted data were plotted. The results showed that the FIS model is promising and efficient and can successfully predict the amount of rainfall.

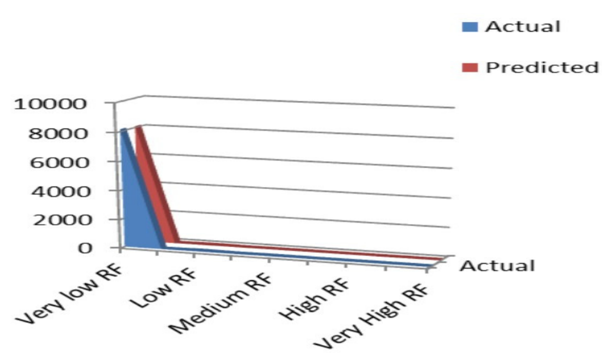


Figure 13: Actual Values versus Predicted Values[4]

ERROR MEASURES[4]

The following error measures were calculated to ascertain the efficiency of the fuzzy rule-based model.

Prediction Error (PE) =

$$\frac{(|y\,predicted\ -\ y\,actual|)}{(y\,actual)}$$

The predictive model is good if the PE is sufficiently small, i.e., close to 0.

Root Mean Square Error (RMSE)

RMSE is an excellent indicator of prediction accuracy. It is frequently used to measure the differences between values predicted by a model and the values observed from the thing being modeled. These individual differences are also called residuals.

$$RMSE\ =\ \sqrt{\frac{\sum_j^N (yj\ -\ y\hat{}j)2}{N}}$$

Where y_{ou} are observed values, $y\hat{}_j$ are predicted values for rainfall, and N is the number of observations.

Mean Absolute Error (MAE)

the smaller the MAE, the better the model fit.

$$MAE\ =\frac{|yj\ -\ y\hat{}j|}{N}$$

Where y_j are observed values, $y_j\ \hat{}$ are predicted values for rainfall, and N is the number of observations.

$$Acccuracy\ =\ 100\ -\ RMSE$$

FUZZY LOGIC				
MSE (mm/h)	RMSE (mm/h)	MAE (mm/h)	PE	ACCURACY (%)
965.6	7.98	16.4	0.00999	92.02

Table 6: Calculated Error Measures[1]

6. APPLICATION OF RAINFALL FORECASTING

Important predictions include weather warnings since they are used to safeguard life and property. Depending on precipitation and temperatures, forecasts are crucial for agriculture and commodities market participants. Utility companies use temperature forecasts to estimate demand over the coming days.[1], [2], [4]

7. CONCLUSION

We used the Fuzzy Inference System (FIS) method to anticipate the rainfall in this study. Table 5 shows that there were just a few variations from the projected rainfall estimate. Prediction error (PE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and prediction accuracy were used to evaluate the Fuzzy Logic model's performance.[1], [4] The prediction model may be utilized for rainfall forecasting because of the data's relatively low PE, RMSE, and MAE values.

8. FUTURE WORK

To improve the Fuzzy Logic approach, Artificial Neural Networks and Genetic Algorithms might be used in conjunction with it. It is also possible to improve the Fuzzy Inference System by employing larger data sets and more rainfall factors.[1], [2], [4]

9. ACKNOWLEDGMENT

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