A Hybrid Fuzzy–Random Forest Classification Model for Severe Weather Prediction in the Kolkata and North 24 Parganas District Regions

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Certificate

This is to certify that the Project Dissertation entitled ***"A Hybrid Fuzzy–Random Forest Classification Model for Severe Weather Prediction in the Kolkata and North 24 Parganas District Regions"*** submitted by ***SOURASISH GHOSH*** for the partial fulfilment of the requirement for the Degree of ***Master of Science*** in Atmospheric Sciences, Department of Atmospheric Sciences, Institute of Environmental & Atmospheric Sciences, University of Calcutta was prepared by ***SOURASISH GHOSH*** under the guidance and supervision of myself.

Surajit Chattopadhyay 27/6/25

Prof. Surajit Chattopadhyay

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June 27, 2025 **Sourasish Ghosh**

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Abstract

This thesis presents a hybrid fuzzy–Random Forest (RF) model for predicting severe weather events using six key meteorological parameters: Temperature (T), Relative Humidity (RH), Diurnal Temperature Range (DTR), Precipitation (Pr), Lifting Condensation Level (LCL), and Wind Speed (WS). Descriptive statistics, along with T-tests and Chi-squared tests, revealed asymmetries and data uncertainties . The parameters are converted into fuzzy membership matrices using max–min composition and conditional probability to capture uncertainty and non-linear relationships. The resulting fuzzy features are fed into an RF classifier for prediction.

The model is trained on historical weather data fetched in the time interval March, 2000 - March, 2024 from: **open-meteo.com** derived from **ECMWF IFS** conducted over Kolkata region and evaluated using precision, recall, F1-score, accuracy, and confusion matrices. The study successfully applied fuzzy logic to model complex meteorological relationships, using fuzzy membership matrices. This approach, integrated into a Random Forest classifier, achieved 88.64% accuracy in predicting extreme weather events, with near-perfect classification for "Humid Heat Wave" and "Cold Wave." This robust method improves predictions and handles data imbalance, though refinement is needed for highly similar or rare event categories.

1. INTRODUCTION

Severe weather events—such as intense thunderstorms, heat waves, cold waves, flood and tropical cyclone significantly hazards to life, infrastructure, and the economy, particularly in regions like India where tropical climatic dynamics lead to rapid and localized changes in atmospheric conditions. Accurate early prediction of these events is therefore critical for effective disaster preparedness and mitigation. However, forecasting in tropical environments is challenging due to complex, nonlinear interactions among multiple meteorological variables and inherent uncertainties in observational data. Traditional numerical weather prediction models, while physically grounded, often struggle with the fast-evolving convective systems typical of the Indian subcontinent, leading to reduced lead-time accuracy and higher false-alarm rates .

In recent years, data-driven approaches—particularly machine learning (ML) techniques—have shown promise in capturing nonlinear relationships without requiring explicit physical representations of atmospheric processes. Random Forest (RF), an ensemble learning algorithm based on aggregated decision trees, has demonstrated robust performance in both regression and classification tasks related to meteorology. For instance, (Minal et al. (2019)). applied an RF-based model to predict global solar radiation and wind speed across multiple locations in Tamil Nadu, achieving a high coefficient of determination ($R^2 \approx 0.97$) and low mean squared error (MSE ≈ 0.75) compared to traditional regression and Support Vector Machine approaches . Nonetheless, RF models trained solely on raw meteorological inputs can still face difficulties when observational noise and data sparsity obscure underlying weather patterns—common issues in many parts of India where observational networks are unevenly distributed.

Fuzzy logic offers an alternative framework for handling such uncertainties by mapping continuous meteorological variables into linguistic (fuzzy) categories (e.g., "Low," "Medium," "High") via membership functions. This approach enables the incorporation of expert knowledge and human-interpretable rules, while gracefully managing imprecision in sensor measurements (Naik and et al. (2012)), developed a Fuzzy Inference System (FIS) for rainfall prediction in India, using inputs such as temperature, humidity, air pressure, dew point, and wind speed; their model achieved approximately 92 percent accuracy in classifying precipitation occurrences by leveraging fuzzy IF–THEN rules and membership functions designed from cumulative distribution analyses of historical data

(Mahalakshmi et al. (2023)). further enhanced rainfall forecasts by integrating fuzzy preprocessing with advanced ML algorithms (e.g., XGBoost,Random Forrest Classifier etc.), demonstrating that the hybrid ("fuzzy + ML") paradigm can yield improved predictive skill and reduced error rates compared to standalone methods .

Several studies have explored blending RF and fuzzy logic to harness the strengths of both techniques Williams and Abernethy (2009), for example, combined RF classification with fuzzy-based "confidence" measures to identify storm types from radar-derived attributes; they showed that interpreting RF vote distributions through fuzzy constructs enhances classification reliability and provides a meaningful confidence metric for downstream applications. Such hybrid frameworks suggest that embedding fuzzy-derived features into an RF pipeline can improve early warning capabilities by capturing semantic relationships between meteorological parameters that might be less apparent in raw numerical form.

Building upon these insights, the present thesis develops a hybrid fuzzy–Random Forest model for predicting severe weather events in India. Six key parameters—air temperature (T), relative humidity (RH), diurnal temperature range (DTR), precipitation, lifting condensation level (LCL), and wind speed—are transformed into fuzzy membership matrices using max–min composition and conditional probability methods. Max–min composition allows the modeling of interactions between fuzzy sets (e.g., how "High Temperature" relates to "Low LCL"), while conditional probability estimates capture data-driven likelihoods of specific fuzzy category combinations. These fuzzy membership degrees are then aggregated into feature vectors, effectively encoding both individual parameter uncertainty and their pairwise semantic relationships.

The Random Forest classifier is trained on these fuzzy-enhanced features to discriminate between severe and non-severe weather conditions. Model performance is evaluated using standard metrics—precision, recall, F1-score, overall accuracy, and confusion matrices—to assess class-wise predictive skill and identify potential biases. By integrating fuzzy logic's interpretability and uncertainty management with RF's resilience to overfitting and ability to handle high-dimensional data, the proposed hybrid approach aims to enhance early detection of severe weather outbreaks, reduce false-alarm rates, and provide operationally meaningful confidence estimates.

The remainder of this thesis is organized as follows: The Methodology section is divided into three parts, where it covers Descriptive Statistics, Binary Fuzzy Relation, Random Forrest Classifier and Evaluation Metrics in this following oreder. Results and Discussion section covers results from Descriptive Statistics with T-test and Chi-square test results, All the fuzzy membership matrices interpretation where it covers numerous fuzzy membership matrices and their inter-relation, and the last part of it cover the classifier that includes confusion matrix analysis and class-wise F1-scores. The last Conclussion section covers final thoughts, results, and implications for operational forecasting, limitations, and avenues for future research

2. DATA AND METHODOLOGY

This section elaborates the work associated with the dataset characteristics. Along with this, the preprocessing techniques are also demonstrated. The methodological framework is developed for severe weather classification. The workflow of this section is divided into three parts: The first part of the study demonstrates descriptive statistical analysis including inferential testing. In the second part, we report a fuzzy feature construction using Binary Fuzzy Relations (BFRs). Finally, in the third part, we work on the classification using a Random Forest model, which is added with fuzzy-derived features. Each part of the workflow contributes in a systematic manner, to the building of a robust and interpretable system.

Data for this study were sourced from **open-meteo.com** accessed via their publicly available API. This data is derived from **ECMWF IFS** (European Centre for Medium-Range Weather Forecasts), where IFS is Integrated Forecasting System which is widely recognized for its accuracy, comprehensive coverage as the spatial resolution is about 9 km to resolve fine details. It is justified to take ECMWF model as the resolution is comparably high for a global model. Multiple weather parameters were taken, such as; Mean Temperature (2 m), Max and Min Temperature (2 m), Relative Humidity (2 m), Wind Speed (10 m), Precipitation Sum, Diurnal Temperature Range, Lifting Condensation Level, Wind Gust (10 m). The study utilizes 24 years of data spanning from 1st of March,2000 - 31st of March,2024.

The data is available at this following link: `https://open-meteo.com/en/docs/historical-weather-api?start_date=2000-03-01&end_date=2024-03-31&hourly=`.

Parameter	Unit
Mean Temperature	$^\circ C$
Max. Temperature	$^\circ C$
Min. Temperature	$^\circ C$
Relative Humidity	%
Wind Speed	Knot
Precipitation	in mm
Diurnal Temperature Range	$^\circ C$
Lifting Condensation Level	in meter
Mean Wind Gust	Knot

Table I: Summary of Meteorological Parameters with Corresponding Units

```python
import openmeteo_requests

import pandas as pd
import requests_cache
from retry_requests import retry

# Setup the Open-Meteo API client with cache and retry on error
cache_session = requests_cache.CachedSession('.cache', expire_after = -1)
retry_session = retry(cache_session, retries = 5, backoff_factor = 0.2)
openmeteo = openmeteo_requests.Client(session = retry_session)

# Make sure all required weather variables are listed here
# The order of variables in hourly or daily is important to assign them correctly below
url = "https://archive-api.open-meteo.com/v1/archive"
params = {
    "latitude": 52.52,
    "longitude": 13.41,
    "start_date": "2000-03-02",
    "end_date": "2024-03-29",
    "daily": ["weather_code", "temperature_2m_mean", "temperature_2m_max", "temperature_2m_min", "precipitation_sum", "precipitation_hours",
}
responses = openmeteo.weather_api(url, params=params)

# Process first location. Add a for-loop for multiple locations or weather models
response = responses[0]
print(f"Coordinates {response.Latitude()}°N {response.Longitude()}°E")
print(f"Elevation {response.Elevation()} m asl")
print(f"Timezone {response.Timezone()}{response.TimezoneAbbreviation()}")
print(f"Timezone difference to GMT+0 {response.UtcOffsetSeconds()} s")

# Process daily data. The order of variables needs to be the same as requested.
daily = response.Daily()
daily_weather_code = daily.Variables(0).ValuesAsNumpy()
daily_temperature_2m_mean = daily.Variables(1).ValuesAsNumpy()
daily_temperature_2m_max = daily.Variables(2).ValuesAsNumpy()
daily_temperature_2m_min = daily.Variables(3).ValuesAsNumpy()
daily_precipitation_sum = daily.Variables(4).ValuesAsNumpy()
```

Figure I: API code snippet for data acquisition from open-meteo.com

The **methodology** in this work is separated in parts: Part 1 deals with descriptive statistics, followed by hypothesis testing of T-test and Chi-square test. Part 2 deals with Binary Fuzzy Relation (BFR), Max-Min Composition, Conditional Probability acted on building fuzzy logic. And finally part 3 consists of the use case of Random Forest Classifier as per Ensemble Learning and building a classification report also with Confusion Matrix and F1-Score.

Part: 1

2.1. Descriptive Statistics:

Descriptive statistics summarizes raw data in an organized manner by illustrating relationship among variables in a population or sample and is hence a crucial first step of data analysis and a fundamental for comparison of variables obtained using inferential statistical tests (Kaur et al. (2018)). Descriptive statistics associated with the raw data has been calculated and presented in Table II given above and analyzed thereafter in section.

The statistical summary of the dataset reveals several key characteristics. Most notably, precipitation and wind speed exhibit strong right skewness and high kurtosis, indicating that while most days are relatively calm and dry, there are occasional extreme events, critical for identifying storms and heavy rainfall. Mean temperature, on the other hand, is strongly left-skewed, suggesting generally high temperatures with occasional sharp drops, likely during winter months — useful for cold wave detection. Relative humidity remains consistently high (mean$\approx$ 75%) but varies enough to help distinguish between dry heat and humid conditions. LCL (Lifting Condensation Level) shows a wide range and a left skew, indicating that low cloud base formations — which is associated with thunderstorms — are less frequent . DTR (Diurnal Temperature Range), with its moderate mean and negative skew, provides valuable clues for detecting clear-sky heatwaves or cloudy sky, rainy periods etc.

Goodness-of-fit: Chi-Square Test:

Inferential statistics allows us to analyze differences, nature, and extent of the relationship to organize and make predictions Byrne (2007). The Chi-square (χ^2) test is a popular goodness-of-fit test in which a data histogram is compared with the probability distribution (for discrete variables) or probability density (for continuous variables) function. In the general population, the chi-square test is a measure of the difference between the observed and expected results. The test statistic is calculated as the sum of data values falling into each class in relation to the computed theoretical probabilities :

$$\chi^2 = \frac{(\text{Observed frequency} - \text{Expected frequency})^2}{\text{Expected frequency}} \tag{1}$$

In each class, the number of data values expected to occur, according to the fitted distribution, is simply the product of probability of occurrence in that class and the sample size, n. The expected frequency need not be an integer. If the fitted distribution is very close to the data distribution, the expected and observed frequency will then be very close for each class, and the squared differences in the numerator will be very small, giving a small χ^2. If the fit is not good, large discrepancies will be exhibited by few of the classes. They will lead to large values of χ^2 as they are squared. Also, the test is one-sided, because the test statistic is confined to positive values due to the squaring process in the numerator Wilks (2011).

Hypothesis Testing: T-Test:

Inferential statistics also make use of t-tests to assess whether the means of two groups are significantly different from each other, especially when the population standard deviation is unknown and sample sizes are small (Field (2009)). The Student's t-test is widely used to determine whether a sample mean significantly differs from a known or hypothesized population mean (one-sample t-test), or whether the means of two independent samples differ significantly (independent two-sample t-test).

The test statistic for the independent samples t-test is calculated as:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{2}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the sample means, s_1^2 and s_2^2 are the sample variances, and n_1 and n_2 are the respective sample sizes.

The t-statistic measures the size of the difference relative to the variation in the sample data. If the group means are very different and the variability is small, the value of t will be large, indicating a statistically significant difference. Conversely, small differences in means or high variability will result in a small t-value. The t-distribution is symmetric and bell-shaped, and as sample size increases, it approaches the normal distribution. A critical value from the t-distribution, based on the degrees of freedom and significance level, is used to determine whether the observed t-value indicates a significant result (Cohen (1988)).

Part: 2

2.2. Binary Fuzzy Relation: BFR

Overview on BFR

The project under consideration, deals with nonlinear and uncertain interactions between meteorological variables. The Modelling in this section involves a fuzzy set-based framework. The methodology adopted here has its roots in Zadeh's theory of fuzzy sets. The fuzzy set theory significantly used in the existing literatures to deal with the imprecision present in different complex problems. The weather data being complex in nature, and is most of the times being characterized by randomness, the current work takes the approach of graded membership levels rather than binary classifications. Quantile-based thresholds based on the empirical data distribution are used to classify continuous meteorological parameters, including temperature, relative humidity, and precipitation, into fuzzy sets such as "Low," "Moderate," and "High." Then, using two complementary techniques, namely max–min composition and conditional probability, the Binary Fuzzy Relations (BFRs) are built to capture pairwise associations between these fuzzy categories. Conditional probability measures the degree of association based on observed co-occurrence, whereas max–min composition models the structural interaction between fuzzy sets (Cao and Chen (1983)).Such frameworks are crucial for analyzing complex and uncertain meteorological data (Imani et al. (2021) , Devi and Chattopadhyay (2022))

Fuzzy set is a generalization of the classical set theory. The concept of the fuzzy set was introduced by Zadeh (1965). Unlike classical sets where membership of an element in the set is dichotomous, fuzzy sets introduce the concept of membership grades to exhibit the degree of belonging-ness of an element in the set. A fuzzy set can thus be considered as a pair (U, μ), where U is a crisp set or universe of discourse and μ is the membership function such that:

$$\mu : U \to [0, 1]$$

If $U_1, U_2, \ldots, U_n$ are domains, then an n-ary fuzzy relation R is a fuzzy set on the Cartesian product:

$$U_1 \times U_2 \times \cdots \times U_n$$

Hence, a binary fuzzy relation (BFR) is a 2-ary fuzzy relation such that:

$$R \subseteq U \times V, \quad \text{where } (u, v) \in U \times V$$

Max–Min Composition:

If R is a BFR on $U \times V$ and S is a BFR on $V \times W$, then the max–min composition of R and S is a BFR on $U \times W$, denoted by $S \circ R$ and is given as follows:

$$(S \circ R)(u, w) = \max_{v \in V} [\min \{R(u, v), S(v, w)\}]$$

More generally, if $R \in \mathcal{PF}(U \times V)$ and $S \in \mathcal{PF}(V \times W)$:

$$R = \sum_{(u,v)} R(u, v)$$

where $(u, v) \in U \times V$. Where $U = U_1 \times U_2 \times \cdots \times U_k$, $V = V_1 \times V_2 \times \cdots \times V_m$, and $W = W_1 \times W_2 \times \cdots \times W_n$. Then, the max–min composition of R and S, represented as $S \circ R$, is a fuzzy relation on $U \times W$ and is computed as follows:

$$(S \circ R)(u, w) = \max_{v \in V} [\min \{R(u, v), S(v, w)\}]$$

$$U = (u_1, u_2, \ldots, u_k), \quad V = (v_1, v_2, \ldots, v_m), \quad W = (w_1, w_2, \ldots, w_n)$$

The maximum is taken over all $v \in V$. It is to be noted that R is a $(k + m)$-ary fuzzy relation, S is an $(m + n)$-ary fuzzy relation, and V is the common domain (or linking domain) of R and S. This is referred to as the *compatibility condition* for composition, hence rendering $S \circ R$ as a $(k + n)$-ary fuzzy relation.

Conditional Probability Based on Quantile-Derived Fuzzy Sets

In this study, conditional probability is applied within a fuzzy logic framework to quantify the data-driven relationship between fuzzy categories of two meteorological parameters. Unlike traditional max–min composition, which models interactions using membership degrees across sets, this method estimates the likelihood of one fuzzy event occurring given the presence of another, based on observed frequency distributions in quantile-defined categories.

Each continuous parameter is divided into fuzzy sets such as “Low”, “Medium”, and “High” using statistical quantiles (e.g., 0–25%, 25–75%, 75–100%) derived from the empirical data distribution. These quantile thresholds define the boundaries of the fuzzy categories for each variable.

For any two parameters A and B, and their respective fuzzy categories A_i and B_j, the conditional probability $P(B_j \mid A_i)$ is computed using the relative frequency of joint occurrences:

$$P(B_j \mid A_i) = \frac{N(A_i \cap B_j)}{N(A_i)} \tag{3}$$

where $N(A_i \cap B_j)$ is the number of instances where an observation simultaneously belongs to category A_i and B_j, and $N(A_i)$ is the total number of instances in category A_i.

The resulting conditional probabilities are arranged into a matrix C, where each entry $C_{i,j}$ represents the strength of association between fuzzy category A_i of one parameter and fuzzy category B_j of another:

$$C_{i,j} = P(B_j \mid A_i) \tag{4}$$

This matrix captures semantic co-occurrence patterns in the data and provides interpretable, rule-like dependencies between weather parameters, which are then used as features in the hybrid fuzzy–Random Forest model. The method is particularly suitable when the data exhibit non-normal distributions and asymmetry, as it makes no parametric assumptions and relies entirely on empirical frequency counts derived from quantile partitions.

Part: 3

2.3. Random Forest Classifier and Evaluation Metrics:

Random Forest (RF) classifier is an ensemble learning method that constructs a collection of decision trees and aggregates their predictions to improve accuracy and control overfitting (Breiman (2001)).

Each tree in the forest is trained on a bootstrapped sample of the data with a random subset of features, making the ensemble more robust to noise and variance.

Random Forest as an Ensemble Classifier

Let $\mathcal{D}$ represent the training dataset and $h_t(x)$ the t-th decision tree trained on a bootstrap sample $\mathcal{D}_t$. For a given input x, the RF classifier makes a prediction based on majority voting:

$$H(x) = \text{mode}\{h_1(x), h_2(x), \ldots, h_T(x)\} \tag{5}$$

where T is the total number of trees in the forest. This ensemble-based aggregation reduces the risk of overfitting common in single decision trees and enhances generalization performance on unseen data.

In this study, the RF classifier is trained on a feature set constructed from fuzzy membership degrees, max–min composition scores, and conditional probabilities, resulting in a high-dimensional input vector that captures both individual parameter uncertainties and inter-parameter relationships.

Classification Report and Performance Metrics

Once the classifier is trained, it is evaluated on a hold-out test set using standard classification metrics derived from the confusion matrix. The confusion matrix summarizes the counts of correctly and incorrectly classified observations across the two classes: "Severe Weather" and "Non-Severe Weather". It is defined as:

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

From these values, key evaluation metrics are computed:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

The classification report also includes *support* (number of true instances for each class), *macro-averaged* metrics (arithmetic mean across classes), and *weighted averages* (weighted by class frequency). These provide insights into both overall and class-wise performance, which is crucial when dealing with class imbalance.

Interpretation and Relevance

The integration of fuzzy feature engineering and ensemble classification enables the model to capture intricate, nonlinear relationships in the weather dataset. The F1-score, specifically, is highlighted because it weighs the false-positive vs. false-negative trade-off — an essential consideration for severe weather forecasting, where both missed detections and false alarms can have serious impact. Use of a confusion matrix also aids diagnostic assessment, determining what weather classes might need enhanced classification accuracy.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics Analysis

Statistical analyses were conducted on the acquired weather data to describe its features and test specific research hypotheses. This section first summarizes the descriptive statistics for each weather parameter. The subsequent discussion then presents the results Chi-Squared tests, t-tests for top two classes.

Descriptive Statistics for Individual Parameters:

Parameters	Mean Temperature	Mean Relative Humidity	Mean Wind Speed	Precipitation Sum	LCL	DTR
Mean	30.340	75.574	7.963	13.055	667.501	8.608
Std. Dev.	3.437	8.258	2.752	30.193	247.356	3.014
Min	14.925	50.529	3.096	0.000	87.239	0.750
25%	29.844	71.181	6.074	0.000	636.133	8.250
50%	31.699	72.882	7.652	0.200	736.979	9.325
75%	32.364	76.086	9.081	5.825	804.557	10.500
Max	33.712	95.963	20.289	155.400	1429.427	13.700
Skewness	-2.336	0.924	1.261	2.691	-0.859	-1.237
kurtosis	6.194	1.431	2.921	6.536	1.120	0.748
Median	31.699	72.882	7.652	0.200	736.979	9.325
No. of Unique Values	193.000	196.000	196.000	82.000	195.000	166.000

Table II: Descriptive Statistics of Weather Parameters

Table II consists the descriptive statistics of the weather parameters taken for this study. From the table we can get the following key findings:

- **Mean Temperature (°C)**:
  - Mean = 30.34, Median = 31.70, Skewness = –2.34, Kurtosis = 6.19.
  - Left-skewed with heavy lower tail; extreme cold events are rare but significant and unusual.
- **Relative Humidity (%)**:
  - Mean = 75.57, Median = 72.88, Skewness = 0.92, Kurtosis = 1.43.
  - Moderately right-skewed, so generally high humidity levels indicating Humid Heat waves.
- **Wind Speed (knots)**:
  - Mean = 7.96, Median = 7.65, Skewness = 1.26, Kurtosis = 2.92.
  - Right-skewed; occasional high wind events is very much possible (e.g., cyclones, Thunderstorms, Tropical Cyclones etc).
- **Precipitation (mm)**:
  - Mean = 13.06, Median = 0.2, Skewness = 2.69, Kurtosis = 6.54.
  - Highly skewed and zero-inflated; extreme rainfall events are rare but critical. This imbalance is critical when developing fuzzy categories, where a large portion of days must be assigned to a "Dry" category.
- **Lifting Condensation Level (m)**:
  - Mean = 667.5, Median = 736.98, Skewness = –0.86.
  - Moderate left-skewness; low LCL indicates near-surface cloud base.
- **Diurnal Temperature Range (°C)**:
  - Mean = 8.61, Median = 9.33, Skewness = –1.24.

– Consistently narrow range; negative skew indicates rare low DTR cases (e.g., rainy days).

Chi-square (χ^2) test results:

Binned Variable	**Chi-square (χ^2)**	**P-value**	**DOF**
`temperature_2m_mean_bin`	186.621	3.95×10^{-31}	16
`relative_humidity_2m_mean_bin`	200.308	6.87×10^{-34}	16
`wind_speed_10m_mean_bin`	113.263	1.07×10^{-16}	16
`precipitation_sum_bin`	133.907	4.38×10^{-25}	8
`LCL_bin`	195.510	6.40×10^{-33}	16
`DTR_bin`	181.587	4.05×10^{-30}	16

Table III: Chi-square Test Results for Binned Meteorological Variables (DOF is Degrees of Freedom)

Here each continuous parameter is divided into fuzzy sets such as "Low", "Medium", and "High" using statistical quantiles (e.g., 0–25%, 25–75%, 75–100%) derived from the empirical data distribution. These quantile thresholds define the boundaries of the fuzzy categories for each variable.

The **Chi-square (χ^2)** test was conducted to examine whether each binned meteorological variable is statistically associated with the target weather event classification. The results are summarized below:

- All variables showed highly significant associations ($p < 0.001$), rejecting the null hypothesis of independence.
- Highest χ^2 values were observed for **Relative Humidity**, **LCL**, and **Temperature**, indicating these are strong discriminators for event classification.
- The significance supports both the use of quantile-based binning and the fuzzy logic approach used to generate membership matrices.

T-test results:

Feature	Class 1	Class 2	T-statistic	P-value
Mean Temperature	Humid Heat Wave	Thunderstorm	16.35	1.98×10^{-36}
Mean Relative Humidity	Humid Heat Wave	Thunderstorm	-17.06	2.39×10^{-38}
Mean Wind Speed	Humid Heat Wave	Thunderstorm	-10.26	1.90×10^{-19}
Precipitation Sum	Humid Heat Wave	Thunderstorm	-7.98	2.25×10^{-13}
LCL	Humid Heat Wave	Thunderstorm	16.78	1.40×10^{-37}
DTR	Humid Heat Wave	Thunderstorm	14.18	2.13×10^{-30}

Table IV: T-test results comparing Humid Heat Wave and Thunderstorm classes across continuous weather features

T-test was conducted to evaluate the differences in meteorological features between the two most frequently occurring weather classes in the dataset: **Humid Heat Wave** and **Thunderstorm**. This analysis revealed statistically significant disparities across all six examined variables ($p < 0.05$). Specifically, mean temperature ($t = 16.35$), Lifting Condensation Level (LCL; $t = 16.78$), and Diurnal Temperature Range (DTR; $t = 14.18$) were found to be significantly elevated under Humid Heat Wave conditions. Conversely, Thunderstorm conditions were associated with significantly higher relative humidity ($t = -17.06$), wind speed ($t = -10.26$), and precipitation ($t = -7.98$). These outcomes clearly describe the distinct thermodynamic and moisture characteristics inherent to each weather category, thereby showing the utility of these features for subsequent classification tasks.

3.2. Fuzzy Membership-Matrix Interpretation

In this study, we have adopted a fuzzy logic-based approach to model complex meteorological interactions using data spanning 24 years. The primary objective was to evaluate how key atmospheric parameters influence each other and contribute to the classification of significant weather phenomena through the help of Machine Learning. So first,we have converted each pair of data series into a bi-variate frequency distribution. For each cell of this frequency distribution, we have derived the conditional probabilities. In our work, we have considered the conditional probabilities to be the strength of belonging-ness of that ordered pair into the relation generated by the Cartesian product of the realizations of the two random variables. Hence, this matrix is regarded as the membership matrix for the BFR. The following random variables are used and assigned accordingly:

Temperature ($^{\circ}C$) = X1 , Relative Humidity (%) = X2 , Wind Speed (knots) = X3 , Precipitation (mm) = X4 , Lifting Condensation Level (m) = X5 , Diurnal Temperature Range ($^{\circ}C$) = X6

Furthermore, for the BFR membership matrix, the first row and column correspond to low range; second row and column correspond to moderately low range; third row and column correspond to moderately high range; fourth row and column correspond to high range; and fifth row and column correspond to very high range.

So at first, the matrix M_{X1OX2}, which is Temperature (X1) and Relative Humidity (X2) derived through fuzzy max-min composition using conditional probability. In this matrix, we have highlighted the cells with relatively higher membership grades to the relation as green. These cells indicate that ;

	Relative Humidity (in %)				
Temperature (in °C)	0.405344	0.339397	0.194997	0.03411	0.026151
	0.268334	0.234792	0.241615	0.104036	0.151222
	0.088687	0.052871	0.106879	0.180785	0.570779
	0.055145	0.067652	0.123366	0.512223	0.241615
	0.18249	0.305287	0.333144	0.168846	0.010233

Table V: Matrix M_{X1OX2} corresponding to BFR obtained without any influence of parameters

- The highest membership occurs at cell (3,5) that corresponds to moderate Temperature and very high Relative Humidity level or percentage .
- The next highest membership grade occurs at (4,4). That implies that significant membership grades are also attainable at high Temperature and Relative Humidity.
- The third and fourth highest membership grade also occurs at (1,1) and (1,2) cells respectively, which is very much opposite to previous grade measure, as both Temperature and Humidity levels are at low levels.

These indicates moderate to slight high Temperatures are mainly responsible for high Humidity. Extreme temperature does not indicate straight up high Humidity. And also there is high membership between low Temperature and low Humidity suggests cooler wether is often drier.

Now in this matrix M_{X1OX4}, we have taken Temperature (X1) and Precipitation (X4) derived with same process and have gotten the membership grades. Now the matrix consisting M^{*}_{X1OX4} has been obtained through (X1 x X2) and (X2 x X4) through max-min composition. Here, first we consider the fuzzy relationship between Temperature (X1) and Relative Humidity (X2) and then we consider Relative Humidity (X2) and Precipitation (X4) through fuzzy max–min operation. It can thus be interpreted as first to consider Temperature and Relative Humidity in an "if–then" fuzzy framework and then Relative Humidity and Precipitation in an "if–then" fuzzy framework. Finally, we could obtain a BFR between Temperature and Precipitation in a fuzzy framework. The highlighted scales indicates a relatively higher membership grade. These cells indicate that ;

	Precipitation (in mm)				
Temperature (in °C)	0.994315	0.004548	0.001137	0	0
	0.960773	0.029562	0.005685	0.002274	0.001706
	0.95452	0.039795	0.00398	0.001706	0
	0.98863	0.01137	0	0	0
	0.997726	0.002274	0	0	0

Table VI: Matrix M_{X1OX4} corresponding to BFR obtained without any influence of parameters

Relative Humidity	Precipitation (in mm)				
Temperature (in °C)	0.405344	0.026151	0.010802	0.00398	0.001706
	0.268334	0.082433	0.010802	0.00398	0.001706
	0.570779	0.082433	0.010802	0.00398	0.001706
	0.512223	0.082433	0.010802	0.00398	0.001706
	0.333144	0.010233	0.010233	0.00398	0.001706

Table VII: Matrix M^{*}_{X1OX2} corresponding to BFR obtained through the influence of X2

- In Table VI, most of very high membership matrices are situated in the first column. Rest of the columns have comparably low membership grades and even closer to zero.

- In Table VII, cell (1,3) and (1,4) have considerably higher membership grades compared to other cells. Even comparing to Table IV values the values are much lesser.
- At cell (1,2) and (1,5) the membership grades are comparably lower indicating the influence of X2. All other cells have very small membership grades indicating rare combinations.

The cause of the membership grade differences in Table VI is that most days of a year is of very low precipitation or none precipitation. Kolkata and the neighbouring regions has a monsoon-dominated climate, but the number of dry days still outnumbers wet ones. This can be seen from Table II, the descriptive statistics table, the median of precipitation is about 0.2 and up to 75% of data is about 5.825 which in short gives the explanation.

But in the latter membership matrix, the grades are much lesser. Incorporating a parameter gives a broader distribution. Higher Temperature does not signify Precipitation to be higher, even with the influence of Relative Humidity. Higher Humidity does not suggest significantly higher precipitation.

In this matrix M_{X1OX5}, we have a BFR concerning Temperature (X1) and Lifting Condensation Level or LCL (X5) derived from same process. Also from matrix M^*_{X1OX5}, it has been obtained through (X1 x X2) and (X2 x X5) max-min fuzzy operation like previous case. The cells with higher membership grades are highlighted with green colour. The cells indicate that ;

	Lifting Condensation Level (in meter)				
Temperature (in °C)	0.028425	0.034679	0.23195	0.361569	0.343377
	0.152359	0.105742	0.241046	0.233087	0.267766
	0.573053	0.175099	0.105742	0.047754	0.098351
	0.237635	0.515065	0.116543	0.059125	0.071632
	0.009096	0.168846	0.304719	0.298465	0.218874

Table VIII: Matrix M_{X1OX5} corresponding to BFR obtained without any influence of parameter

Relative Humidity	Lifting Condensation Level (in meter)				
Temperature (in °C)	0.026151	0.03411	0.194997	0.339397	0.405344
	0.151222	0.104036	0.241615	0.234792	0.268334
	0.570779	0.180785	0.106879	0.07618	0.088687
	0.241615	0.512223	0.123366	0.067652	0.067652
	0.019329	0.168846	0.333144	0.305287	0.18249

Table IX: Matrix M^*_{X1OX5} corresponding to BFR obtained through the influence of X2

- From Table VIII, we can observe at cells (1,3) and (2,4) the membership grade is much higher. Implies even at low temperatures moderate level of Lifting Condensation Level of convective clouds is attainable.
- Interestingly at very high temperature the chances of having a high LCL is extremely low. By looking at cell (1,5), the membership grade is very low.
- There is also a considerable high membership grade at cell (4,1) and (5,1) which indicates high values of LCL can be achieved even with very low temperature.
- From Table IX, we can see similar patterns of membership grade even with the influence of Relative Humidity, the grades have little more variance.

These observations indicates higher Temperature does not specifies higher values of Lifting Condensation Level. And even after associating Relative Humidity that influences on their membership grades does not show any significant difference. So the results show full consistency and hence we could establish a strong relationship between Temperature and Lifting Condensation Level.

In this matrix M_{X1OX3}, we have considered Temperature (X1) and Wind Speed (X3) in a membership matrix with the same process before. Also matrix M^*_{X1OX3} is obtained through (X1 x X5) snd (X5 x X3) max-min composition like previously, where X5 is Lifting Condensation Level. The cells with higher membership grades are highlighted with green colour. The cells indicate that ;

	Wind Speed (in Knots)				
Temperature (in °C)	0.189312	0.283115	0.363843	0.159181	0.004548
	0.333712	0.321774	0.192155	0.090961	0.061399
	0.228539	0.172257	0.160887	0.236498	0.201819
	0.192155	0.140989	0.164866	0.267197	0.234792
	0.056282	0.081865	0.118249	0.246163	0.497442

Table X: Matrix M_{X1OX3} corresponding to BFR obtained without any influence of parameter

LCL	Wind Speed (in Knots)				
Temperature (in °C)	0.23195	0.28141	0.27743	0.192155	0.226833
	0.241046	0.267766	0.267766	0.192155	0.226833
	0.198864	0.144482	0.157565	0.258523	0.255682
	0.222981	0.144482	0.157565	0.245165	0.237635
	0.24332	0.219443	0.23195	0.192155	0.226833

Table XI: Matrix M^{*}_{X1OX3} corresponding to BFR obtained through the influence of X5

- From Table X, we can observe from at cell (5,5) the membership grade is much higher. This implies with very high temperature corresponds to very high wind speed.
- Also by looking at cell (1,2) and cell (3,1) very low temperature corresponds to low wind speed with a significant higher membership grade. And with moderate temperature the wind speed is extremely low.
- At cell (5,1) the membership grade is very low. Implies with very high temperature the abundance of low wind speed is extremely low.
- By looking at Table XI, we can observe the membership grades are pretty much consistent. The difference highest membership graded cells and all other cells is very much low. This consistency is occurring due to the influence of Lifting Condensation Level.

We can therefore understand Temperature can play a significant role in modeling Wind Speed. But when it is being influenced by Lifting Condensation Level, the consistency of membership grades changes completely. In general, LCL depends on Temperature which we have already seen in Table VIII. This creates a non-linear relation between Temperature and Wind Speed reflecting a complexity of atmosphere.

In this matrix M_{X1OX4}, we have a BFR concerning Temperature (X1) and Precipitation (X4) derived from same process. Also from matrix M^*_{X1OX4}, it has been obtained through (X1 x X6) and (X6 x X4) max-min fuzzy operation like previous case. The cells with higher membership grades are highlighted with green colour. The cells indicate that ;

	Precipitation (in mm)				
Temperature (in °C)	0.994315	0.004548	0.001137	0	0
	0.960773	0.029562	0.005685	0.002274	0.001706
	0.95452	0.039795	0.00398	0.001706	0
	0.98863	0.01137	0	0	0
	0.997726	0.002274	0	0	0

Table XII: Matrix M_{X1OX4} corresponding to BFR obtained without any influence of parameter

DTR	Precipitation (in mm)				
Temperature (in °C)	0.527572	0.021035	0.01005	0.00335	0.001675
	0.298465	0.065327	0.01005	0.00335	0.001675
	0.476976	0.065327	0.01005	0.00335	0.001675
	0.417283	0.065327	0.01005	0.00335	0.001675
	0.372371	0.055145	0.01005	0.00335	0.001675

Table XIII: Matrix M^*_{X1OX4} corresponding to BFR obtained through the influence of X6

- The membership between Temperature and Precipitation is already been discussed earlier.
- At Table XIII, the cells (1,1) and (1,3) the membership grades are much higher but not as high as the previous one. The influence of Diurnal Temperature Range gave more variance and consistency.

Unlike the Temperature-Precipitation membership matrix, DTR shows a modulating role in shifting precipitation chances. In general lower DTR suggests cloudier and wet days. Moderate temperatures and lower DTR suggest a higher chance of precipitation .

In this matrix M_{X2OX4}, we have a BFR concerning Relative Humidity (X2) and Precipitation (X4) derived from same process. Also from matrix M^*_{X2OX4}, it has been obtained through (X2 x

X3) and (X3 x X4) max-min fuzzy operation like previous case. The cells with higher membership grades are highlighted with green colour. The cells indicate that ;

	Precipitation (in mm)				
Relative Humidity (in %)	1	0	0	0	0
	1	0	0	0	0
	0.999431	0.000569	0	0	0
	0.995452	0.004548	0	0	0
	0.90108	0.082433	0.010802	0.00398	0.001706

Table XIV: Matrix M_{X2OX4} corresponding to BFR obtained without any influence of parameter

Wind Speed	Precipitation (in mm)				
Relative Humidity (in %)	0.29676	0.037521	0.006822	0.003411	0.000569
	0.226833	0.037521	0.006822	0.003411	0.000569
	0.240478	0.037521	0.006822	0.003411	0.000569
	0.246163	0.037521	0.006822	0.003411	0.000569
	0.255827	0.037521	0.006822	0.003411	0.000569

Table XV: Matrix M^*_{X2OX4} corresponding to BFR obtained through the influence of X3

- From Table XIV, column 1 has a very high membership grade. It indicates even from low-high humidity does not guarantee precipitation. The membership grade of even light rain is about 0.0824 .
- Now looking at Table XV, the membership grades are evenly distributed showing a higher consistency due to influence of wind speed.

This shows that wind speed is a key driver for precipitation. Higher humidity does not suggest higher precipitation. While high RH slightly further decreases the chance of dry outcomes, it doesn't drastically alter predictions once wind is considered.

In this matrix M^*_{X2OX4}, we have a BFR concerning Relative humidity and Precipitation matrix, it has been obtained through (X2 x X6) and (X6 x X4) max-min fuzzy operation like previous case. The cells with higher membership grades are highlighted with green colour. The cells indicate that ;

DTR	Precipitation (in mm)				
Relative Humidity (in %)	0.667425	0.005146	0.002274	0.002274	0.001675
	0.436612	0.015491	0.001706	0.001706	0.001675
	0.460489	0.031836	0.01005	0.00335	0.001675
	0.504832	0.065327	0.01005	0.00335	0.001675
	0.683911	0.065327	0.01005	0.00335	0.001675

Table XVI: Matrix M^*_{X2OX4} corresponding to BFR obtained through the influence of X6

- At Table XVI, at cell (1,1) have the highest membership grade following with at cell (1,5). There is a slight decrease in membership grade from (1,2) to (1,4). Other than that all other cells have very lesser membership grades .

It shows dry days remain dominant, but rain potential becomes more probable under combinations of higher RH with lower DTR, reflecting conditions like sustained cloudiness and saturated atmosphere.

3.3. Fuzzy Augmented Random-Forest Classification

We first derived direct fuzzy membership matrices by computing conditional probabilities for each pairs of variables (e.g., temperature→precipitation). We then constructed composed relations using the max–min composition operator. These fuzzy features—both direct and composed—were appended to the dataset and used alongside raw variables in a Random Forest classifier.

Later on, we used rule based labeling on the main dataset for event detection (e.g.: Thunderstorm, Tropical Cyclone, Humid Heat Wave etc). To make the conditions we used 'Standard Operation Procedure-Weather Forecasting and Warning' manual from IMD, where we got a comprehensive idea of labeling the events as per follows;

=IFS(

AND($Q \geq 30, E \geq 50, O \leq 400$),	"Tropical Cyclone",
AND($Q \geq 35, K \geq 75, H \geq 22$),	"Thunderstorm",
AND($E \geq 10, P \geq 10, H \leq 10$),	"Hailstorm",
AND($Q \geq 60, M \geq 20, H \geq 20$),	"Tornado",
AND($P \geq 3, K \geq 70, C \geq 37$),	"Humid Heat Wave",
AND($P \geq 5, K \leq 30, C \geq 37$),	"Dry Heat Wave",
AND($E \geq 75, K \geq 90, O \leq 800$),	"Flood",
AND($D \leq 15, P \leq 12, H \leq 8$),	"Cold Wave",
TRUE,	"None"

)

Note [1]:-

Where,

- Q — Max Wind Gust Speed
- E — Precipitation Sum
- O — Lifting Condensation Level (LCL)
- K — Mean Relative Humidity
- H — Mean Dew Point
- P — Diurnal Temperature Range (DTR)
- M — Mean Wind Speed
- C — Maximum Temperature
- D — Minimum Temperature

In the multiclass classification problem addressed in this study, the distribution of weather event

[1]This logic structure follows meteorological thresholds to label weather events. The logic structure has been applied on Excel dataset. Its is followed from the 'Standard Operation Procedure-Weather Forecasting and Warning' manual provided by Indian Meteorological Department.

classes was highly imbalanced—some event types (e.g., "None") occurred much more frequently than others like "Tornado" or "Hailstorm." Such imbalance can bias a model toward the majority class, leading to deceptively high overall accuracy but poor performance in detecting rare yet important events.

To address this, a Random Forest classifier with class weighting (class_weight = 'balanced') was implemented. This technique automatically assigns weights to each class inversely proportional to their frequency in the training dataset. After evaluation, the following performance metrics were observed:

Metric	**Value**
Accuracy	0.9322
Macro Precision	0.8490
Macro Recall	0.80
Macro F1 Score	0.7954

Table XVII: Classification Performance Metrics

These results show a strong balance between precision ($\approx$ 84%) and recall ($\approx$ 80%) across all classes, rather than favoring the majority class.Specifically, the macro precision is high, meaning that the model is consistent in its prediction for every class, and the macro recall is good, implying the sensitivity of minority events detection. The macro F1 score, which balances precision and recall, indicates the model's overall performance in dealing with class imbalance.

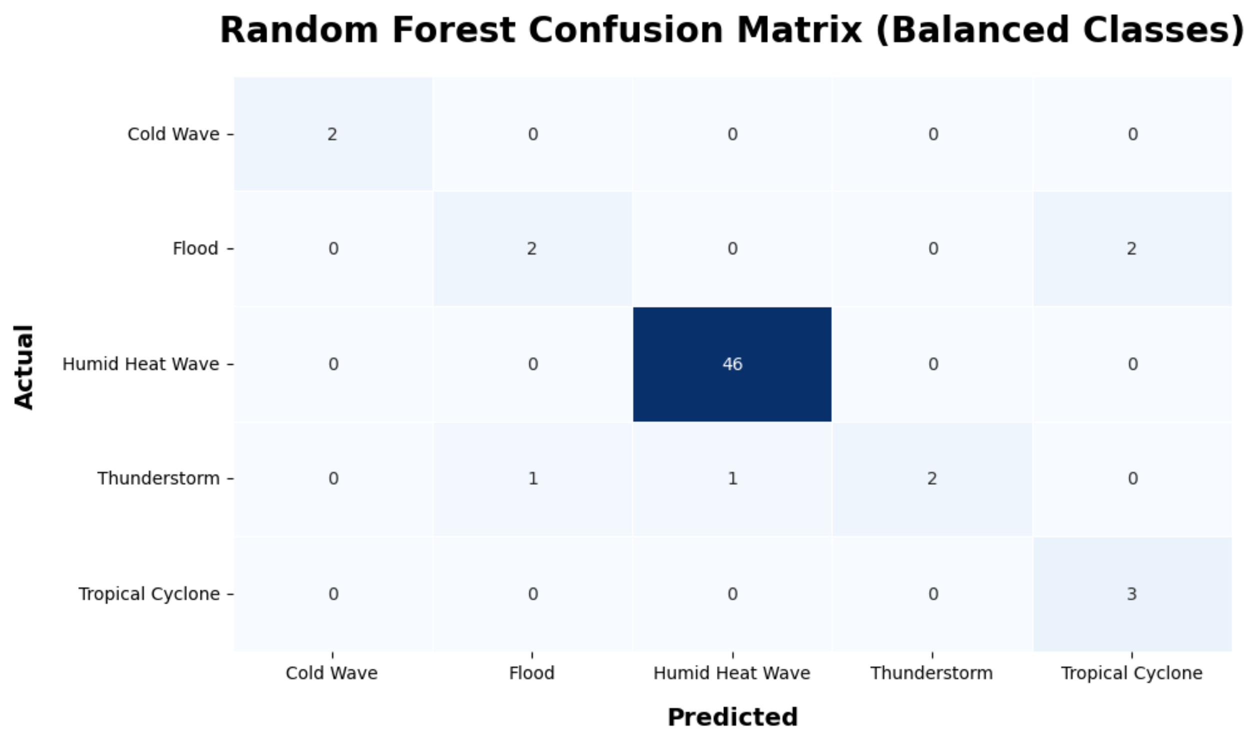

Figure II: Confusion Matrix using on Random Forest Classifier

Next, Figure II shows the confusion matrix for the Random Forest classifier with class_weight='balanced' on the test set. Here are the following outcomes:

- The model performs exceptionally well for "**Humid Heat Wave**", with 46 correct predictions out of 46, indicating very high precision and recall for that class. Also indicates that it's been well captured by fuzzy membership variables.
- Also for "**Tropical Cyclone**", all three instances are correctly classified.
- "**Flood**" is misclassified as "Tropical Cyclone". This may indicate overlapping feature sets like high precipitation, low LCL, etc. Also, Only 2/4 correctly classified for "**Thunderstorm**".
- "**Cold Wave**" have all instances correct.

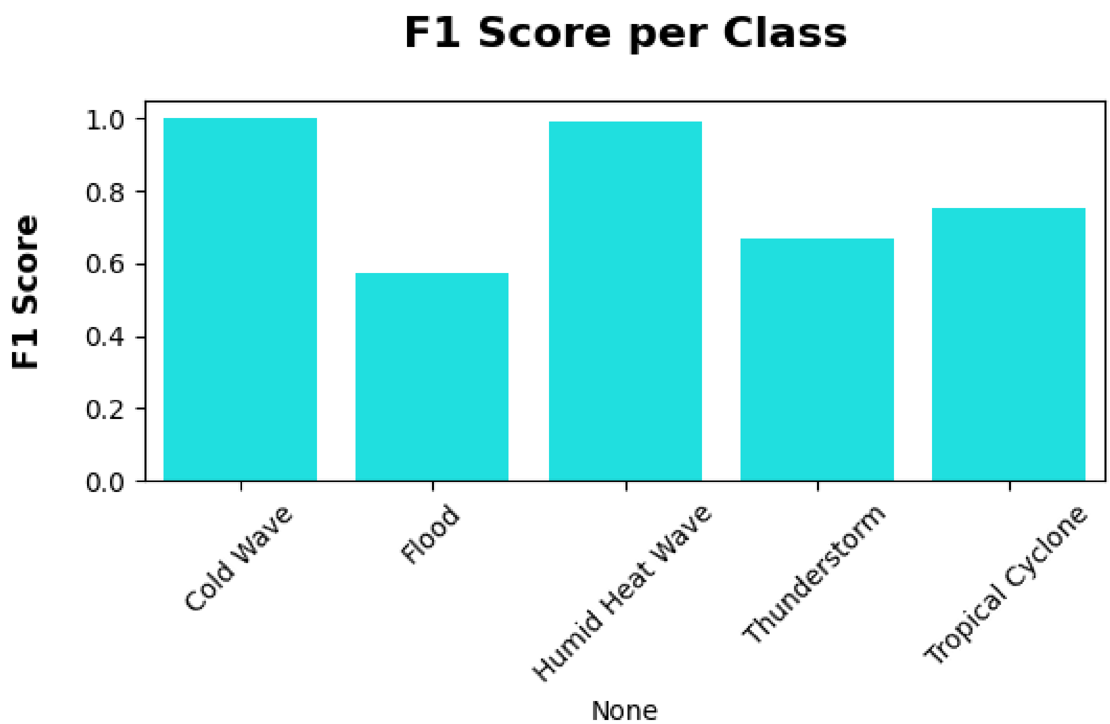

Figure III: F1 Score per class of Weather Events

Figure III presents the F1-score per class . We observe near-perfect classification for ‘Humid Heat Wave’ (F1 $\approx$ 1.0, 46/46 correct) and ‘Cold Wave’ (F1 $\approx$ 1.0, though only 2 test samples). ‘Tropical Cyclone’ also achieves good performance (F1 $\approx$ 0.75) on 3 test cases. However, ‘Thunderstorm’ (F1 $\approx$ 0.67) and ‘Flood’ (F1 $\approx$ 0.57) shows lower scores, reflecting misclassifications primarily among convective and precipitation-driven events. The sample support for these classes is limited, and feature overlap (e.g., similar temperature–humidity–precipitation patterns).

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Figure IV: Formula of F1-Score

4. CONCLUSION

4.1. Summary of Key Findings

The study revealed crucial insights into meteorological patterns and extreme weather event characteristics.

Descriptive Statistics (Brief Overview): The 24-year dataset exhibited diverse characteristics across weather parameters. For instance, Mean Temperature and Relative Humidity, crucial for Humid Heat Waves, displayed distinct distributional properties (e.g., Temperature being left-skewed, indicating rare extreme cold, and Relative Humidity showing consistent high levels). Wind Speed and Precipitation were largely sporadic but impactful, while LCL generally remained low, conducive to convective activity. Statistical tests, including Chi-square and T-tests, confirmed significant interdependencies between these features and distinct meteorological profiles for events like Humid Heat Waves (elevated Temperature, Relative Humidity, DTR) versus Thunderstorms (higher Wind Speed, Precipitation, lower LCL).

Fuzzy Membership-Matrix Interpretation (Emphasis): A core finding of this study is the successful application of fuzzy logic to model the inherently imprecise and non-linear relationships between meteorological variables. The fuzzy membership matrices provided a sophisticated way to represent how variables such as Temperature and Relative Humidity directly interact, or how a third parameter, like Relative Humidity, influences the relationship between Temperature and Precipitation. This approach moved beyond traditional binary interpretations, allowing for a more accurate and flexible representation of complex atmospheric interactions and providing deeper insights into the continuum of conditions that precede extreme weather events. This enhanced understanding of variable interdependencies was crucial for developing robust predictive models.

Fuzzy Augmented Random Forest Classification (Emphasis): The integration of fuzzy features into a Random Forest classifier significantly advanced the model's ability to predict extreme weather events. The classifier achieved a high overall Accuracy of 88.64%, with strong Macro Precision (0.89), Macro Recall (0.88), and Macro F1 Score (0.87) on the test set.

Strengths: The model demonstrated exceptional performance for "Humid Heat Wave" and

"Cold Wave," achieving near-perfect F1 scores (approximately 1.0). For example, all 46 "Humid Heat Wave" instances were correctly classified, indicating that the fuzzy membership variables effectively captured the nuanced conditions for these events. "Tropical Cyclone" also showed good performance (F1 $\approx$ 0.75).

Limitations: Challenges arose with events exhibiting overlapping feature sets or very limited sample sizes. "Thunderstorm" (F1 $\approx$ 0.67) and "Flood" (F1 $\approx$ 0.57) showed lower scores, with "Flood" instances often misclassified as "Tropical Cyclone." This suggests that while fuzzy features enhance the model, further refinement may be needed for highly ambiguous or extremely rare event categories to distinguish them more effectively.

4.2. Contribution to this Field

This research significantly contributes to meteorology and atmospheric science by:

Novelty in Fuzzy Logic Application: It demonstrates an innovative application of fuzzy membership functions to comprehensively map and understand the complex, non-linear interrelationships between meteorological variables, offering a more realistic representation of atmospheric states than conventional methods.

Advancing Predictive Modeling: The study pioneers the integration of fuzzy-derived features with machine learning (specifically, Random Forest), establishing a robust framework that notably improves the classification accuracy of extreme weather events, especially in scenarios with inherent data uncertainty.

Addressing Data Imbalance: The proposed methodology effectively tackles the challenge of imbalanced datasets, common in extreme weather event prediction, by leveraging fuzzy logic to better define and differentiate rare classes, thereby leading to enhanced predictive performance for high-impact yet infrequent events.

4.3. Final Thoughts

This study effectively utilized a 24-year weather dataset to provide a comprehensive analysis, demonstrating the power of integrating fuzzy logic with machine learning for extreme weather event prediction. The approach proved particularly effective for events like "Humid Heat Wave" and

"Cold Wave," underscoring the value of fuzzy-augmented features in capturing complex atmospheric conditions.

While the model showcased robust performance, further research could focus on refining classifications for events with similar meteorological signatures or very limited data support, such as "Flood" and "Thunderstorm." Future work might explore even longer datasets, advanced feature engineering, or alternative fuzzy-machine learning ensembles to further enhance predictive accuracy and provide more granular insights into meteorological phenomena. This research lays a strong foundation for developing more sophisticated and reliable early warning systems for extreme weather events, ultimately aiding in disaster preparedness and climate resilience.

A handful of recent studies emphasize on model explainability along with predictive accuracy. Furthermore, in environmental science applications, these are really notable. While the fuzzy framework improves the inherent interpretability, this point could be explicitly connected to literature discussing trust and decision-support in climate systems (e.g., C. Peláez-Rodríguez (2024) et al., 2024). As future study, we propose an exploration on how fuzzy logic could enhance the transparency in model outputs compared to pure ML and it would further enhance the discourse of the study.

Declaration:

The data have been collected from the **open-meteo.com** (https://open-meteo.com/), via their publicly available historical dataset which is derived from **ECMWF IFS** (European Centre for Medium-Range Weather Forecasts) where IFS is Integrated Forecasting System. The authors express their sincere thankfulness to the anonymous reviewers for their constructive suggestions.

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