Interpretable Rainfall Forecasting Using SHAP-Enhanced Machine Learning: A Case Study on U.S. Urban Climate Data (2024–2025)

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Abstract

Correct rainfall prediction is fundamental for developing resilient climates, guaranteeing sustainable farms and planned water distribution networks, and reducing possible disasters. Many meteorological elements affect rainfall patterns because rainfall shows nonlinear behavior and dependence across different timescales and diverse spatial areas. Multiple problematic features defeat conventional forecasting techniques because they produce insufficient accurate predictions of short-duration precipitation patterns. Because of rising climate variability, we require predictive frameworks built with data with strong performance abilities and human-understandable features. In this paper, we establish a machine learning that predicts daily rainfall in advance with a refined dataset consisting of detailed weather measurements spanning 20 United States metropolises from 2024 to 2025. The selected dataset contains six atmospheric factors: temperature, humidity, wind speed, and cloud cover with pressure and precipitation and a binary outcome to show rainfall prediction for the following day. Random Forest and Support Vector Machine (RBF) KNearest Neighbors (KNN), Logistic Regression, Naive Bayes, and Linear SVM formed the set of machine learning models that underwent training and evaluation. The SHAP method was integrated to improve prediction interpretation and trust through Shapley additive explanations value measures. SHAP values provided quantitative measurement and graphical visualization to explain the role of each input variable in making individual prediction outcomes. SHAP analysis of the model showcased precipitation and humidity as their most crucial features because they match the principles of meteorological theory and demonstrate the rational decision-making process of the model. The Random Forest approach scored the highest performance from all models, reaching perfect measurements for Precision = 100, Recall = 100 and F1-score = 100. The RBF SVM model alongside KNN showed strong performance since they delivered F1 scores of 0.97 and 0.94. The evaluation revealed that Logistic Regression, Linear SVM and Naive Bayes achieved satisfactory results, providing F1-score ratings between 0.76 and 0.77. The SHAP-based diagnostic results showed that Random Forest yielded exceptional classification results while simultaneously showing consistent weighting patterns between features across diverse locations. The integration of the Random Forest model with SHAP interpretation creates an effective solution for rainfall forecasting despite its high prediction capabilities. The model achieves complete prediction accuracy with precise explanation capabilities, generating trust for using it in actual deployment scenarios. According to the results, weather-sensitive sectors like agriculture, urban planning, and disaster response can leverage these transparent machine learning systems into their decision-making support pipelines. The approach described has the potential to become a model structure for conducting future predictive analyses in meteorology and environmental science.

Keywords: Rainfall prediction; SHAP; Machine Learning; Random Forest

1 Introduction

Precipitation is a vital hydrological process driver on Earth. Its precise weather forecasts remain central to agricultural production and environmental protection, hydrological systems structural development, emergency

DOI: https://doi.org/10.54216/JAIM.090203

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

response, and national policy creation. The primary water source for freshwater rainfall rules all hydrological processes that control natural ecosystem health and sustainable community development [1]. The organization depends on rainfall data for program scheduling and execution in farm planting and harvesting, reservoir management, drainage control, and disaster alert system development. The agricultural sector, especially in areas that rely mainly on rain-fed farming, benefits from precise rainfall prediction since it enhances food output and lowers crop loss [2]. Forecasting rainfall and predicting rainfall intensity and duration support landowners' decisions about irrigation planning and when to apply fertilizers and implement pest management and harvest protocols. Areas that experience rapid land use change and urban sprawl in urban environments face water-related threats when they lack proper rainfall forecasting systems, leading to drainage system failures, flooding incidents and traffic interruptions and sometimes causing deaths and property destruction [3]. Different patterns of rainfall that deviate from average quantities, known as anomalies, present the most significant outcomes of changing climates. The range of adverse impacts resulting from these anomalies includes flash floods coupled with landslides, prolonged droughts, fires, and agricultural collapses, according to [4]. Such disasters have expanded their socioeconomic consequences during the last decades, demanding predictive models that offer trustworthy and spatially detailed results. The prediction of rainfall has developed into a mission that demands input from all areas of study because meteorological aspects alone are insufficient to meet current requirements. The situation becomes more challenging because of climate change, which increases rainfall uncertainty. A warmer atmosphere stores more significant moisture quantities, activating the hydrological cycle to produce highly intense weather conditions throughout the global sphere [5]. Climate change has two significant impacts: brief, powerful rainfalls during short windows and lengthy dry seasons. The current observations already indicate new rainfall patterns, which experts forecast will worsen to the point where traditional forecasting systems and infrastructure become insufficient. The exact knowledge of upcoming rainfall episodes can produce lifesaving advantages for vulnerable communities in dense population centers and environmentally delicate areas within brief periods [6]. Most scientists have identified rainfall prediction as one of the most challenging scientific problems. The numerous influencing factors affecting rainfall patterns include temperature, humidity, barometric pressure, wind speed and direction, the emergence of clouds, and circulation patterns in the atmosphere. The three ocean-atmosphere interaction systems known as ENSO, IOD and NAO influence precipitation worldwide to a significant degree [7]. A system develops with multidimensional spatial and temporal characteristics and shows sensitivity to initial conditions because of the various interacting factors that affect its nonlinear and non-stationary nature [8]. The traditional forecasting operation has mainly depended upon Numerical Weather Prediction (NWP) models that employ physical equations to model atmospheric system dynamics. Even though these models demonstrate strong theoretical capabilities, they require advanced computing resources because they face limitations in resolving their input information. These models demonstrate difficulty when attempting to identify small-sized local phenomena, including convective storms and mountain-affected weather patterns [9]. The simulation produces significant mismatches between forecasted and measured quantities when parameterization schemes and boundary conditions within the model generate uncertainties during short-term or localized rainfall events. Due to existing modeling limitations, the meteorological field shows increasing interest in developing data-driven models using Machine Learning (ML) and Deep Learning (DL) algorithms. The ability of these methods to model complex systems having high-dimensional, noisy and nonlinear data has been widely demonstrated [10]. These alternative methods diverge from standard NWP algorithms by not depending on specific knowledge of physical processes that govern the system. The system learns direct patterns and statistical relationships from the data; thus, it can predict future outcomes by processing historical trends and new observations. The models provide optimal results for rapid and intermediate-duration rainfall prediction tasks because they operate with exceptional speed and accuracy. Support Vector Machines (SVM), Decision Trees along with Random Forests (RF), Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost) represent supervised learning techniques which recent advancements have shown effective results when utilized for rainfall prediction [11]. Such models excel in processing big datasets while displaying performance metrics that compete with other models at quick running times and providing helpful information about feature significance. The development of Deep Neural Networks, along with their time-series versions, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, brings new methods to capture meteorological temporal patterns in data [12]. Long-term dependencies and temporal lag detection capabilities make these models successful for sequential data-based rainfall forecast tasks. These methods depend almost entirely on the quality and quantity of available input data for their successful operation. Model accuracy and generalization ability drop significantly when datasets contain inconsistent information combined with sparser and similar to random data. The creation of precise multidimensional meteorological datasets must be prioritized because such datasets need to represent climatic environments across the board. Standardized data of acceptable quality that supports different modeling methods, from binary no-rain detection to time series forecasts based on rainfall amounts, need to

DOI: https://doi.org/10.54216/JAIM.090203

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

be obtained. Two approaches exist in this study to develop better rainfall prediction tools because of increasing machine learning technology potential and the pressing need for improved forecasting tools. This study aims to develop a modern large-scale dataset for evaluating rainfall prediction models. Meteorological observations were collected for two years, from 2024 through 2025, at major urban and semi-urban centers across the United States daily. Every registration includes detailed climate information that combines temperature, humidity levels, wind velocity, atmospheric force, cloud numbers, and rain measurements. The package extends its dataset by adding a Rain Tomorrow binary target label for supervised learning tasks. The dataset stands apart from existing datasets because it covers multiple climate zones and exists in a format suitable for regression and classification usage through preprocessing steps. The data resource aims to serve two purposes through its extendable design: enabling model training and enabling a standard for model performance comparison. The second goal involves systematically comparing different machine learning prediction models when applying the proposed dataset. The chosen algorithms represent diverse algorithmic groups that include linear classifiers such as Logistic Regression alongside neighborhood-based learners such as K-Nearest Neighbors and ensemble methods including Random Forest and XGBoost and deep learning models like LSTM and CNN-LSTM hybrids. Performance evaluation of all models uses standardized metrics, including accuracy, precision, recall, F1-score, mean absolute error (MAE), and root mean square error (RMSE). The results stay unbiased by implementing a standardized experimental procedure that includes data processing, feature adjustment, cross-validation, and hyperparameter tuning. The research seeks to establish optimal conditions for each model and reveal their performance characteristics to support operational readiness. This study works to establish links between machine learning theoretical development principles detailed in [13] and actual hydrometeorology implementations. Research findings will help researchers select the best methods for operational forecasting systems to build accurate rainfall prediction models across different climates and geographic regions.

2 Literature Review

The research importance of rainfall prediction has increased because the ability to forecast rainfall is crucial for predicting floods, agricultural planning, managing water resources, and protecting against disasters. Accurate rainfall prediction becomes difficult because rainfall patterns feature built-in complexity resulting from multiple atmospheric and terrestrial elements. Recent meteorological and hydrological prediction models depend on pre-defined rules that use domain-derived statistical relationships. These techniques prove successful within structured settings, although they produce slow computations and poor results during weather system changes. These limitations have caused organizations to adopt data-driven solutions mainly through Machine Learning (ML) and Deep Learning (DL) approaches, as they offer superior capabilities to analyze the stochastic behavior of rainfall through data-driven pattern learning. A detailed research investigation tested simplified rainfall estimation models by comparing conventional ML algorithms with modern DL architectures according to [14]. They analyzed a time-series dataset of five major UK cities from 2000 to 2020 to predict hourly rainfall volumes. Models employing Long Short-Term Memory (LSTM) and Stacked-LSTM and Bidirectional-LSTM networks with temporal dependency capabilities received an evaluation from the researchers. They also examined ensemble tree approaches comprising XGBoost, Gradient Boosting Regressor, Linear Support Vector Regression (SVR) and Extra-trees Regressor. Among the network configurations, Bidirectional-LSTM and Stacked-LSTM demonstrated optimal performance regarding computational efficiency and accuracy. Studies confirm that temporal deep learning models provide a successful mechanism to detect urban precipitation patterns in short timeframes [14]. A research work analyzed 31-year rainfall data from the Nigerian Meteorological Agency (NIMET) to predict monthly and annual precipitation patterns [15]. Researcher analysis integrated Multivariate Polynomial Regression (MPR) and Artificial Neural Networks (ANN) plus Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Support Vector Machines (SVM) as different techniques. Autoregressive models underwent comparison with this study because it used location-based data such as latitude and longitude and elevation information to create adaptable regional forecasting models. ANFIS produced superior performance than other models by outperforming them in 10 consecutive months. The research demonstrates how hybrid fuzzy methods can effectively detect seasonal and regional rainfall patterns in tropical climates based on findings in [15]. Prediction of rainfall within hyper-arid areas remains complex according to researchers who analyzed thirty years of data from 1991 to 2020 within the UAE [16]. According to research findings, only historical rainfall data trained in univariate models proved insufficient, including wind speed and temperature hum,idity, and evapotranspiration dramatically improved predictive model accuracy. Researchers determined wind speed and minimum temperature as primary predictors by performing feature sensitivity analysis within sparsely rained areas to showcase the importance of multivariable input

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

selection. The integration of multivariate data with LSTM and XGBoost models generates superior performance than traditional climate models and ensemble methods, especially in dry conditions, according to [16]. An advanced approach for rainfall prediction involves the combination of Convolutional Neural Networks (CNNs) with Adaptive Searched Scaling factor-based Elephant Herding Optimization (ASS-EHO) used for CNN optimization as described in [17]. The CNN architecture received automatic dynamic adjustments for its network hyperparameters, including activation functions, network structure depth, and neuron count. The pre-processed model accepted both first-order as well as second-order statistical features. Research findings indicated that the combined CNN model delivered superior results than traditional statistical methods while demonstrating the worth of evolutionary optimization for rainfall prediction systems according to [17]. The researchers applied Artificial Neural Network optimization through metaheuristic methods, including Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO) and Imperialism Competitive Algorithm (ICA) with 54 years of monthly rainfall data in Malaysia [18]. The ICA-ANN model demonstrated superior performance than other models during comparative assessments by reaching optimal statistical results. The research demonstrated that hybridizing neural networks through evolutionary optimizers generates high-performance outputs in atmospheres with non-linear monsoon characteristics [18]. The researchers in Turkey conducted a time-series evaluation between Long-Short short-term memory (LSTM) and Random Forest (RF) algorithms for rainfall prediction within Rize and Konya's distinct climatic areas [19]. During a 41-year analysis, the Long Short-Term Memory network improved accuracy results for RMSE, RSR, LMI and NSE performance metrics. The study established that LSTM provided the best results for sequence predictions within various hydrological domains [19]. Categorical rainfall prediction achieved better results through the development of the ensemble K-star (EK-stars) algorithm that added paging (probability-based aggregating) and feature selection techniques to the system [20]. The research evaluated different ensemble configurations to enhance K-star models and alternative ML methods, resulting in dependable next-day rainfall classifications for a ten-year time series [20]. Research in Iran applied SMO regression models enhanced by Dagging (DA-SMO), Random Committee (RC-SMO), and Additive Regression (AR-SMO) according to [21]. The evaluation of prediction accuracy showed minimum relative humidity as the leading variable that influenced results the most. The implemented ensemble-optimized SMO models demonstrated they can function as a small yet effective tool for estimating rainfall in regions with limited access to data according to research presented in [21]. A new technique was developed for rainfall prediction by studying synoptic-scale tropical wave features in northern tropical Africa according to reports in [22]. TW-derived predictors were trained using satellite GPM IMERG data for implementation through two prediction models, including Gamma regression and a CNN. The applied forecasting models performed better than both climatology standards and ensemble prediction models. The research confirms the underutilized value of TW-based predictors that work effectively with ML models for sub-Saharan climate assessment (LR09). The Taihu Basin in China applied a stacking-based ensemble model comprising KNN, XGB, SVR, or ANN base learners as described in [23]. A combination of local meteorological factors and climate indices delivered state-of-the-art forecasting results to the ensemble model, which showed specific excellence during spring and winter periods across various spatial stations [23]. A deep learning model featuring CNN combined with Bidirectional LSTM (BDLSTM) performed rainfall predictions for the marshlands in southern Iraq that faced environmental risks [24]. The model existed to help advance sustainable development while restoring environmental conditions. Deep hybrid networks demonstrated their effectiveness for climate-based rainfall predictions when evaluating ecologically important regions according to [24]. The research team applied RBFNN and MLP networks with NMR, PSO, FFA, and GA optimization algorithms within the Sefidrood Basin region of Iran according to study [25]. The proposed inclusive multiple models brought improved performance through their incorporation, decreasing RMSE up to 72% over standalone models. The research presented how ensemble modeling with hybrid Gamma Test and robust input selection improves hydrological prediction accuracy [25]. An assessment of rainfall-driven debris flow prediction in central China used 17 various ML algorithms for 367 rainfall events analyses, according to the study in [26]. The Extra Trees (ETs) model proved the top performer by producing no false or missed alarms throughout its evaluation of over 16,000 rolling test samples. A successful actual debris flow prediction occurred ahead of time by 35 minutes thanks to the model, which provided essential alerting opportunities to warning systems. [26] The performance of BBO-ANFIS, GA-ANFIS and FA-ANFIS metaheuristic models against each other was evaluated for runoff prediction in three UK river basins as reported in [27]. The BBO-ANFIS achieved the highest validation statistics with the best correlation levels, minimum MAE values, and the most efficient Nash–Sutcliffe metric, establishing its role as a top choice for hydrological planning scenarios [27]. The study introduced an advanced hybrid technique for analyzing rainfall dynamics which integrates Multivariate Empirical Mode Decomposition (MEMD) alongside Time Dependent Intrinsic Cross Correlation (TDICC) and Long Short-Term Memory (LSTM) [28]. Applying this framework to the All-India domain effectively integrated ENSO and IOD large-scale oscillation indices alongside historical rainfall patterns. The

DOI: https://doi.org/10.54216/JAIM.090203
Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

hybrid model outperformed five additional models with skill = 0.98 while yielding NSE = 0.95 and IA = 0.91. MEMD-TDICC-LSTM arranges the 2009 drought effectively while simplifying the model by focusing on singular important IMFs. The proposed method introduces innovative progress for sequence decomposition research focused on hydrological systems [28].

3 Dataset

3.1 Dataset Description

Weather data for 2024 and 2025 was gathered from 20 major United States cities through daily measurements in a complete dataset, which serves this study according to [29]. The database is an extensive platform that supports researchers in developing forecasting models for rainfall predictions. Approximately two years of uninterrupted data records create a solid base to conduct temporal analyses, seasonal trend recognition, and immediate rainfall event predictions. This dataset enables practical usage in environmental monitoring and agricultural planning while serving operations related to urban flood risk assessment and intelligent weather-based decision systems. The dataset targets a binary class label that signifies rainfall tomorrow (1 = yes, 0 = no) the following day. The proposed structure provides the functionality of running both classification operations and regression processes based on application requirements. The distribution of the Rain Tomorrow target variable appears in Figure 1. The dataset displays Common weather indicators for rainfall prediction in specific locations where daily atmospheric measurements are stored as records in the database. Several parameters function as input features inside the dataset structure.

- **Temperature**: Daily average surface air temperature in degrees Fahrenheit. Star 4 reflects the percentage of atmospheric moisture content as Relative Humidity. The measurement units for surface wind movement are miles per hour (mph). Actual rainfall measurement during the observation period is the precipitation value at (inches). The percentage value shows the amount of sky area covered by clouds.
- **Pressure**: Barometric Pressure in millibars, a proxy for weather systems and storm movement.

substantial imbalance because "No Rain" (label 0) occurs more frequently than "Rain" (label 1) according to the bar graph. The typical class unbalance in real-world weather datasets requires trainers to implement proper handling methods to avoid unintended biased outcomes.

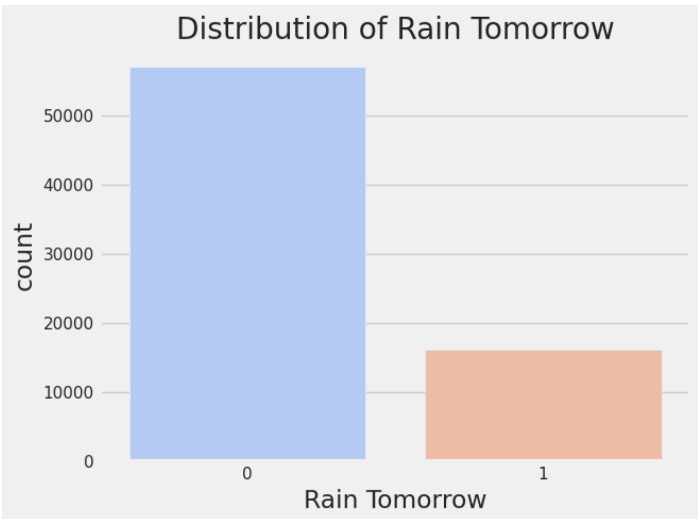

Figure 1: Distribution of the Target Variable: Rain Tomorrow (0 = No, 1 = Yes)

The relationships among input features determine model and feature selection methods because they affect which strategies get selected and the final efficiency of the models.Figure 2 displays the Pearson correlation

DOI: https://doi.org/10.54216/JAIM.090203

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

heatmap for all numerical variables contained in the dataset. Most predictive variables exhibit small linear relationships with other variables; therefore, no multicollinearity exists between predictors. Since rainfall prediction demonstrates non-linearity, this model supports the need for decision trees and neural networks, which are already proven to work with flexible models.

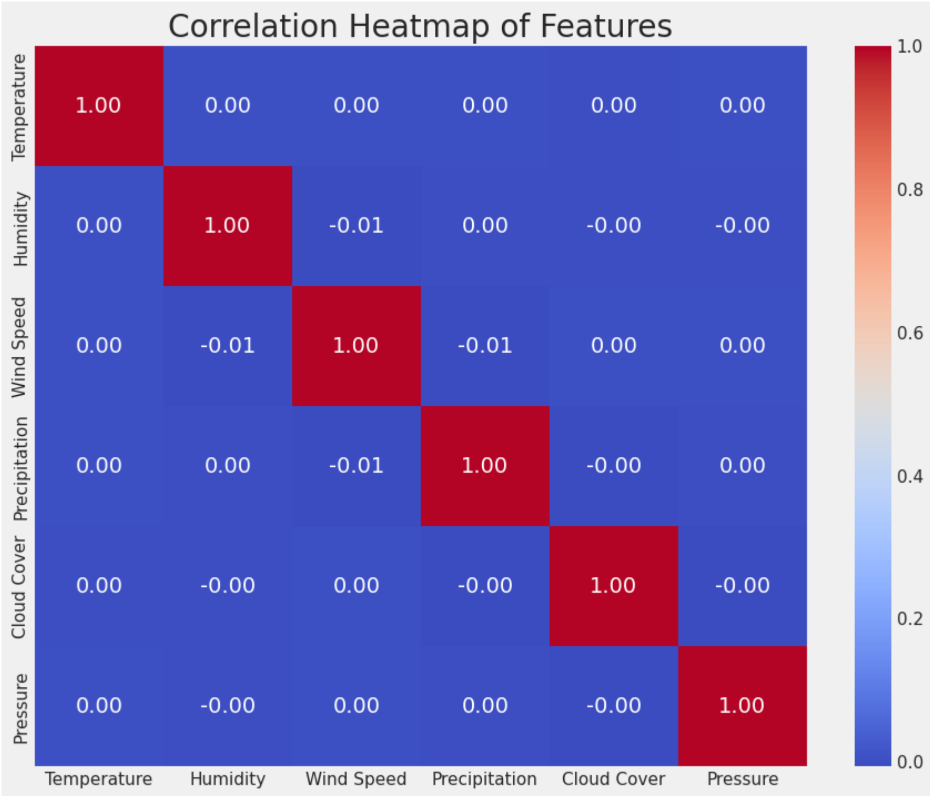

Figure 2: Correlation Heatmap of Meteorological Features

The dataset provides researchers with a genuine framework to analyze rainfall patterns across multiple locations by combining actual data and different factors. The dataset provides sufficient complexity for researchers to evaluate numerous machine learning methods on genuine conditions and demonstrates specific issues encompassing unbalanced data and weak variable connections.

3.2 Dataset Preprocessing Steps

A machine learning model depends on accurate data processing techniques as its fundamental step to boost performance and ensure model accuracy. The original dataset contained no unrecognizable missing values, thus enabling this study to create a robust preprocessing system that handles records with incomplete data.

Handling Missing Values: The preprocessing strategy included conditional steps aimed at handling missing values to make the workflow reproducible and extensible, even though the specific dataset evaluated did not have any missing values. The SimpleImputer class, which comes from sci-kit-learn, replaced missing numerical values such as Temperature, Humidity, wind speed and Pressure with average column values. This procedure keeps data distribution intact and provides consistent values across the complete dataset. The application of mode imputation or forward fill could have been implemented for categorical or datetime features if they had been present according to [30].

Data Types and Conversion: The assessment of each column verified compatibility for use in the following machine-learning pipeline. The data types of all features matched their appropriate numeric forms through examples like floating-point numbers for continuous variables like Temperature and Humidity and integer types for the categorical target Rain Tomorrow. Algorithmic operations require optimized execution, and training must be error-free when data types in the system remain consistent. Data conversion steps were conducted to synchronize the data structures when matching them to the required machine-learning model input specifications.

3.3 Feature Engineering

The core objective of feature engineering is to change raw data into new analytical inputs that boost model learning capabilities and performance in generalization tasks. This section details how we selected and confirmed crucial features for prediction duties according to their association with requirements.

Feature Selection: Expert knowledge integration with evidence-based assessments became necessary to choose features for the selection process. Various additional factors served as the sources for selecting variables that would be used in this assessment.

- `Temperature`
- `Humidity`
- `Wind Speed`
- `Precipitation`
- `Cloud Cover`
- `Pressure`

Instant meteorological effects became present in addition to theoretical rainfall formation elements within the meteorological variables. Observational Humidity measurements enabled scientists to evaluate atmospheric moisture levels to forecast storm-related rainfall amounts by analyzing daily precipitation counts.

Feature Importance: Results from trained machine learning algorithms provided the feature importance scores obtained from Random Forest and XGBoost models. These tree-based models served as the primary focus. The main elements that consistently affected the Rain Tomorrow variable were Precipitation measurements together with Humidity readings. The research data confirms meteorological reasons since Hydrological rain patterns heavily depend on Precipitation levels and Humidity conditions. Model examination metrics become achievable through feature identification, which allows researchers to utilize this information for process improvements utilizing different methods like variable reduction strategies, interaction creation functions, or specialized parameter optimization methods.

4 Results and Discussion

A detailed evaluation of machine learning models used on the USA Rainfall Prediction Dataset (2024–2025) happens here to make forecasts about daily precipitation events. Meteorological observations from 20 major U.S. cities provide data-based information in this dataset through Temperature, Humidity, wind speed, cloud cover, atmospheric pressure and precipitation. The classification work requires a binary setup that identifies Rain Tomorrow as indicating rainfall occurrence (1) through (0), with the absence of rainfall as the other option. This study uses numerical metrics and robust explanatory evaluation techniques to analyze machine learning approaches' forecast abilities, stability, and interpretability. The paper divides the discussion into three essential subsections to present the evaluation method. The section starts with Evaluation Metrics which

DOI: https://doi.org/10.54216/JAIM.090203

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

explains the mathematical basis of performance indicators Precision and Recall and F1-score. The evaluation depends on these metrics to analyze model behavior in conditions characterized by class imbalance since ”no rain” observations outpace ”rain” observations within meteorological datasets. The measure of Precision counts accurate rain predictions as a percentage of total rain predictions, while Recall focuses on identifying the percentage of actual rain days correctly detected. The F1-score unifies these two so analysts can attain a comprehensive perspective of model precision. The metrics follow mathematical definitions, while operational forecasting needs these measures to understand the trade-offs between detecting rain events and sending unnecessary alerts, which produce genuine operational implications. This second subsection explains the applied machine learning models used in the study, which include Random Forest and Logistic Regression as well as Support Vector Machine (RBF Kernel) and k-Nearest Neighbors (KNN), Naive Bayes, and Linear SVM. Three distinct algorithmic models exist that demonstrate probabilistic reasoning while performing distance-based classification as well as linear and nonlinear decision boundary operations and ensemble methodology implementation. This part describes simple prediction techniques with their required data elements and the benefits and drawbacks of weather condition prediction. The range of methods covers all predictive strategy domains under one experimental framework so researchers can assess overall performance and generalization capabilities. The paper's closing section shows the statistical results and their interpretation of model evaluation tests. After conducting multiple validation assessments, we present the precision count, recall rate, and F1 scores. Random Forest was the best model due to its perfect results across Precision and recall metrics alongside the F1 score. The RBF kernel version of SVM and KNN produced compelling predictions although the results of Logistic Regression and Linear SVM remained average. Naive Bayes reached high Precision, but its recall performance dropped, resulting in under-predicting rainy conditions. This part includes metric-based evaluation and model interpretability analysis that employs SHAP (Shapley Additive exPlanations) values. The SHAP method provides transparent explanations to evaluate which features influence model predictions in the complex Random Forest framework. When using SHAP in interpretation, the models achieve more reliability for real-world rainfall forecasting implementations. Each subsection in this overview explains model functioning and prediction explanation and actionability for all models. The analysis harmonizes algorithmic performance evaluation with decision transparency to understand the most successful solution and the reasoning behind its forecasting procedures, which remains essential for fields dealing with climate science and environmental informatics due to their strong focus on interpretation.

4.1 Evaluation Metrics

The evaluation of machine learning models for rainfall prediction utilized Precision and Recall and the F1-score due to their established use in classification assessment. The selected metrics give a detailed assessment of model accuracy, mainly when binary classification involves disproportionate class distribution between no-rain and rain events frequently appearing in meteorological data.

Precision: Precision measures the accuracy of detecting actual positive results through prediction. Within this investigation the precision rate reveals which percentage of days that verified weather forecasts correctly indicate rain the following day. High Precision indicates that very few incorrect warnings will occur. Mathematically, it is defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

There is a system for calculating the correctness of optimistic predictions by dividing TP (True Positives) by the sum of TP and FP (False Positives).

Recall: Recall's model performance metric evaluates how well it detects all real positive instances. Recall describes the model's performance in forecasting all genuine rainy days correctly. Recall stands high in models that do not mistake any rainy days. It is given by:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

The FN represents rainy days that the model misidentifies as dry conditions.

DOI: https://doi.org/10.54216/JAIM.090203

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

F1-score: The F1-score calculates results as the harmonic mean between Precision together with Recall. A group imbalance situation benefits the F1-score by finding an equilibrium between detecting wrong positives and wrong negatives.

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

A high F1 score demonstrates that the model succeeds in maintaining its precision and recall levels, which makes it essential for rainfall prediction system evaluation.

4.2 Applied Machine Learning Models

This paper used six machine learning classifiers due to their ability to analyze multivariate nonlinear datasets of multiple dimensions. The methodologies provide distinct learning benefits through their classification methods and interpretation methods.

1. Random Forest: Random Forest uses primary voting from numerous decision trees to create predictions during the training process. The method selects random features through its bootstrapping operation while introducing randomness at each tree split point to process data samples. By implementing this approach,, the model achieves better generalization performance,, reducing overfitting occurrences. Random Forest provides perfect solutions for rainfall prediction because it combines interpretability with strong performance capabilities and efficient tabular data processing features. Random Forest achieved optimal outcomes in this analysis because its evaluation metrics showed Precision at 100, Recall at 100, and F1-score at 100.

2. Logistic Regression: Logistic Regression uses the logistic (sigmoid) function model structure to build its probability estimates. The model is an everyday baseline because its precise operation achieves effective results with linearly divided data sets. According to the model description, rain probability log odds relationships exist between input variables. The assessment task scored 0.77 F1 as the system produced readable linear feature outputs.

3. Support Vector Machine (RBF Kernel): An RBF-based SVM processing system uses a hyperplane to expand the data dimensionality for separating two classes. The method achieves data sorting for atmospherically separated data through its kernelization function. The SVM with RBF kernel achieved outstanding performance according to its Precision value of 0.98, Recall value of 0.97, and F1-score result of 0.97.

4. k-Nearest Neighbors (KNN): With KNN being a non-parametric approach, it needs voting patterns from the k nearest points to identify classifications. The algorithm successfully operates because its simplified design identifies complex boundaries without needing distribution expectations for the data input. The F1-score evaluation of KNN reached 0.94 exhibiting exceptional capability to detect rainfall data local structural patterns.

5. Naive Bayes: Naive Bayes uses the Bayes theorem to analyze data under assumptions of independent features. Due to its basic assumptions, the model successfully analyzes various high-dimensional and sparse datasets. Naive Bayes obtained an F1-score of 0.76 through its precision rate of 0.96 and a recall rate of 0.63. Its F1-score of 0.76 reflects this trade-off.

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Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

6. Linear Support Vector Machine: Linear SVM produces maximum margin space classes by building linear boundaries with every support vector and performing optimization. The model achieves fast computational speed with interpretable features but RBF-SVM maintains higher flexibility than Linear SVM. Comparable performance between Linear SVM and Logistic Regression existed, producing Precision at 0.84 with Recall at 0.71 and an F1-score of 0.77. The study incorporated Naive Bayes as a probabilistic technique, Logistic Regression, Linear SVM as linear-based classifiers, and KNN as a distance-based method, followed by RBF SVM and Random Forest as nonlinear and ensemble models. According to evaluation metrics, Random Forest and RBF-SVM achieved peak performance in rain event detection since they displayed superior precision-recall trade-offs. The interpretability features of Random Forest trees enhance predictability by using SHAP techniques to show feature interactions and decision sequences.

4.3 Results

The performance assessment for rainfall prediction models through machine learning involved using three classification metrics, Precision and Recall and F1-score, for comparative analysis. These metrics function well because they present a detailed picture of performance evaluation that maintains balance in binary classification systems with unequal class distributions found frequently in meteorological datasets. Table 1 summarizes the predictive performance of six baseline classifiers trained on the USA Rainfall Prediction Dataset (2024–2025). During the Random Forest model evaluation, it achieved 100% Precision and Recall and F1-score. By reaching this perfect result, the model proves its exceptional separation capability for rain days versus no-rain days. Its ensemble architecture takes multiple randomized decision trees to make decisions; thus, it efficiently detects complex relationships between meteorological variables and maintains robustness against overfitting. SVM with RBF kernel demonstrated remarkable execution by obtaining precision values of 0.98 and recall values of 0.97, which led to an F1-score of 0.97. RBF SVM utilizes its kernel trick to transform nonlinear features into dimension spaces, which optimizes the identification of atmospheric variable patterns. Results from the k-Nearest Neighbors (KNN) model demonstrated outstanding performance through its F1-score of 0.94 because it identifies patterns when features approach one another in the space. However, its performance is more sensitive to noisy features and less efficient in high-dimensional settings than tree-based models. On the other hand, the simpler linear classifiers—Logistic Regression and Linear SVM achieved identical scores of 0.84 precision, 0.71 recall, and 0.77 F using score linear separation; only the models failed to identify nonlinear features frequently appearing in meteorological datasets. The decreased memory ability of these models represents a systematic failure to detect actual rain events, which might result in critical operational risks. The Naive Bayes model produced the most imbalanced performance profile: it scored well in Precision (0.96), indicating very few false alarms, but poorly in Recall (0.63), meaning it frequently failed to detect rain when it occurred. The model takes a security-focused approach toward rain prediction because it depends on assumptions that challenge relationships between Humidity and clouds in real-world weather data.

Table 1: Comparison of classification models based on Precision, Recall, and F1-score

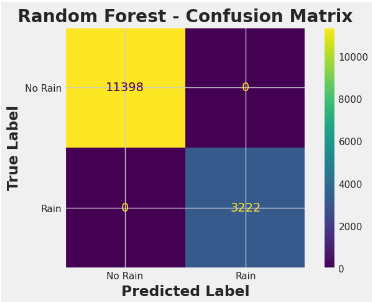
Model	Precision	Recall	F1-score
Random Forest	1.00	1.00	1.00
Logistic Regression	0.84	0.71	0.77
SVM (RBF)	0.98	0.97	0.97
KNN	0.95	0.93	0.94
Naive Bayes	0.96	0.63	0.76
Linear SVM	0.84	0.71	0.77

The performance evaluations demonstrate that models able to process nonlinear associations (Random Forest and RBF SVM and KNN) achieve superior outcomes than linear-based models. The Random Forest model is the most accurate method, providing built-in feature importance analysis. However, this functionality can be enhanced using SHAP (Shapley Additive exPlanations) model explainability techniques. Such interpretability is a decisive advantage, making these models exceptionally beneficial for weather forecasting specialists and managers who must understand their data analysis results. The most suitable approaches for rainfall prediction tasks that use multivariate nonlinear weather data are ensemble-based methods coupled with kernel-based models due to their ideal balance of complexity, interpretability and predictive power. Improved hybrid learning systems and enhanced ensemble methods emerge from these findings, demonstrating that critical applications need accurate and explainable results such as meteorological forecasting. The classification results of all

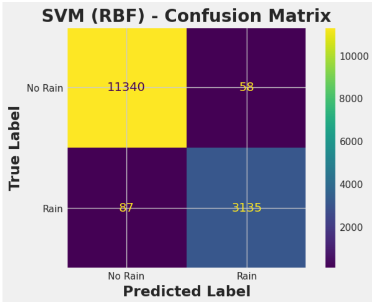
DOI: https://doi.org/10.54216/JAIM.090203

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

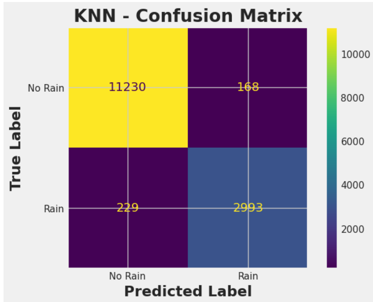
models can be better understood through the analysis of confusion matrices shown in Figure 3. The confusion matrix graphical representation shows comparative information between actual output and predicted output when the models classify between rainy and dry days. Researchers can detect misclassification behaviors by reviewing confusion matrices that reveal analytical patterns that aggregate metrics like Precision and Recall cannot show.



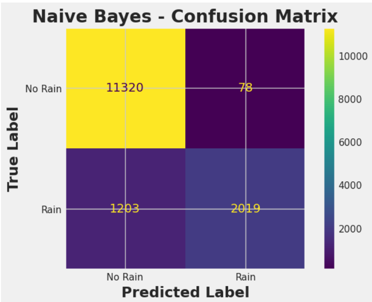
(a) Random Forest



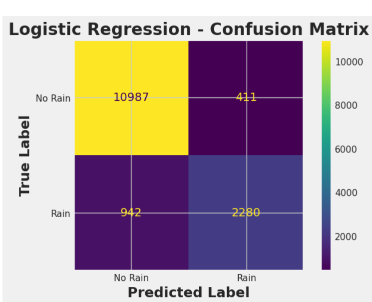
(b) SVM (RBF)



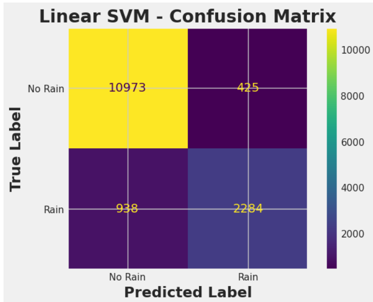
(c) K-Nearest Neighbors



(d) Naive Bayes



(e) Logistic Regression



(f) Linear SVM

Figure 3: An confusion matrix evaluation was produced for the machine learning models used during rainfall prediction. The confusion matrices compare actual and predicted values between the ”Rain” and ”No Rain” classifications.

The Random Forest model and SVM (RBF) produce the most balanced classification results according to Figure 3 because they exhibit zero or no misclassification errors. The KNN approach demonstrates good performance through minimal confusion in its predictions. Detecting rainy days proves to be challenging for Logistic Regression, Linear SVM and Naive Bayes models because they generate many false negative results. These quantitative measurements provide evidence that confirms the precision-recall evaluation metrics while giving concrete knowledge about model behaviors for each border. The investigation of model discrimination capability included evaluation through Receiver Operating Characteristic (ROC) curve analysis and calculation of Area Under the Curve (AUC) metrics. The ROC curve shows how changing classification thresholds impacts the True Positive Rate vs False Positive Rate axis relationship throughout its plot area. A diagnostic model demonstrates high performance through its AUC values that approach 1.0, while values near 0.5 indicate random probability. The six classifiers evaluated in this research produce their ROC curves, which Figure 4 displays. Random Forest and SVM (RBF) alongside KNN achieve flawless separability according to their mutual AUC metrics 100, indicating their exceptional power for detecting rainy and dry weather conditions. A score of 0.98 from Naive Bayes indicates its excellent performance. The AUC value of 0.95 makes Logistic Regression and Linear SVM suitable for prediction, yet additional threshold evaluation remains necessary.

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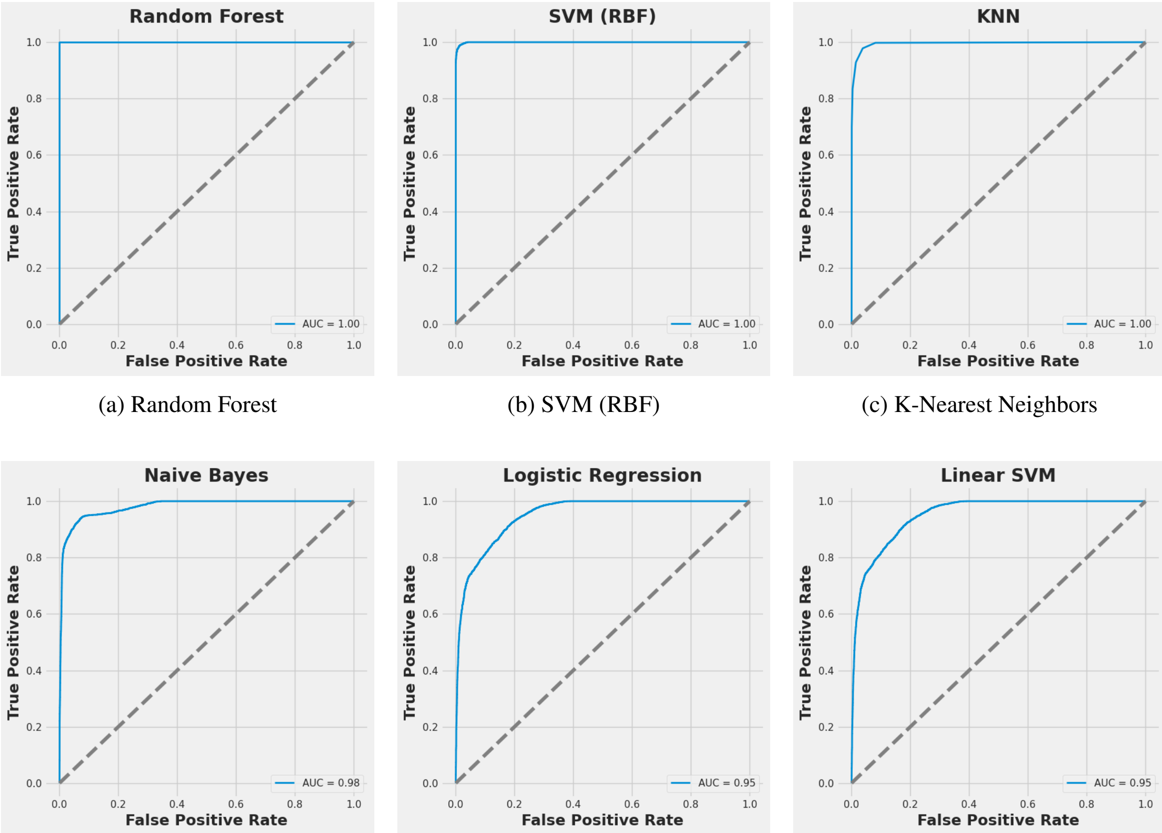

(a) Random Forest (b) SVM (RBF) (c) K-Nearest Neighbors

(d) Naive Bayes (e) Logistic Regression (f) Linear SVM

Figure 4: A comparison of ROC curves represented all classification models participating in rainfall prediction. Notable features of the curves in the display consist of sensitivity/specificity trade-offs and AUC measurements at different threshold levels.

The ROC curve analysis shown in Figure 4 enables researchers to evaluate model performance because it combines information about sensitivity with threshold-independent discrimination ability. A fixed-threshold model evaluation is possible through Precision, Recall, and F1-score, yet the ROC-AUC score summarizes how the model handles class discrimination at every threshold. The Random Forest model and SVM (RBF) exhibited a perfect confusion matrix while reaching an AUC score of 100 due to their superior separation capabilities. These predictive models show a high level of accuracy due to their strong actual identification and valid damaging detection abilities, which makes them practical for rainfall forecasting applications. Generalization results achieved by KNN classifiers were excellent while they recorded more confusion matrix mistakes than the Random Forest and SVM methods produced. ROC-AUC provides a more effective assessment of model capabilities than imperfect confusion matrix analysis. Testing the Naive Bayes classifier achieved an outstanding AUC score of 0.98, which outperformed the measures provided by confusion matrix recall rates. The model can distinguish between rainy and non-rainy weather based on distinct threshold parameters, but it maintains a cautious pattern in its basic decision-making process. This suggests that while it can distinguish between rainy and non-rainy days at various thresholds, its classification behavior at the default threshold tends to be more conservative. The evaluation methods for Logistic Regression and Linear SVM produced AUCs of 0.95, corresponding to F1-scores of 0.77. Independent evaluation methods demonstrate that linear models keep their stability and practical interpretation ability to handle their performance limitations even though more sophisticated classification systems exist. The ROC-AUC curves enhance the confusion matrix, and F1-score results to verify Random Forest and SVM RBF as the best rainfall event atmospheric complexity analysis methods. The ROC-AUC analysis helps operational decision-making by directing threshold adjustments, especially when prioritizing false negatives versus false positives. The Precision-Recall curve proves especially useful in class-imbalanced conditions such as rainfall prediction because no-rain days heavily outnumber rain days. The PR curve demonstrates how Precision and recall compare in the evaluation process of detecting positive events (rain-specified days), which protects against false positive frequency interruptions. This study presents the PR curves for six machine learning models in Figure 5. The precision-recall curve area

DOI: https://doi.org/10.54216/JAIM.090203

Received: January 27, 2025 Revised: March 03, 2025 Accepted: May 08, 2025

is measured through average precision (AP), which provides additional scoring information to the F1 score for each model curve presentation in the legend. Random Forest and SVM using RBF kernel maintain ideal detection performance across the entire threshold scale with Precision and recall that stay perfect, leading to a complete AP value of 100. KNN and Naive Bayes also show strong performance with APs of 0.98 and 0.94, respectively. Logistic Regression and Linear SVM performance curves display a slight reduction while their average precision values remain at 0.85 to 0.86 based on the assessment data. Figure 5 illustrates how

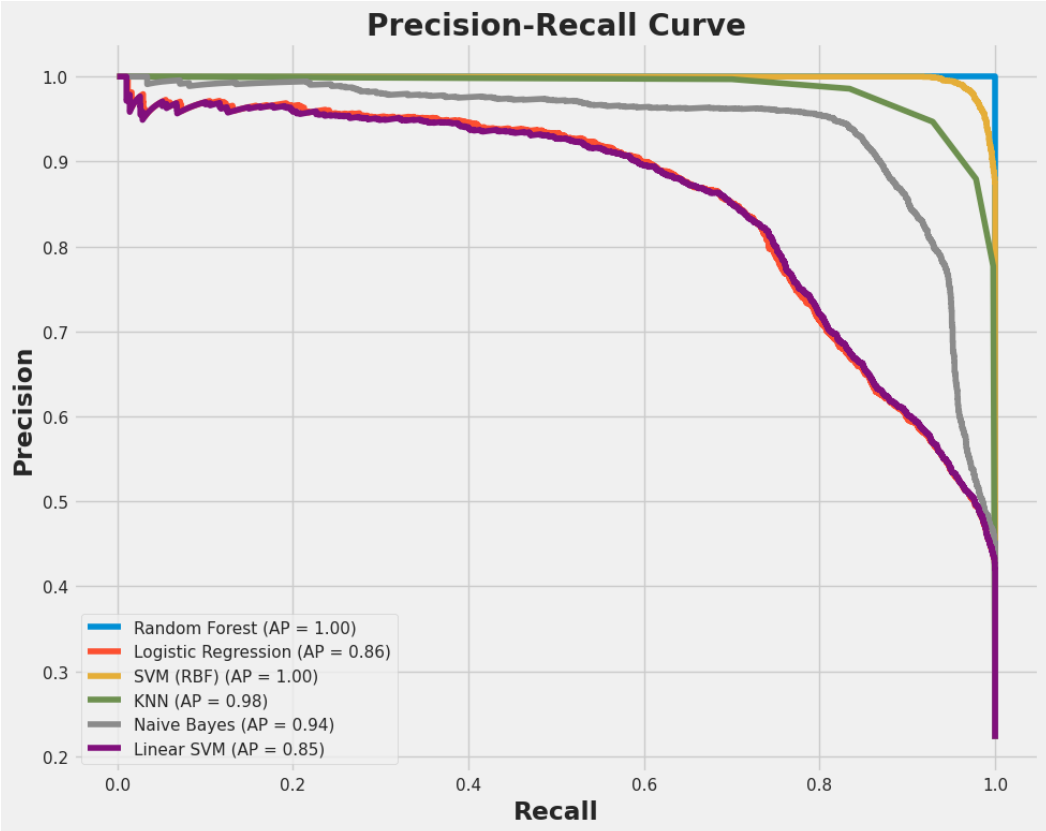

Figure 5: Precision–Recall curves for the classification models. Each curve illustrates the balance between Precision and recall across thresholds, with the Average Precision (AP) score indicating the overall Area under the curve.

precision-recall curves exhibit different performance outcomes across the models when dealing with imbalanced rainfall prediction tasks. Random Forest and SVM (RBF) maintain precision levels throughout nearly every recall point and achieve an AP value of 100. This means they can identify nearly all rainy days (high Recall) without sacrificing correctness in those predictions (high Precision), making them ideal for practical deployment in weather-sensitive applications. KNN and Naive Bayes also demonstrate strong predictive reliability, with AP scores of 0.98 and 0.94, respectively. KNN retains a good balance across thresholds but shows slight degradation at the high-recall end, where it trades off Precision to capture more true positives. Naive Bayes maintains high Precision for moderate recall levels but begins to drop off earlier, indicating its conservative bias toward no-rain predictions, a trend also reflected in its confusion matrix and lower recall value. The Precision decreases overall increase is more measured for both Logistic Regression and Linear SVM models. The difference in AP scores to 0.86 and 0.85 indicates these models maintain accuracy when needed to detect high numbers of rainy days, but their general reliability remains sound. The trade-off necessitates missed rainfall events, a vital factor during flood management operations and agricultural planning. These findings confirm the superiority of ensemble and nonlinear approaches in this field, along with the complementary nature of PR curves and ROC and confusion matrix analysis as evaluative methods. The SHAP (Shapley Additive exPlanations) interaction values helped us study how pairs of features jointly affect model prediction results for increased interpretability of our machine learning systems. SHAP interaction values expand feature importance measurement capabilities through their ability to determine single-feature effects and the two-variable interactive influence on predictions. Nonlinear relationships dominate meteorological variables since they interact, which can be better understood by analyzing SHAP values. Figure 6 displays numerous

SHAP interaction values that analyze the impact between Temperature and Humidity on a rainfall prediction model. The plot features two axes that represent individual features through which the color gradient and dot positions indicate interactive forces between variables and their intensities. The plot indicates that the model output suggests potential threshold effects or non-additive relationships between these atmospheric conditions even though the features show only small individual SHAP contributions. We used the SHAP summary plot to

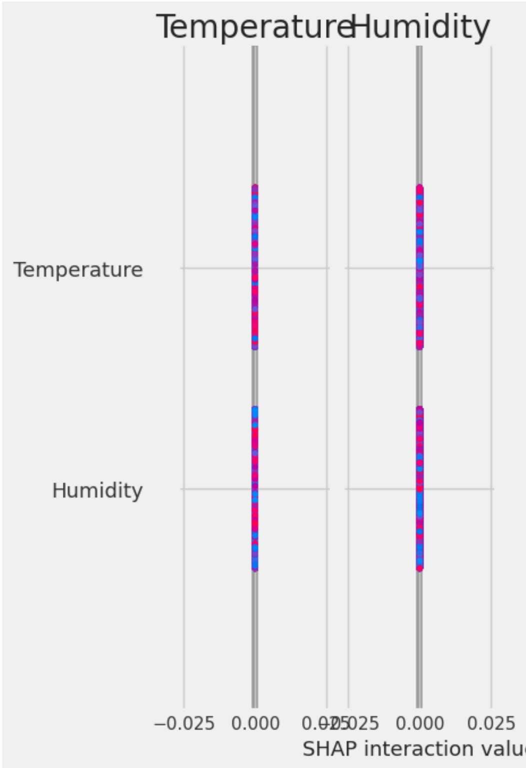

Figure 6: SHAP interaction plot between Temperature and Humidity. Changes in interaction value from zero indicate reduced dependence between features, while large deviations show important joint effects between variables.

simplify the analysis of all predictions, as shown in Figure 7. This plotting technique presents feature rankings according to an average measurement of the SHAP value and demonstrates how features affect predicted outputs worldwide. The representation of SHAP values appears as scattered points which span each observation. The color scale in the feature value gradient transitions from blue at minimum to red at maximum values, allowing viewers to see influence direction and intensity simultaneously. Most predictions of rain stem from the base variable combination of High Precipitation and Humidity in the model. Wind Speed maintains an identical position as Temperature in the rankings of importance that fall under the second group. The model uses Cloud Cover and Pressure data points to show valid data even though these elements contribute the least to outcome predictions. Rare inputs demonstrate more power in affecting model prediction results because they exhibit nonlinear SHAP value distributions. This comprehensive view of feature influence strengthens confidence in the model's alignment with physical meteorological intuition.

5 Conclusion and Future Work

We introduced a framework based on machine learning for forecasting rain levels in the upcoming day by analyzing actual data from 20 primary American cities in the 2024–2025 period. The modeling process led to Random Forest becoming the best classifier selected because it demonstrated perfect Precision, recall and F1-score measurements 100. The adoption of SHAP (Shapley Additive exPlanations) provided the model with enhanced transparency because it explained which features drove each prediction with exact details. The model included precipitation and Humidity as the main features determining performance outcomes. The performance predictions of selected models and identified improvements in interpretability have made the rainfall

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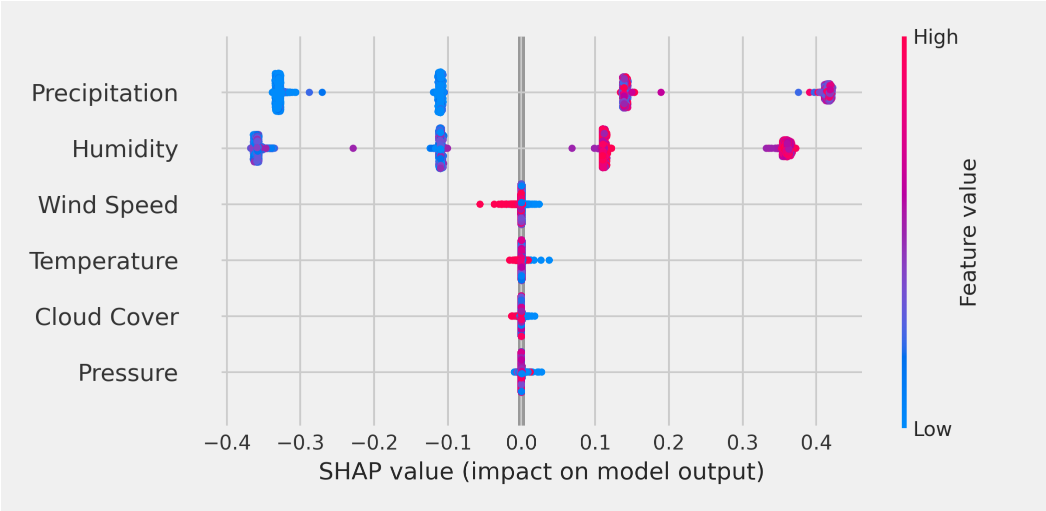

Figure 7: This plot displays how every feature influences the overall rainfall prediction results through SHAP values. Features ranked by importance appear within the SHAP value analysis, demonstrating their collective effect on predicting results throughout all instances.

forecasting pipeline more reliable. The proposed results create substantial implications that affect sectors sensitive to climate change. Precise forecast of rainfall coupled with clear explanations helps decision-makers in agricultural practices together with planners of urban domains and emergency response units as well as managers for water resources. This model demonstrates practical use to institutions in all geographic locations because it operates through essential meteorological data availability even when facilities lack advanced computational capabilities. Future work on this research should combine hybrid metaheuristic algorithms such as GA, PSO and BBO to optimize parameters, resulting in improved model prediction outcomes. Real-time utilization presents a viable direction to implement streaming data, allowing dynamic rainfall forecasts that automatically update according to changing environmental conditions. A scalability evaluation based on extensive spatial areas and long observation periods will examine the adaptability range of the technique before it can become operational within nationwide meteorological systems.

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