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Performance of Machine Learning Algorithms to Predict the Rainfall Data of Khulna and Jashore District in Bangladesh

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Abstract

Predicting rainfall accurately is vital for agricultural stability, disaster management, and sustainable water use, particularly in climate-vulnerable zones such as southwestern Bangladesh. This study investigates long-term rainfall patterns and develops predictive models for two key districts, Khulna and Jashore, using four supervised machine learning algorithms: Multiple Linear Regression (MLR), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbors (KNN). Based on long-term meteorological data for the years 1980–2023, i.e., temperature (maximum and minimum), humidity, wind speed, and sunshine hours, the research manifests clear spatial variations in rainfall behavior. The analysis reveals distinct spatial and temporal rainfall characteristics: Khulna exhibits higher and more variable rainfall due to its coastal location, while Jashore displays relatively stable but lower rainfall, increasing its susceptibility to dry spells. Among the models under consideration, Random Forest gave the highest accuracy value, which was the minimum RMSE and MAE and the maximum R^2 value, particularly in Khulna. In Jashore, although the overall model accuracy was lower, Random Forest was still the most effective because its RMSE (1.568) and MAE (1.23) were lower than those of the other models. The findings suggest that region-specific forecasting models are essential for understanding local precipitation dynamics. Furthermore, ensemble-based techniques like Random Forest prove especially capable of handling the nonlinear and irregular nature of rainfall, offering practical support for policy formulation in agriculture and climate adaptation strategies.

Keywords: Rainfall prediction, Machine learning algorithms, Random Forest, Precipitation forecasting, Climate variability, Southwestern Bangladesh.

AMS Classification: 62P12, 68T09.

1. Introduction

Climate change has increased the frequency and intensity of weather-related disasters including drought, cold waves, floods, and heat waves, but the most devastating one among them is drought (Mishra & Singh, 2010; Wilhite, 2016). Rainfall strongly affects global circulation and local weather; stratiform rain is common in high latitudes while convective rain dominates the tropics, and about 70–85% of rainfall energy comes from latent heat released during precipitation formation (Alpers & Melsheimer, 2004; Barry & Chorley, 2009; Salby, 1996; Simpson et al., 1996). In July 2021, record-breaking floods in Europe left 200,000 properties without power, while torrential rain (201.9 mm/hour) in China's Henan province displaced over one million people—each event causing roughly $12 billion in damages (Liang, 2022). Rising temperatures, changing rain patterns and uncontrolled water utilization are worsening droughts in vulnerable regions such as the Mediterranean, south-west North America, East Africa, and South Asia (Diallo, 2008; Li & Rodell, 2024; Naumann et al., 2021). Bangladesh, though flood-prone, faces rising drought risks. Northwestern regions like Rajshahi and Rangpur suffered severe droughts from 2010–2012 due to monsoon rainfall deficits (M. N. Rahman & Azim, 2021; Shahid & Behrawan, 2008). No significant alteration in monsoon rain in Bangladesh although during this season more than 75% of the rainfall of the country arrives (M. A. Rahman et al., 2017; M. R. Rahman et al., 1997). Rainfall prediction matters because it protects agriculture, supports water management, reduces disaster risks, strengthens climate adaptation, and safeguards economies. Western Bangladesh needs adaptation for agricultural sustainability as Kharif rainfall and temperatures rise, with 71% of annual rainfall trends detected by the Mann-Kendall test (Kamruzzaman et al., 2018). Accurate rainfall prediction is crucial, as both excess and shortage of rainfall can harm crops, despite the importance of consistent patterns for healthy plant growth (Alimagham et al., 2024; Barrera-Animas et al., 2022). Rainfall prediction with different Machine learning, deep learning algorithms and different statistical distributions are found for different geographical locations (Afruz et al., 2023; M. R. Islam et al., 2023; Khondoker et al., 2025). Studies using ML, DL, and statistical models show that rainfall prediction supports: Urban planning, Infrastructure design and Sustainable agricultural policy.

Based on MAE and RMSE values, the prediction of daily rainfall amounts shows better performance using XGBoost in Ethiopia and MLR in India when significant atmospheric parameters are used as inputs (Grace & Suganya, 2020; Liyew & Melese, 2021). The dynamic nature of rainfall makes predictions difficult which led to better MSE scores by LSTM and an even better MSE result of 41.1% the BLSTM-GRU model compared to LSTM (Chhetri et al., 2020). Accurate prediction of rainfall and drought is key to disaster prevention and agricultural stability, in which machine learning models like regression, ARIMA, RF, RNN, LSTM, and especially ConvLSTM showing higher performance in simulating complicated patterns and enhancing predictability for long-term rainfall and short-term droughts (Mohammed et al., 2020; Zhang et al., 2023). Different rainfall prediction researches in Bangladesh concluded that Gradient Boosting gave an 88.35% accuracy at 3,645 climate points, and MLP models were excellent in explaining rainfall patterns. Besides this, PM10, O_3, PM2.5, NO_x, and wind speed were important factors in defining rainfall changes in Dhaka, and it was preferable to predict by utilizing combinations of different models rather than predicting by utilizing separate models (Ahammad et al., 2024; Hussain et al., 2024; A. R. M. T. Islam et al., 2022). While machine learning has been applied to predict the rainfall of Bangladesh is available but the study for southern part of Bangladesh specifically Jashore and Khulna district is rare. The previous studies also have a tendency to focus on short-term data with few predictors such as maximum and minimum temperature where the role of sunshine hours, humidity, and wind speed remains uninvestigated. Imprecise rainfall forecasts undermine agricultural and water resource efficiency, demanding improved Machine Learning-based prediction systems using long-term climate data.

This study aim to investigate the pattern and trend of rainfall data in the case of Jashore and Khulna and compares the prediction performance of rainfall data with different machine learning algorithms. The goal is to select the most suitable machine learning algorithms for predicting rainfall data. The data compute monthly rainfall trends and seasonality to reveal rainfall patterns in these two districts. Some common machine learning algorithms, like Multiple Linear Regression (MLR), Random Forest (RF), Decision Tree, and KNN, are used to predict rainfall data, using climatic variables like minimum and maximum temperature, wind speed, sunshine, and humidity. Lower values of Root Mean Squared Error (RMSE) and Mean Absolute Error, along with a higher value of R-squared, help identify the most suitable machine learning model for predicting rainfall data. The findings of this study can be used by Bangladesh's climate resilience policy for advanced forecasting methods, policymakers, and stakeholders to aid in making decisions on disaster preparedness and water resources management.

2. Study Area and Data Collection

This research concentrates on two of the most significant places in southwestern Bangladesh, namely Khulna (22.8456° N, 89.5403° E) and Jashore (23.1667° N, 89.2167° E), that are representative of all climatic conditions required for proper prediction of rainfall. Khulna and Jashore, being nearer to the Bay of Bengal, are more humid (mostly above 80%); rainier during the year (between 1,800 mm and 2,000 mm); and have moderate temperature variations (mostly 12°C to 36°C).

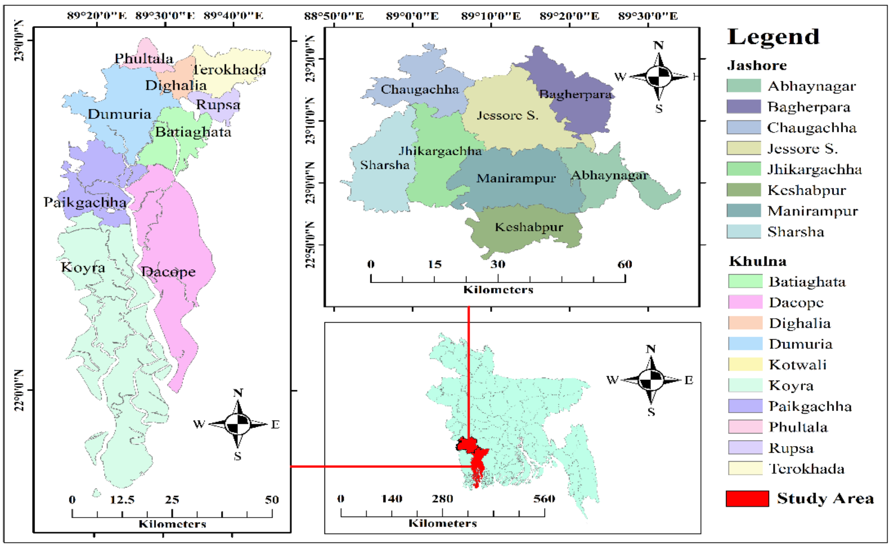

Figure 1: Two meteorological stations in southwestern Bangladesh (By-Author)

The Bangladesh Meteorological Department (BMD) provided meteorological data for January 1980 to December 2023.

The dataset contains monthly reports of rainfall and readings for mean temperature, min and max temperature values, as well as relative humidity, wind speed, and sunshine duration. Results of the research show clear trends between the chosen variables in rain patterns. Fully consistent and reliable quality control procedures were utilized to analyze the data from January 1980 to December 2023. Smoothing techniques were employed when preprocessing the data to eliminate outliers and missing values. Feature contribution in the input features was balanced by normalizing all of them to the range [0, 1] through Min-Max Normalization because they were all quantitative in nature and on different scales such as temperature (°C), Humidity (%),Wind Speed (m/s) and Sunshine (hrs).

3. Methodology

We used four supervised machine learning algorithms—Multiple Linear Regression (MLR), Random Forest (RF), K-Nearest Neighbors (KNN), and Decision Tree (DT) to predict rainfall from climatic variable. All the models contain the inherent patterns of data in a different way, ranging from complex nonlinear relationships to linear dependence.

3.1 Multiple Linear Regression (MLR)

MLR makes the assumption that there is a linear relationship between several independent variables (such as temperature, humidity, and wind speed) and the dependent variable (rainfall). The general form of the model is (Hayes, 2023):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

where Y is the rainfall, $X_1, X_2, \dots, X_n$ are the input features, β_0 is the intercept, β_n are the coefficients, and ϵ is the error term. MLR is useful for understanding the contribution of each variable but may underperform in capturing nonlinearities.

3.2 Random Forest (RF)

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the average prediction for regression tasks. It enhances model robustness and reduces over fitting by combining outputs from diverse trees built on random feature subsets.

The predicted output $\hat{Y}$ is computed as (Ren et al., 2017):

$$\hat{Y} = \frac{1}{T} \sum_{t=1}^{T} h_t(X)$$

where T is the number of trees and $h_t(X)$ is the prediction from the t^{th} tree. RF is well-suited for modeling complex, nonlinear relationships with high accuracy.

3.3 K-Nearest Neighbors (KNN)

A non-parametric technique called KNN uses the average of the K- nearest training samples in the feature space to forecast the rainfall value. The distance between samples is usually measured using Euclidean distance (Peterson, 2009):

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} \left(x_j - x_{ij}\right)^2}$$

The predicted value is then:

$$\hat{Y} = \frac{1}{K}\sum_{i=1}^{K} y_i$$

where y_i are the rainfall values of the K-nearest neighbors. KNN is simple and effective for capturing local data patterns.

3.4 Decision Tree (DT)

A decision tree minimizes a loss function, e.g., Mean Squared Error (MSE), by recursively splitting the dataset along input variables. Every leaf node is a predicted output, and every interior node is a decision rule. The model partitions the input space into regions with fairly homogeneous outputs.

The predicted value at each leaf node is (Charbuty & Abdulazeez, 2021):

$$\hat{Y}_l = \frac{1}{N_l}\sum_{i=1}^{N_l} y_i$$

where N_l is the number of samples in leaf l, and y_i are the observed values. DTs are interpretable and handle both numerical and categorical data efficiently.

3.5 Performance Evaluation

Three measures, RMSE, MAE, and R^2 were used to approximate the models' performance in prediction. The lower the RMSE values, the better the performance, and RMSE quantifies the average magnitude of the errors. A simpler measure of precision is provided by MAE, which estimates the mean absolute error. R^2 quantifies the variance explained by the model; the closer the values are to 1, the better the fit.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad \mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$$

4. Results and Discussion

The table-1 provides a summary of the several natural factors, such as wind speed, sunshine, temperature, and humidity, control precipitation events. The data span January 1980 to December 2023 with a total of 528 observations for these features in the Khulna and Jashore districts of Bangladesh. Khulna had the maximum average humidity (80.56%) and thus was wetter in climate. Jashore had the maximum wind speed (2.23 m/s) and maximum temperature (38.81°C). The different climatic tendencies needed to make precise regional rainfall forecasting are encapsulated in these variables. Khulna's higher humidity and sunshine make it potentially more favorable for crops that thrive in moist, sunny conditions, and Jashore’s drier air and higher wind may suit different types of crops or may increase evapotranspiration.

Table 1: Descriptive Statistics of Key Meteorological Variables (1980-2023)

Station	Statistic	Max Temp (°C)	Min Temp (°C)	Avg Temp (°C)	Humidity (%)	Wind Speed (m/s)	Sunshine (hrs)
Khulna	Minimum	22.23	9.96	17.18	63.9	0.06	2.27
	Maximum	37.68	27.71	31.7	91.65	5.02	9.65
	Mean	31.3	21.84	26.57	80.56	1.23	6.54
	SD	3.16	5.01	3.91	5.69	0.83	1.79
Jashore	Minimum	22.59	8.94	16.54	55.13	0	1.46
	Maximum	38.81	27.4	31.92	90.48	7.45	9.16
	Mean	31.82	20.99	26.41	78.7	2.23	5.71
	SD	3.3	5.46	4.23	6.52	1.47	1.65

Figure-2 shows the long-term monthly rainfall trends from 1980 to 2023 for two districts, such as Jashore and Khulna. In the figure the X-axis represents years from 1980 to 2023 with decade markers (1990, 2000, 2010, 2020), and the Y-axis represents monthly rainfall in millimeters up to 750 mm, with maximum rainfall during monsoon periods. Typical of tropical monsoon climates, both areas exhibit great fluctuation. Some of the heaviest rainfall spikes—close to 750 mm—seem to match up with major flood years like 1988, 1998, 2004, and 2020. Since the 1990s, the rainfall pattern feels more erratic and intense, hinting at the growing impact of climate change. Between these two districts, Khulna, which is close to the Bay of Bengal, would most likely have higher and more variable rainfall from cyclones and sea-surface effects, while Jashore has relatively lower and more uniform rainfall. Khulna's higher precipitation supports aquaculture but enhances flood risk, while Jashore must prioritize rainwater harvesting for efficient management of dry seasons.

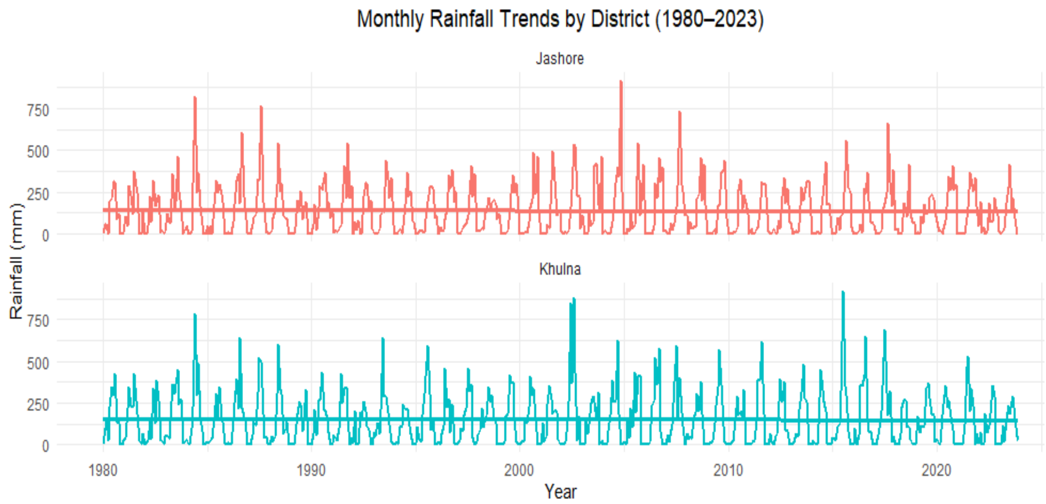

Figure 2: Monthly Rainfall Trend (1980–2023) – District Comparison (Jashore vs. Khulna)

Figure 3 structures the data to emphasize seasonal patterns, especially during the monsoon months (June–September). The X-axis represents months (January–December), with explicit labelling for monsoon months (June–September) and the Y-axis represents rainfall in millimeters (mm). In analyses of rainfall patterns, the Interquartile Range (IQR) rule is typically the preferred and widely recognized method for detecting outliers.

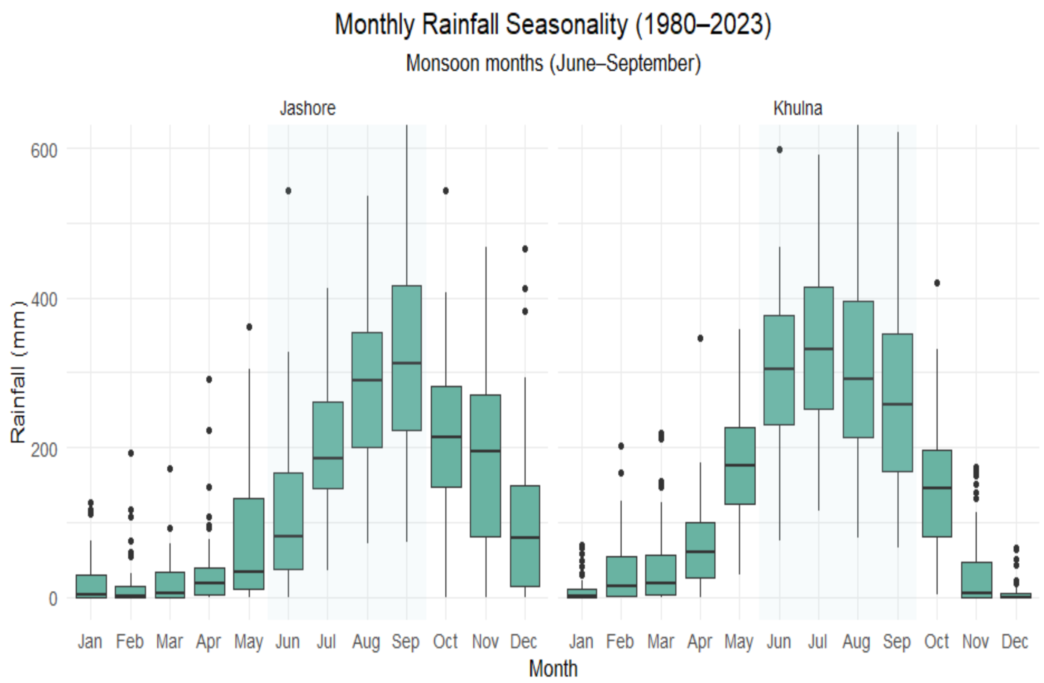

Figure 3: Seasonal Rainfall Distribution (1980–2023) in Jashore and Khulna

Rainfall in Khulna is seasonal, with boro rice having moderate pre-monsoon rainfall and heavy monsoon rainfall—coastal and cyclonic origin—supplying most of the annual amount. Post-monsoon has a smaller rainfall peak, and the dry season experiences little rain, putting a test on irrigation-based rabi crops. June–September accounts for the bulk of annual rainfall in both districts. Khulna shows higher monsoon totals (e.g., 1200–1500 mm) compared to Jashore (e.g., 900–1100 mm). Khulna shows higher rainfall due to maritime influence, whereas Jashore shows more stable distribution but is vulnerable to dry spells.

4.1 Machine Learning based Rainfall Prediction

Performance of any machine learning algorithm is assessed by comparing the result with pre-classified data. We use one part for training the models and the other part for testing and validation. In this study we split the total data set, with 80% as training data and the rest, 20%, as test data set. The machine learning algorithm uses climatic variables to predict rainfall and also climatic variable split into an 80% training set and a 20% testing set. Figures 4 and 5 represent the comparison between the predicted and actual rainfall.

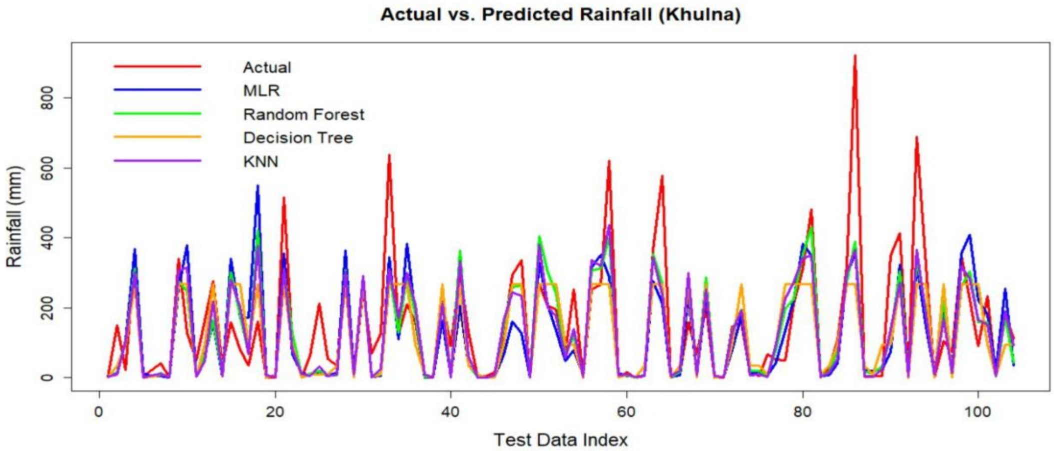

Figure 4: Comparison of Actual vs. Predicted Rainfall in Khulna Using Different ML Algorithm

Figure-4 overlays test points and graphs measured rainfall (red) against four model estimations: MLR (blue), Random Forest (green), Decision Tree (orange), and KNN (purple). Under extreme rain events (600–800 mm), the Random Forest model (green) closely follows actual values (red), while the MLR model (blue) greatly underestimates, the Decision Tree model (orange) sometimes replicates accuracy but has multiple misses, and the KNN model (purple) scatters over the true values. For moderate rainfall (200–400 mm), all models perform very well, with Random Forest and MLR being equally good and Decision Tree and KNN less consistent. Under dry conditions (0–100 mm), MLR may consistently overestimate, Random Forest should be very accurate, and KNN predictions will tend to cluster around the recent ones. Random Forest would be the optimal estimator for Khulna's complex rainfall. The very high frequency of events leads decision trees and KNN to underestimate them, implying model flaws in volatile situations. The random forest model is outlier-resistant as it uses ensemble averaging, and automatic feature selection helps to ignore noisy predictors.

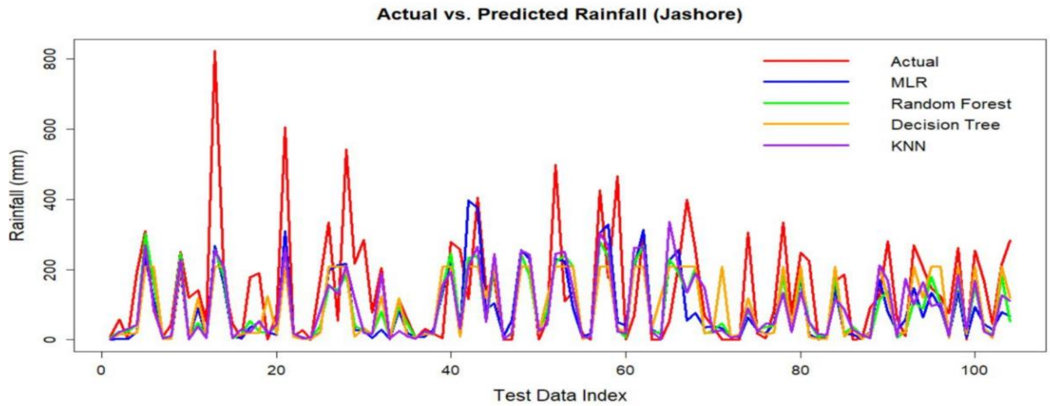

Figure 5: Comparison of Actual vs. Predicted Rainfall in Jashore Using Different ML Algorithm

The figure-5 compares actual rainfall measurements against predictions from four machine learning models in Jashore, Bangladesh. Actual rainfall reaches extreme values near 800 mm, while MLR (blue line) tends to over predict peak events in the 400–800 mm range, and Random Forest (green line) smooth's these extremes but to a lesser extent. At the maximum rainfall events (600–800 mm), the Random Forest model (green) tracks actuals (red) most closely, while MLR (blue) substantially underestimates rainfall. The Decision Tree model (orange) occasionally catches up with reality but frequently falls behind, while KNN (purple) comes wildly past actuals. On the other hand, with moderate rainfall (200–400 mm), all models perform well, with Random Forest and MLR showing similar accuracy, while Decision Tree and KNN are less consistent. Under dry conditions (0–100 mm), MLR tends to overestimate, Random Forest remains precise, and KNN clusters predictions near recent data. Random Forest is the best model for predicting rainfall in Jashore because it can handle unusual data well and ignore irrelevant information, while Decision Tree and KNN have trouble with changes in the data. The predicted rainfall values follow a clear pattern, but the actual rainfall does not show a consistent sequential trend. This is because these two regions occasionally experience extreme weather events such as hurricanes and tornadoes. Khulna is affected by heavy rainfall more frequently than Jashore due to these conditions. Feature importance was assessed using model-specific approaches. In MLR, coefficients and significance levels were used to interpret variable influence. For Random Forest and Decision Tree models, importance was based on how much each feature reduced prediction error and contributed to splits. In KNN, the impact of each variable was evaluated by observing changes in prediction accuracy when features were included or removed.

Table 2: Model Performance for Rainfall Prediction

Station	Model	RMSE	MAE	R-square
Khulna	Multiple Linear Regression	1.288	1.03	0.632
	Random Forest	**1.124**	**0.855**	**0.721**
	Decision Tree	1.291	0.96	0.638
	KNN	1.176	0.873	0.694
Jashore	Multiple Linear Regression	1.612	1.262	0.373
	Random Forest	**1.568**	**1.23**	**0.397**
	Decision Tree	1.792	1.352	0.271
	KNN	1.581	1.231	0.391

4.2 Model Validation

The model performance was quantified using three statistical metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). The table-2 shows the performance of four different machine learning models test data—Multiple Linear Regression (MLR), Random Forest, Decision Tree, and K-Nearest Neighbors (KNN)—used for rainfall prediction at two stations: Khulna and Jashore. Random Forest on the Khulna station has the minimum RMSE (1.124) and MAE (0.855) and maximum R^2 value (0.721). The KNN model follows with an RMSE of 1.176, MAE of 0.873, and R^2 of 0.694. Decision Tree and MLR models possessed comparable values for R^2 with 0.638 and 0.632, respectively, with higher error metrics compared to Random Forest and KNN.

These results indicate that Random Forest is highly able to explain intricate patterns in the rainfall data and accounts for about 72.1% of the variability in the observed values. At the Jashore station, Random Forest has the lowest RMSE of 1.568, MAE of 1.230, and R^2 of 0.397. KNN produced the same findings (RMSE = 1.581, MAE = 1.231, $R^2 = 0.391$) and MLR provided an R^2 of 0.373. The poorest among them was the Decision Tree model with the highest RMSE (1.792), highest MAE (1.352), and lowest R^2 (0.271). Although the finding provides a better fit compared to the other models, the R^2 value reveals that the model accounts for less than 40% of rainfall variation. A 5-fold cross-validation technique was applied to evaluate model performance. In this method, the dataset was divided into five equal subsets. Each subset was used once as a test set while the remaining four subsets were used for training. The process was repeated five times. The models produced consistent results across all folds, indicating stability and reliability in the predictions.

The model accuracy is comparatively higher at Khulna than Jashore, which means that the rainfall prediction at Khulna is more stable and consistent regardless of various algorithms. The results also demonstrate that the performance of the models is not identical at various stations but is instead greater at Khulna.

5. Conclusion and Recommendation

This study provides a comparative evaluation of machine learning models for rainfall forecasting in southwestern Bangladesh's Khulna and Jashore districts from long-term climatic records (1980–2023). The results indicate that rainfall in both districts exhibits strong seasonal variation, with the majority of the rainfall occurring during the monsoon season (June–September). Spatial and temporal patterns of precipitation are very different in the two regions. Khulna, being close to the Bay of Bengal, experiences higher and more variable rainfall, particularly in extreme events such as cyclones. This variability is evident in the frequent spikes in rainfall observed in major flood years like 1988, 1998, and 2020. On the other hand, Jashore has a more consistent but lower rainfall distribution, making it more susceptible to prolonged dry spells. The increasing irregularity in rainfall patterns since the 1990s in both districts suggests an intensifying influence of climate change.

Random Forest is consistently the top performer at both stations, Khulna and Jashore district based on model evaluation criteria. These findings indicate that rainfall prediction in Khulna is more stable and reliable, likely due to stronger seasonal signals and climatic influences from the nearby coast. The performance of the models in Khulna is ranked as follows: In Khulna, the ranking of models is as follows: Random Forest > KNN > Decision Tree > MLR. In Jashore, the ranking is: Random Forest ≈ KNN > MLR > Decision Tree. The results of this study can be utilized for the development of localized climate adaptation policies, early warning systems, and sustainable water resource management planning in Bangladesh's vulnerable regions. Future work must involve the integration of deep learning architectures with spatial databases to further advance generalizability and accuracy of rain forecasts.

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