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ARTICLE

Comparative Analysis of Traditional and Machine Learning Models for Rainfall Forecasting in Barishal District of Bangladesh

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ABSTRACT

Rainfall prediction is crucial for agricultural planning and water resource management, as Bangladesh's agriculture heavily depends on rainfed irrigation. Existing forecasting models are complex and costly, both budgetarily and computationally. As a result, our study evaluates the comparative performance of forecasting models, comprising two traditional time series models (Exponential Smoothing (ES) and Seasonal Autoregressive Integrated Moving Average (SARIMA)), and one machine learning model (Long Short-Term Memory (LSTM)). The monthly rainfall data for Barishal, Bangladesh, spanning the period from 1970 to 2022, were obtained from the Bangladesh Meteorological Department. The models' performance was assessed using root mean square error (RMSE), mean absolute error (MAE), correlation coefficient (R), Nash-Sutcliffe efficiency coefficient (NSEC), and Kling-Gupta Efficiency (KGE). The ES and SARIMA models perform closely. With RMSE, MAE, R, NSEC, and KGE values of 109.35, 73.60, 0.79, 0.62, and 0.74, respectively, the ES model performs better than the SARIMA model. On the other hand, the machine learning model LSTM struggled with the test data, resulting in a higher RMSE (150.34), MAE (100.95), and lower R (0.60), NSEC (0.27), and KGE (0.60) values. This indicates that for the small dataset, the LSTM machine learning model is less effective. Therefore, our suggestion is to use a statistical model, especially the ES model, to forecast monthly rainfall in the Barishal division, as it is effective and computationally efficient. These findings are beneficial for policy development, the pesticide industry, tourism, event management, water conservation, and predicting floods and droughts.

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Keywords: Time Series Analysis; Exponential Smoothing; ARIMA; SARIMA; LSTM

1. Introduction

Rainfall is one of the most significant meteorological variables, which is used for the prediction of floods and monitoring pollutant concentration [1,2]. Also, the prediction of rainfall is a significant concern globally due to its impact on various economic sectors, including agriculture, fishing, tourism, infrastructure, and water resource management [3–7]. The forecasting of rainfall is challenging because of the dynamic behavior and complex patterns [8].

Bangladesh is an agricultural country. Rice, wheat, maize, and barley are the main cereals grown here, while jute, tobacco, sugarcane, cotton, and tea are the key cash crops [9]. Accurate rainfall forecasting is crucial, as it significantly impacts agricultural productivity. Adequate rainfall can serve as an alternative to irrigation, influencing the yield of crops like sugarcane, rainfed rice, and boro rice [10–13]. Conversely, untimely rains can reduce the effectiveness of insecticides, leading to decreased agricultural output. Rainfall in Bangladesh varies by season and location. The country experiences four distinct seasons: a warm winter from December to February, a hot pre-monsoon summer from March to May, a rainy season from June to September, and an autumnal post-monsoon period from October to November [14]. Therefore, predicting accurate rainfall will be handy in various ways.

Various methods are used to predict rainfall. The ARIMA model is a widely used method for forecasting the rainfall data in different regions of the world [15–18], while multiple linear regression was applied to predict monthly rainfall in Assam [19]. The comparative analysis of ARIMA and ANN was used for forecasting the rainfall in Hyderabad, India [20]. Traditional statistical and physically-based models have long been the standard for weather prediction, but they face several inherent limitations that constrain their effectiveness in modern applications. Conventional statistical models can be computationally intensive and costly to implement, both in terms of processing power and budget [1]. The relationships governing rainfall are fundamentally non-linear. This makes it difficult for conventional linear models, such as Autoregressive Integrated Moving Average (ARIMA) and its seasonal variant SARIMA, to accurately capture the dynamics of precipitation [1,21]. Physically-based models demand a profound understanding of the water cycle and require detailed geophysical data, such as soil profiles and land use characteristics. This information is often laborious to collect and may be unavailable for many regions [21].

In contrast, data-driven machine learning techniques have emerged as a powerful alternative, overcoming many of the drawbacks of traditional methods. ML models excel at identifying and learning complex, non-linear relationships directly from historical data without requiring explicit programming of the physical processes involved. This makes them more flexible and often less expensive to develop and deploy, as they do not necessitate deep, a priori knowledge of the underlying hydrological system [1,21]. The demonstrated superiority of ML in handling the stochastic and dynamic nature of weather data has led to extensive research into various model architectures to further refine forecasting accuracy. In recent times, machine learning and deep learning methods are widely used by researchers to predict rainfall using different algorithms such as feedforward neural networks, recurrent neural networks, long short-term memory (LSTM), gradient boosting, extreme gradient boosting, and linear support vector regressor [1,22–24]. The core strength of Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, lies in their inherent ability to process sequential data. By maintaining an internal state or "memory," they can learn from past observations and identify long-term dependencies, making them exceptionally well-suited for time-series forecasting tasks [1,25]. However, their practical performance varies significantly based on the specific application and dataset characteristics. In a study forecasting hourly rainfall across five UK cities, models based on LSTM, Stacked-LSTM, and Bidirectional-LSTM networks demonstrated the best performance, outperforming both a robust XGBoost model and an AutoML-generated ensemble. Notably, the top-performing architectures were a Stacked-LSTM with two hidden layers and a Bidirectional-LSTM, suggesting that excessive model complexity is not always beneficial [1]. In contrast, a study of four Jordanian cities found that a standard RNN model outperformed both

LSTM and a hybrid CNN-RNN. This outcome highlights the importance of matching model complexity to data characteristics. The researchers reasoned that because the data was recorded hourly, the long-term dependencies that the LSTM leverages may be less salient or insufficient to enhance its performance. The RNN's simpler architecture was better aligned with the short-to-medium term patterns in the data [25]. For a data-scarce basin in Kenya, an LSTM model marginally outperformed a Wavelet Neural Network (WNN) for both rainfall and runoff prediction, showcasing its utility even when data is limited [26]. Thus, the application of machine learning (ML) and deep learning (DL) has fundamentally advanced the field of rainfall and hydrological forecasting, establishing a new state-of-the-art. A comprehensive review of recent studies indicates that deep learning models—specifically Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN)—consistently outperform traditional statistical methods like ARIMA and SARIMA in accuracy and their ability to model complex, non-linear systems [21]. However, there is no universally superior model; performance is highly context-dependent and varies significantly with geographical location, climate type, and data characteristics [1,25]. A critical, cross-cutting finding is that multivariate models, which incorporate a range of meteorological variables such as temperature, humidity, and wind speed, are demonstrably more effective than univariate approaches that rely solely on past rainfall data [25,27]. Despite these advancements, persistent challenges remain, including poor model generalization to new data, difficulty in accurately predicting extreme weather events, and a tendency for systematic underestimation of total precipitation [1,28].

In Bangladesh, several studies have focused on rainfall prediction. Global climate models were used to predict rainfall during the Rabi and Kharif-II seasons [29,30]. For the Dhaka and Sylhet divisions, the ARIMA model has been used to forecast the precipitation [31,32]. Historical data from Barishal for the period 1961–2019 shows a clear warming trend, with the yearly average maximum temperature increasing at a rate of 0.0055 ºC/year and the minimum at 0.0087 ºC/year. During the same period, annual total rainfall in the region showed a declining trend of −0.18488 mm/year, while relative humidity rose sharply [33]. Future projections for the mid-century (2040–2060), derived from ensembles of Global Climate Models (GCMs), forecast continued and significant changes, particularly in rainfall patterns. During the Kharif-II season (Mid-July to Mid-October), precipitation is expected to increase in July, September, and October, but may decrease in August. Similarly, during the Rabi season (January to April), precipitation is projected to increase from January through March but decrease in April compared to the 2010–2018 baseline [29,30]. Regional disparities are pronounced. The Mymensingh and Sylhet divisions are projected to experience dramatic increases in precipitation during the Kharif-II season, while the north-eastern region (Sylhet) consistently shows the highest rainfall and the western region (Rajshahi) the lowest during the Rabi season. These regional variations underscore the need for localized adaptation strategies. Statistical forecasting tools, such as the Autoregressive Integrated Moving Average (ARIMA) model, have proven effective for predicting monthly rainfall in urban centers like Dhaka and Sylhet, providing valuable data for water resource management, urban planning, and flood mitigation [31,32]. The combined findings confirm Bangladesh's high vulnerability to climate change and highlight the critical importance of these projections for safeguarding agriculture, ensuring food security, and managing natural disaster risks.

To the best of our knowledge, there is no comparative study of statistical and machine learning algorithms used to forecast rainfall in the Barishal region. The accurate rainfall forecasting plays a critical role for regions like Barishal, where agriculture, water resource management, and disaster preparedness are directly affected by climatic variability. Monthly rainfall prediction is essential for planning and mitigating adverse impacts of droughts, floods, and irregular rainfall patterns. The presence of strong additive seasonality in the available historical rainfall data necessitates methodological approaches that can effectively capture periodic fluctuations and enhance medium-term predictive accuracy. By comparing the performance of Exponential Smoothing, SARIMA, and LSTM models, this study aims not only to identify suitable forecasting tools tailored to the unique seasonal properties of Barishal's rainfall but also to highlight the strengths and limitations of classical statistical models versus emerging deep learning approaches in real-world, data-constrained scenarios. Furthermore, the study provides actionable insights for local authorities and stakeholders by revealing the practical reliability and diagnostic transparency of interpretable models, while critically examining the potential and requirements of more advanced neural networks. This approach ensures that the research addresses both methodological advancement and practical utility, justifying its relevance for improved climate adaptation, agricultural planning, and resource optimization in the Barishal region.

2. Materials and Methods

2.1. Data Sources and Data Preprocessing

The monthly rainfall data used in this study were obtained from the Bangladesh Meteorological Department (BMD) for the Barishal station, representing ground-based gauge observations following WMO standards. The dataset provides continuous monthly records for the period 1970–2022, with no major gaps in observation. Measurement accuracy is ±0.1 mm according to BMD specifications. Prior to analysis, the dataset was checked for missing values, outliers, and temporal consistency. Outliers were validated using BMD reports to distinguish extreme events from erroneous measurements. No missing data were present. The final quality-controlled dataset was used for model development. The dataset was divided into two parts: training data and testing data. The training part consists of 80 percent of our total datasets, and the testing part consists of 20 percent of our total datasets. After dividing our data into two parts, we fit a model on the training data and forecast for the next 20 percent of the dataset.

2.2. Exponential Smoothing (ES) Model

ES is a well-known time series forecasting model. It assumes that future patterns will be similar to the recent past data. The mathematical formula of simple exponential smoothing is given in Equation (1):

$$\widehat{y}_{t+h|t} = \alpha y_t + (1-\alpha) l_{t-1} \tag{1}$$

where l_t is the level of the series at time t, α is the smoothing parameter[34]. Holt and Winters extended the exponential method to capture seasonality[35,36]. Hyndman et al. suggest 24 variations of the exponential smoothing model[37]. Since the data are monthly and exhibit consistent seasonality across time, we used the Holt–Winters additive ES model with a seasonal period of 12 to capture monthly seasonality.

2.3. (Seasonal) Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is also called Box–Jenkins's methodology, which comprises four steps: model identification, estimation, validation, and forecasting[38]. A seasonal ARIMA (SARIMA) model is formed by including additional seasonal terms in the ARIMA model. It can be written as $SARIMA\ (p,\ d,\ q)\ \ (P,\ D,\ Q)_m$, where ($p$, d, q) represent the non-seasonal autoregressive, differencing, and moving average orders and (P, D, Q) the seasonal autoregressive, differencing, and moving average orders of the model, and m is the seasonal period. The formula of $SARIMA\ (p,\ d,\ q)\ (P,\ D,\ Q)_m$ model is given in Equation (2):

$$\begin{gathered}\left(1-\ \phi_1 B - \ldots -\ \phi_p B^p\right)\left(1-\Phi_1 B^m -\ \Phi_P B^{Pm}\right) \\ (1-B)^d\left(1-B^m\right)^D y_t = c+ \\ \left(1+\ \theta_1 B + \theta_2 B \ldots +\ \theta_q B^q\right) \\ \left(1+\Theta B^m + \ldots +\ \theta_Q B^{Qm}\right)\epsilon_t\end{gathered} \tag{2}$$

where B is the backshift notation, $\phi,\ \ \Phi,\ \ \theta$, and Θ are the parameters of the model. We used the autocorrelation function (ACF) and partial autocorrelation function (PACF) to determine the order of the SARIMA model[39]. The final model was selected based on the lowest AIC value, and parameters were estimated using maximum likelihood. Residual diagnostics were performed to ensure normality, absence of autocorrelation, and homoscedasticity before producing the final forecasts.

2.4. Long-Short Term Memory (LSTM)

The LSTM model is a very popular model for time series forecasting and was proposed by Hochreiter and Schmidhuber in 1997[40]. It consists of a cell, and three gates—forget gate, input gate, and output gate—which can handle the vanishing gradient problem and give more control over the context. The equation for forget, input, and output gate are given in Equations (3)–(5):

$$f_t = \sigma\left(W_f.\left\{h_{t-1},\ x_t\right\} + b_f\right) \tag{3}$$

$$i_t = \sigma\left(W_i.\left\{h_{t-1},\ x_t\right\} + b_i\right) \tag{4}$$

$$o_t = \sigma\left(W_o.\left\{h_{t-1},\ x_t\right\} + b_o\right) \tag{5}$$

where W represents the weight matrix associated with gate, $\{h_{t-1,}x_t\}$ denotes the concatenation of the current input and the previous hidden state, b represents bias with the gate, and σ is the sigmoid activation function. The details can be found in the given references[41–45].

In the LSTM model, normalization is required because it performs the best when input values are within a small, consistent range due to the use of activation functions such as tanh and sigmoid. In our study, minimax normalization was applied using the formula (6). In our LSTM model, we normalize the entire training and testing data, but before calculating accuracy metrics, we transform the data into its original form.

$$X_{sclaled} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{6}$$

In order to define model, we use a sequential constructor. The model consists of a single visible layer with 64 LSTM neurons and one output dense layer. We use the Adam optimizer with a learning rate of 0.01 and the loss function as the mean square error to compile the model. In the model fitting procedure, we use 300 epochs. An epoch refers to one complete pass through the entire training dataset during the training process of a machine learning model. Also, we use a batch size equal to 32. The batch size refers to the number of training examples utilized in one iteration (or step) of the training process. We set verbose equal to 0 to hide the progress in the animated bar. After we fit the model, we make predictions for training and testing data. Then we calculate the root mean square error for the training and test data.

2.5. Model Selection Criteria

To select the best model among the set of models, we use Akaike's Information Criterion (AIC). To compare the performance of ES, SARIMA, and LSTM model we use Root Mean Square Error (RMSE), mean absolute error, correlation coefficient, Nash–Sutcliffe efficiency coefficient, and Kling–Gupta Efficiency.

2.5.1. Akaike's Information Criterion (AIC)

In AIC, we impose a penalty for adding regressors to the model, which has been carried further in the AIC criterion, which is defined as: $AIC = 2k - 2\ln\left(\widehat{L}\right)$. Where k is the number of estimated parameters in the model and $\widehat{L}$ is the maximized value of the likelihood function.

2.5.2. Root Mean Square Error (RMSE)

The error is the difference between the observed value and the predicted value. The square of this error is called the square error, and the mean of this square error is called the mean square error. After taking the square root of the mean square error, we get RMSE. The formula for RMSE is given in Equation (7):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2} \tag{7}$$

Where, n is the number of observations in the model, y_i are the observed values, $\widehat{y_i}$ are the predicted values.

2.5.3. Mean Absolute Error (MAE)

Mean absolute error is the sum of the absolute errors divided by the total number of observations. The formula for MAE is given in Equation (8).

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \widehat{y_i}|}{n} \tag{8}$$

Where, n is the number of observations in the model, y_i are the observed values, $\widehat{y_i}$ are the predicted values.

2.5.4. Correlation Coefficient R

In our study, we showed the relationship between observed values and predicted values. The formula for the correlation coefficient is given in Equation (9).

$$R = \frac{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)\left(\widehat{y_i} - \overline{\widehat{y_i}}\right)}{\sqrt{\left(y_i - \overline{y}\right)^2}\sqrt{\left(y_i - \overline{\widehat{y_i}}\right)^2}} \tag{9}$$

Where, n is the number of observations in the model, y_i are the observed values, $\widehat{y_i}$ are the predicted values, $\overline{y}$ is the mean of observed values, and $\overline{\widehat{y_i}}$ is the mean of predicted values.

2.5.5. Nash-Sutcliffe Efficiency Coefficient (NSEC)

NSCE proposed by Nash and Sutcliffe is used to measure how well the predicted values match the exact values[46]. The formula for NSCE is given in Equation (10).

$$NSEC = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2} \tag{10}$$

Where, y_i are the observed values, $\widehat{y_i}$ are the predicted values, and $\overline{y}$ is the mean of observed values.

2.5.6. Kling-Gupta Efficiency (KGE)

The KGE model is used to measure the prediction efficiency [47]. The formula is given in Equation (11).

$$KGE = 1 - \sqrt{(R-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \quad (11)$$

Where R is the correlation coefficient, α is a variability of prediction errors, and β is the bias term.

2.6. Software and Programming Language

In our study, to analyze our data, we used Python 3.10.12. Also, the Google Colaboratory and the Jupyter notebook from the Anaconda distribution integrated development environment (IDE) were used. To make our work easier and more efficient, we use different Python libraries such as numpy, pandas, math, datetime, matplotlib, statsmodels, sklearn, tensorflow, keras, etc.

3. Results

Here, we use Exponential Smoothing, SARIMA, and LSTM to forecast the monthly rainfall of the Barishal region. To analyze our data, we use the Python programming language.

3.1. Result Analysis of Exponential Smoothing (ES) Model

Figure 1 shows the training and testing data for the rainfall variable. From the graph, we can see that rainfall is at its maximum in the middle of the year and at its minimum at the end of the year. It's repeated every year. So, there is seasonality in the time-series variable rainfall. But there is no trend in the rainfall data. It is a sign of additive seasonality. Since our data shows seasonality with no trend, we chose additive seasonality in the model fitting procedure. Also, our data is monthly, so we use a seasonality parameter equal to 12.

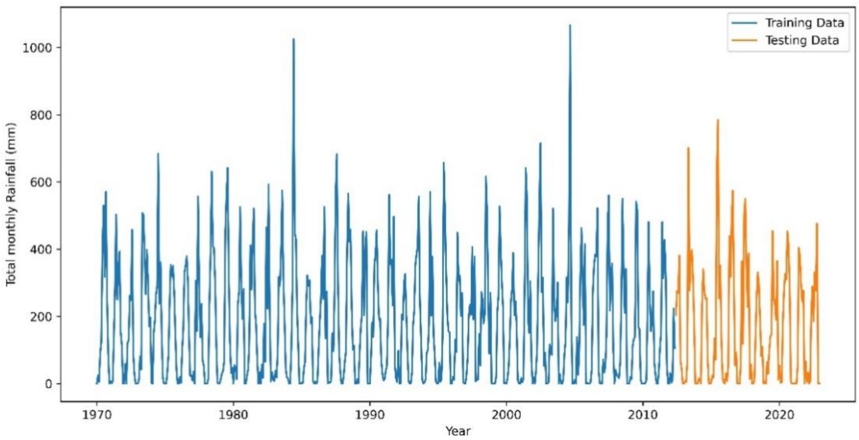

Figure 1. Rainfall training and testing data.

After that, we fit the exponential smoothing model with parameters seasonal equal, additive, and seasonal periods equal 12. Using this model, we forecast for the next 127 steps of rainfall data, which is the same as the test data length. Finally, we compare these forecasted values with the test data values and calculate the different accuracy metrics such as RMSE, MAE, R, NSEC, and KGE. **Figure 2** illustrates rainfall data alongside predicted values. The training data is depicted in blue, the testing data in orange, and forecasted values in green.

3.2. Result Analysis of SARIMA Model

3.2.1. Model Identification and Estimation of Parameter

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is an extension of the ARIMA model. It is used for time series forecasting and analysis, particularly when the data exhibits both trend and seasonality. **Figure 1** shows the rainfall in the Barishal region from 1970 to 2022. We used 80 percent of the data for model development and

20 percent of the data for validation purposes. Since our dataset shows seasonality, we take seasonal differences into account to make the data stationary. **Figure 3** shows the first seasonal difference in the rainfall.

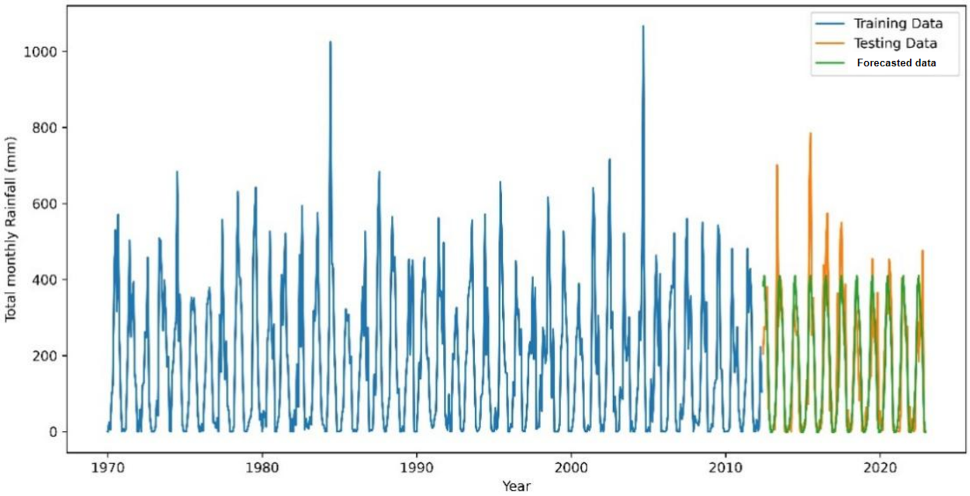

Figure 2. Train, test, and forecast values with the ES model.

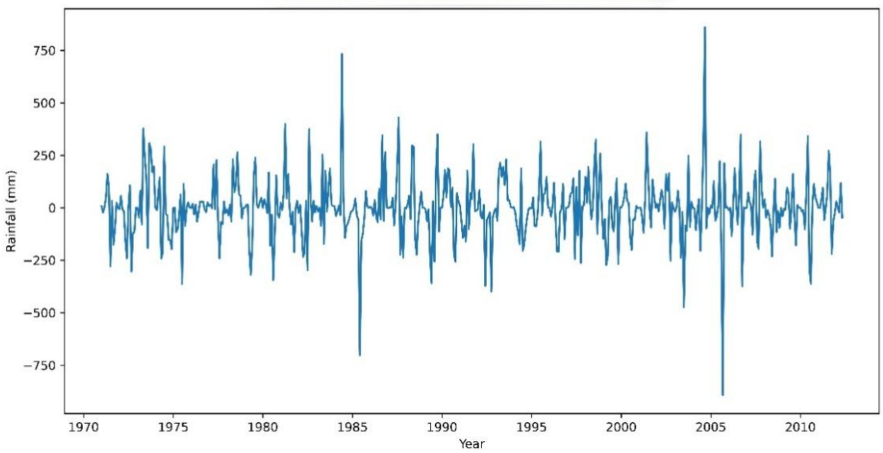

Figure 3. First-order seasonal difference of training data.

After taking into account the seasonal differences, the data does not repeat over the same time period. In order to determine the appropriate order for the SARIMA model, we can use autocorrelation and partial autocorrelation function plots. The PACF plot helps determine the autoregressive order, i.e., p and P, and the ACF plot helps determine the moving average order, i.e., q and Q. The ACF plot in **Figure 4** shows that one seasonal lag, i.e., 12, has significant spikes, which indicates Q = 1, and there are three significant spikes for non-seasonal lag that indicate q = 3. The PACF plot in **Figure 5** shows that more than four seasonal lags, i.e., 12, 24, 36..., have significant spikes, which indicates P = 0, and there are three significant spikes for non-seasonal lag that indicate p = 3. We use the seasonal difference once to make the time series stationary. It suggests D = 1. Therefore, the SARIMA model becomes: $SARIMA\ (3,\ 0,\ 3)(0,1,1)_{12}$. We use a maximum likelihood estimator in order to estimate the parameters of the SARIMA model. **Table 1** shows the estimated parameters.

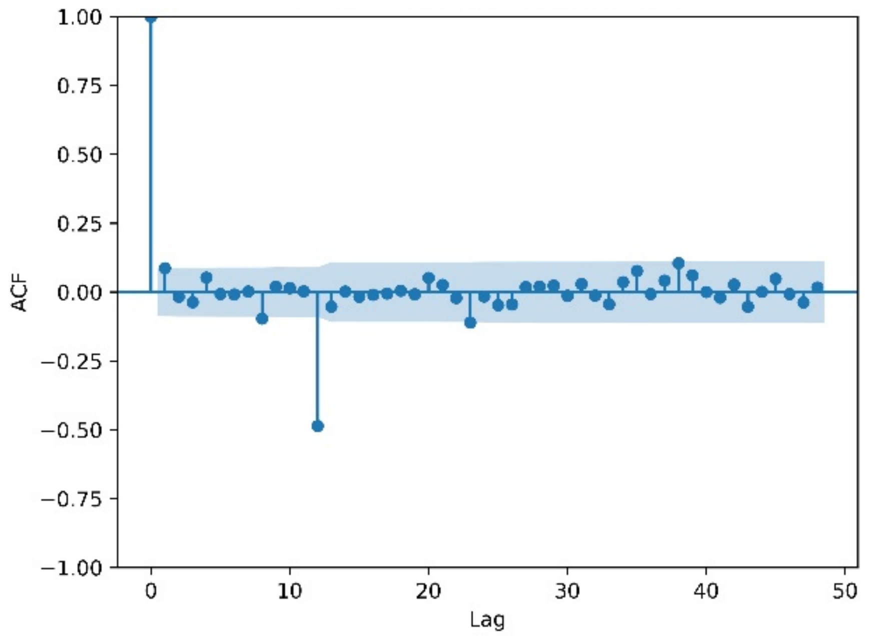

Figure 4. ACF for 1st seasonal difference.

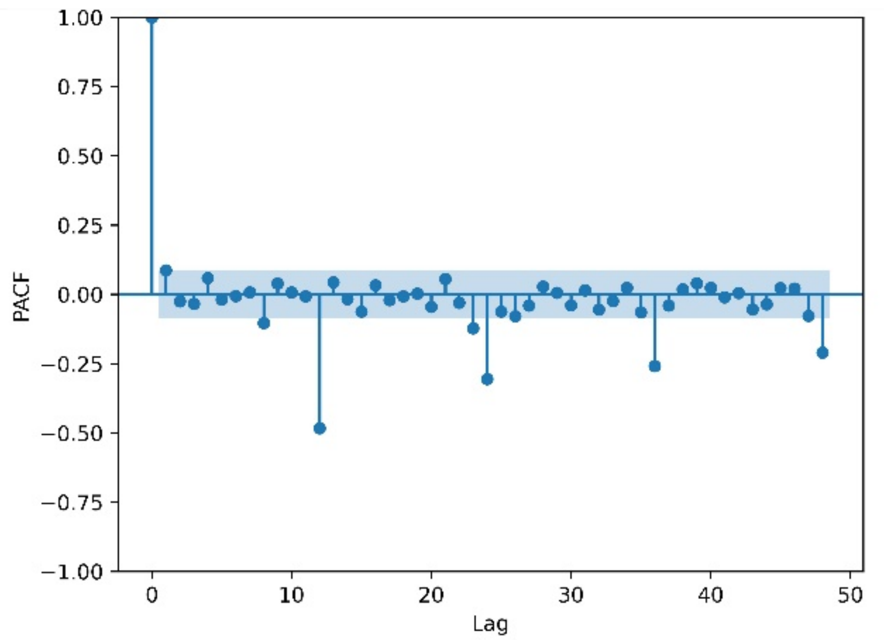

Figure 5. PACF for 1st seasonal difference.

Table 1. SARIMA model estimated parameter with standard error and *p*-value.

Parameters	Coefficient	Std Error	*p*-Value
AR (1)	−0.9966	2.452	0.684
AR (2)	0.9988	4.912	0.839
AR (3)	0.9978	2.464	0.685
MA (1)	−0.9971	3.356	0.766
MA (2)	−0.9989	6.819	0.884
MA (3)	−0.9980	3.468	0.774
Seasonal MA (1)	−0.9997	1.719	0.561

3.2.2. Diagnostic Checking

To determine whether the model accurately represents the pattern of the underlying data, we must assess the model's performance. A well-fitted model's residuals should be normally distributed in the absence of autocorrelation and heteroscedasticity. In order to determine it, we illustrate the residual plot in **Figure 6**, where the histogram in the top right position looks like a normal distribution. Also, the normal Q-Q plot looks like a straight line, which is a sign of residual normality. On the other hand, the bottom right position of **Figure 6** is ACF, and all the spikes inside the significance line indicate the absence of autocorrelation. Standardized residuals in the top left of **Figure 6** are scattered around the ideal line, which indicate homoscedasticity. Since the residuals of our model show normality and the absence of autocorrelation and heteroscedasticity, we can forecast using this model.

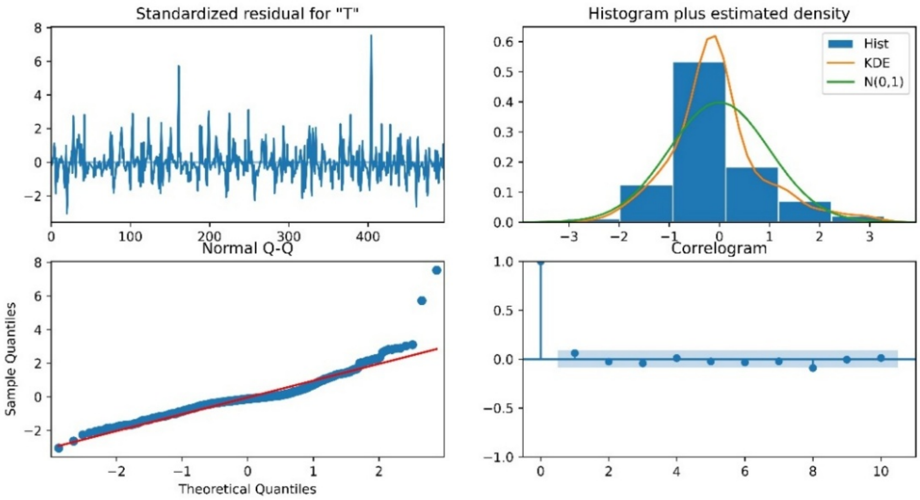

Figure 6. First-order seasonal difference of training data.

3.2.3. Forecasting

We forecast the data for the same length as the training data. Finally, we compare these forecasted values with the test data values and calculate the different accuracy metrics such as RMSE, MAE, R, NSEC, and KGE. **Figure 7** displays rainfall data with forecasted values. The training data is depicted in blue, the testing data in orange, and the forecasted values in green.

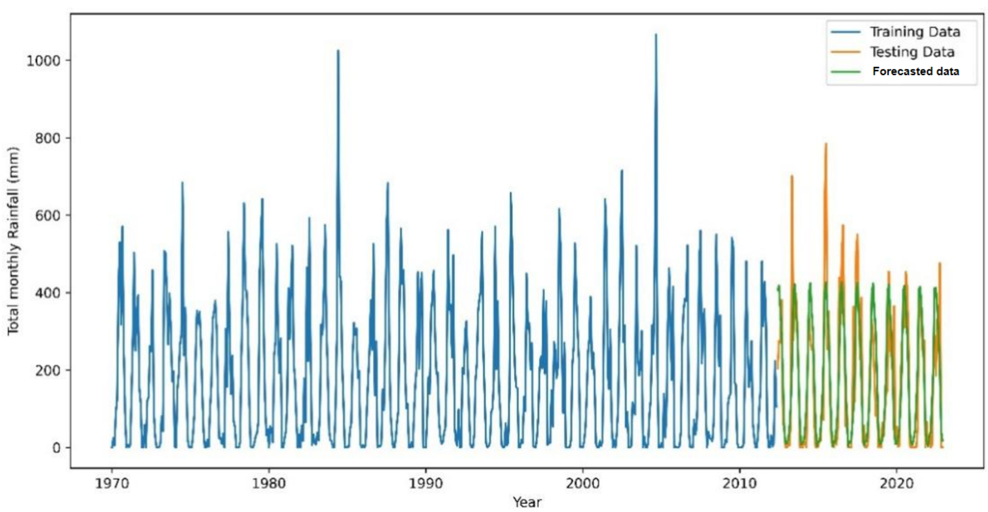

Figure 7. Train, test, and forecasted values with the SARIMA model.

3.3. Result Analysis of the LSTM Model

3.3.1. Data Preprocessing

We divide our dataset into two parts: the training part consists of 80 percent of our total datasets (509 observations), and the testing part consists of 20 percent of our total datasets (127 observations). Because of the small dataset size, no validation set was used for hyperparameter tuning, as has been done in several related studies [28,45]. The LSTM model requires special preprocessing of the data. LSTM requires a three-dimensional dataset, i.e., samples, time steps, and features. For the case of model building, we use samples equal to 509, timesteps equal to 12, and the number of features equal to 1. Also, LSTM is sensitive to the scaling of the dataset. We use the MinMax scalar to transform the values between 0 and 1.

3.3.2. LSTM Model Fit and Evaluation

These steps consist of defining, fitting, predicting, forecasting, and finally evaluating the model's performance. In our LSTM model, we define a sequential constructor with a visible layer of 64 LSTM neurons and one output dense layer. After that, we fit the model and forecast for the testing data. To evaluate the performance of the model, we calculate the evaluation metrics RMSE, MAE, R, NSEC, and KGE. The values for these metrices are represented in the **Table 2** and the values are 150.34, 100.95, 0.60, 0.27, and 0.60, respectively. **Figure 8** depicts the forecasted values along with training and testing data. The blue line represents the training data, the line in orange represents the testing data, and the green line indicates forecasted values. Due to the use of a 12-month time stamp, the forecasted series begins after the first 12 months of the testing period.

Table 2. Accuracy metrices for ES, SARIMA, and LSTM models.

Model	RMSE	MAE	R	NSEC	KGE
ES	109.35	73.60	0.79	0.62	0.74
SARIMA	109.49	73.69	0.79	0.62	0.74
LSTM	150.34	100.95	0.60	0.27	0.60

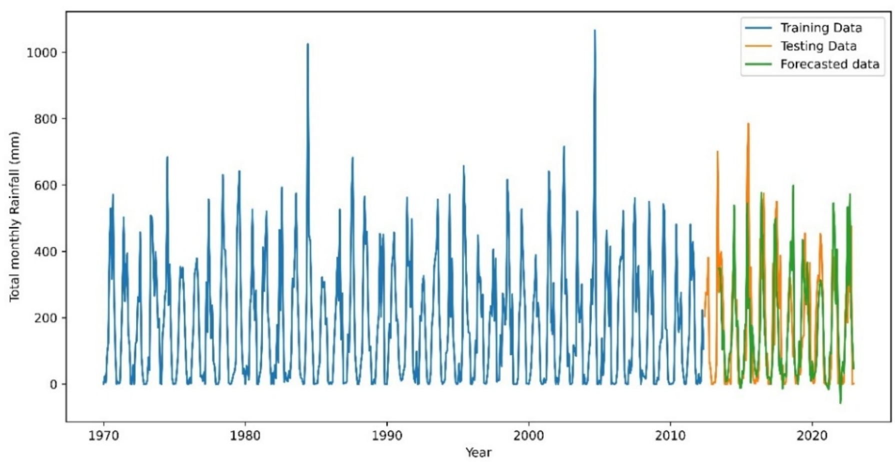

Figure 8. Train, test, and predict train and test values with LSTM model.

4. Discussion

The current analysis evaluates the forecasting performance of three models—Exponential Smoothing, SARIMA, and LSTM—for predicting monthly rainfall in the Barishal region. The evaluation metrics (RMSE, MAE, R, NSEC, and KGE) suggest that classical statistical models outperform deep learning models in this study. The Exponential Smoothing model achieved the lowest forecast error, as measured by an RMSE of 109.35 and an MAE of 73.60. The SARIMA model, benefiting from the inclusion of seasonal and non-seasonal autoregressive and moving average terms, produced a nearly similar RMSE of 109.49 and MAE of 73.69. This result suggests that ES and SARIMA effectively captured the seasonal behavior and overall temporal pattern. Also, in literature, it is found that statistical models are really useful to predict the temperature [15,18,31].

The LSTM neural network, which requires more complex data preparation and is sensitive to feature scaling, produced a higher RMSE (150.34), MAE (100.95), and lower R (0.60), NSEC (0.27), and KGE (0.60), indicating potential overfitting and the need for larger datasets or more advanced tuning. For our dataset, the statistical model performs better than the machine learning method, but many studies found that machine learning algorithms perform better in terms of predicting rainfall [43,45]. The superior performance of the ES model can be explained by its stable additive seasonality. The Holt–Winters additive formulation explicitly decomposes the time series into level and seasonal components, enabling it to efficiently capture recurring monsoon-driven rainfall patterns with relatively constant amplitude over time. Because of the absence of a strong long-term trend and the dominance of seasonal variation, the ES model provides an effective representation of the underlying data-generating process. Its reliance on a limited number of parameters reduces the risk of overfitting, making it particularly robust in data-constrained environments.

Similarly, the SARIMA model demonstrates reliable forecasting performance due to its stochastic structure and well-established diagnostic framework. By incorporating both seasonal and non-seasonal autoregressive and moving average components, SARIMA effectively models serial dependence and seasonal persistence inherent in rainfall time series. An important advantage of SARIMA lies in its diagnostic transparency, allowing for systematic verification of model assumptions through residual analysis. The confirmation of residual normality, homoscedasticity, and absence of autocorrelation in this study indicates that the model adequately captures the temporal dynamics of rainfall variability, thereby supporting the reliability of forecasting.

In contrast, the Long Short-Term Memory (LSTM) model exhibits inferior performance in this application, primarily due to its high data requirements and sensitivity to sample size. Although LSTM networks are capable of learning complex non-linear relationships and long-term dependencies, their effectiveness is contingent upon the availability of large and information-rich datasets. The univariate monthly rainfall series used in this study provides limited training samples, increasing the likelihood of overfitting and reducing generalization capability. Furthermore, unlike classical statistical models, LSTM does not inherently encode seasonal structure, requiring either extensive data, architectural modifications, or additional explanatory variables to adequately capture periodic behavior. Consequently, under the constraints of limited data and the absence of exogenous predictors, the LSTM model fails to outperform simpler statistical approaches.

A limitation shared by all models is the absence of exogenous predictors such as climate indices or meteorological measurements, which could provide a richer context and improve forecast accuracy, particularly for extreme events. One can extend the study by expanding the dataset, integrating exogenous variables such as temperature, relative humidity, wind speed, and spatial rainfall interactions, and exploring ensemble or hybrid modeling approaches, which could substantially enhance the reliability and applicability of forecasts. Additionally, adapting model evaluation methods to prioritize practical needs—such as warning for flood risks, rather than just reducing average error—would make future research even more meaningful to local stakeholders and disaster risk management efforts. Overall, while classical statistical approaches remain robust and interpretable for this rainfall forecasting task, the adoption of advanced deep learning models, such as LSTM, warrants further investigation, given adequate data and methodological enhancements.

5. Conclusions

The comparative analysis of ES, SARIMA, and LSTM models for monthly rainfall forecasting in Barishal reveals that both classical statistical approaches—ES and SARIMA—are highly effective in capturing the underlying seasonal patterns found in the rainfall data. The RMSE values obtained (around 109 for both models on the test set) demonstrate their strong predictive ability and suitability for regional applications. SARIMA's strength lies not only in its performance but also in its diagnostic clarity, as its residuals exhibit normal distribution, homoscedasticity, and a lack of autocorrelation, ensuring its forecasts are unbiased and reliable. On the other hand, the LSTM neural network, while demonstrating the capacity for complex pattern recognition and yielding very low error on the training data, struggled with generalization, as evidenced by its higher test RMSE (150.34). This suggests that advanced deep learning models may require larger datasets, more features, and sophisticated tuning to outperform classical methods in this context.

Importantly, all models were limited by the absence of exogenous variables; the inclusion of climate indices or meteorological observations could potentially enhance forecast accuracy and practical relevance, especially for extreme events. The reliance on RMSE as the sole metric means the models' proficiency in detecting unusual rainfall events or anomalies is not fully evaluated. For future work, expanding the scope to include additional predictors, longer and richer time series, or hybrid model ensembles could improve forecast reliability and robustness. Moreover, tailoring evaluation metrics to reflect the practical needs of stakeholders—such as providing actionable flood warnings—can increase the societal value of these models.

Overall, for the Barishal region, SARIMA and Exponential Smoothing emerge as robust, interpretable, and accessible tools for monthly rainfall forecasting, while the promise of deep learning approaches remains contingent on addressing data and methodological challenges. The findings guide practitioners and policymakers in favoring classical approaches under current data constraints, while also encouraging ongoing innovation and methodological refinement to meet evolving climate forecasting demands.

Author Contributions

S.C., I.A. and M.S.U.R. conceived of the presented idea and developed the theory. S.C. performed the computations, while I.A. and M.S.U.R. verified the analytical methods and supervised the findings of this work. I.A. has collected the climatic data set. All authors discussed the results and contributed to the preparation of the final manuscript.

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All data and materials supporting the findings of this study are available from the corresponding author on request.

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Conflicts of Interest

The authors whose names are listed immediately below the title certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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