Machine-Learning–Based Forecasting of an Extreme Precipitation event over Bangladesh

Tahmidul Azom Sany[1], Torikul Islam Sanjid[2], Md Tashin Ahammad[3], Tanvir Ahmed[4*]

[1]George Mason University, Fairfax, Virginia, USA.
[2, 4] Department of Physics,Shahjalal University of Science and Technology, Sylhet 3114, Bangladesh.
[3]University of Maryland, Baltimore, USA.

*Corresponding Author's Email: tahmed-phy@sust.edu

Abstract

The increasing frequency of intense precipitation events in Bangladesh is intensifying both climatic and socioeconomic challenges. Recent 2022 flooding in the northeastern region, triggered by extreme precipitation, exemplifies the nation's heightened vulnerability to climateinduced disasters and their economic repercussions. Enhancing early warning systems for severe weather events is therefore essential to mitigate the associated risks and reduce potential losses. In recent years, Machine Learning (ML) techniques have gained prominence in climate forecasting owing to their computational efficiency and ability to capture complex nonlinear relationships among atmospheric variables. In this study, the forecasting capabilities of the Random Forest Classifier (RFC) and Artificial Neural Network (ANN) models have been evaluated for predicting extreme precipitation events over Bangladesh with a 24-hour lead time. The analysis also aimed to identify the most influential predictors exhibiting strong correlations with the target variable, next-day precipitation. The findings indicate that Geopotential Height at 1000 hPa, Mean Surface Direct Shortwave Radiation Flux, and Relative Humidity at 500 hPa and 800 hPa are the most significant predictors of next-day precipitation. Furthermore, the comparison of model performance demonstrates that both the RFC and ANN models yield comparable levels of predictive accuracy.

Keywords: Machine Learning; Extreme Precipitation; Artificial Neural Network; Random Forest Classifier.

Bangladesh, with a population of approximately 170 million, is widely recognized as one of the most climate-vulnerable countries in the world [1]. The country is exposed to a broad range of climate-induced hazards, including tropical cyclones and flash floods. In recent years, Bangladesh has been experiencing a noticeable increase in extreme precipitation events, which frequently trigger flash flooding and pose significant challenges to flood management, infrastructure resilience, and socio-economic stability [2]. Observational evidence indicates that the intensity of precipitation over shorter timescales has been rising, leading to more frequent occurrences of extreme precipitation and associated flash flooding [3]. Accurate prediction of extreme precipitation events in advance is therefore crucial for minimizing infrastructure damage and reducing loss of life.

Precipitation events are primarily predicted using Numerical Weather Prediction (NWP) models. These models simulate atmospheric processes based on the fundamental laws of physics and fluid dynamics to forecast various weather phenomena, including extreme precipitation events. In NWP, current atmospheric variables serve as initial conditions from which the models project the evolution of atmospheric states over the following days within a specified domain [4].

Despite several decades of progress in weather prediction—driven largely by advancements in computationally intensive NWP models and data assimilation techniques [5,6] state-of-the-art NWP systems continue to face significant challenges in accurately forecasting the onset and spatial extent of weather events. Moreover, these models demand substantial computational resources, which are often limited in developing countries such as Bangladesh. To overcome these constraints, researchers are increasingly exploring Machine Learning (ML) approaches, which offer greater computational efficiency compared to traditional NWP and promising performance in weather forecasting applications [7,8].

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Machine Learning (ML) methodologies have been employed in the fields of climate and weather prediction for several decades, fulfilling diverse roles such as post-processing of model outputs, data assimilation, and the interpretation of physical processes. In recent years, however, the application of ML has expanded toward direct weather forecasting, where it has shown considerable promise in enhancing predictive capability and efficiency [9]. Owing to their capacity to model complex and nonlinear relationships within large datasets, Machine Learning (ML) algorithms have been extensively employed for forecasting various climatic and meteorological variables [10,11]. These include extreme precipitation [6, 12], wind dynamics [13, 14] and evapotranspiration rates [15].

Recent advancements in Machine Learning (ML), particularly in deep learning architectures, have shown promising capabilities in forecasting persistent weather phenomena up to two weeks in advance [16]. Several studies have applied ML techniques to various aspects of weather prediction. For example, Espeholt et al. [17] introduced MetNet-2, a neural network capable of producing high-resolution precipitation forecasts up to 12 hours ahead, outperforming leading physics-based NWP models over the continental United States within the same forecast range. Similarly, Nunno et al. [18] proposed a hybrid M5P-SVM model that achieved skillful predictions with lead times of up to three months. In South Asia, K.R. Patil et al. [19] demonstrated that CNN model is highly skilled in predicting Indian summer monsoon nearly a year ago and also identifies the patterns of the extreme rainfall events realistically, while Islam et al. [20] utilized Convolutional Neural Networks-Extreme Gradient Boosting (CNN-XGB) hybrid model for the same region which showed superior performance compared to other models used in the study. Khan et al. [21] compared the predictive performance of Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANNs) for identifying extreme weather days in Pakistan, concluding that SVM yielded the highest predictive accuracy.

Most of these existing ML-based weather prediction studies have focused on specific regions with extensive historical datasets. However, due to data limitations, similar research has not been extensively conducted for Bangladesh. The increasing availability of high-resolution, open-source meteorological datasets such as ERA5 reanalysis data [22, 23] has now made it feasible to explore ML-based extreme precipitation forecasting in data-scarce regions. The objective of this study is to develop a data-driven Artificial Neural Network (ANN) and Random Forest Classifier (RFC) model to predict extreme precipitation occurrences across Bangladesh by utilizing the ERA5 reanalysis dataset. The ERA5 product has been widely employed in previous ML-based weather forecasting research owing to its capacity to represent complex and nonlinear relationships within high-dimensional meteorological data, effectively capturing both short-term variability and long-term climatic trends [23]. Another objective of this work is to evaluate the model performance for operational use, with the broader goal of enhancing future extreme precipitation prediction capabilities over Bangladesh.

2. Study area and data:

This study primarily focuses on Bangladesh, a South Asian country bordered by India to the north, east, and west, and by Myanmar to the southeast, with the Bay of Bengal forming its southern boundary. The nation covers an area of approximately 148,000 square kilometers.
Around 80% of the country consists of low-lying plains collectively known as the Bangladesh Plain [24]. Most of this terrain lies below 10 meters above mean sea level, although elevations in the northern part of the plain can reach up to about 105 meters (Fig.1). The reanalysis data

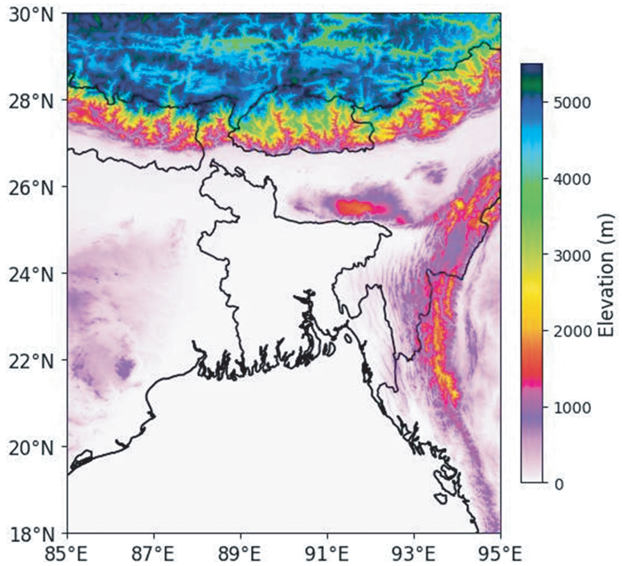

Figure 1: Topographic map of Bangladesh and its surrounding regions, with elevation represented in meters.

From the European Centre for Medium-Range Weather Forecasts (ECMWF) and Enhancing National Climate Services for Bangladesh Meteorological Department (ENACTS-BMD) dataset [25] is used in this study. The ENACTS-BMD dataset is a high resolution (0.05° × 0.05°) dailygridded precipitation data constructed by the Bangladesh Meteorology Department (BMD).

The ERA5 reanalysis data is available at hourly intervals from 1979 to 2021 at both single levels and pressure levels. The horizontal resolution of the data is 0.25° x 0.25°. While ENACTS-BMD precipitation data were utilized for precipitation climatology analysis in Section 3, the ERA5 reanalysis was employed for model training and prediction. ERA5 was selected for this purpose due to its comprehensive suite of high-resolution atmospheric variables, which is essential for the machine learning frameworks. The atmospheric variables used in this study from ERA5 and ENACTS-BMD have been presented in Table I with their sources. Table I. List of atmospheric variables, levels, and data sources utilized in the study

Atmospheric variable	Level	Source
Relative humidity	500, 800, 1000hPa	ERA5 Reanalysis
U wind	500, 800 hPa E	RA5 Reanalysis
V wind	500, 800 hPa	ERA5 Reanalysis
Geopotential	800, 1000 hPa	ERA5 Reanalysis
Mean U,V wind	10 m	ERA5 Reanalysis
Surface pressure	Surface	ERA5 Reanalysis
Mean short-wave radiation flux	Surface	ERA5 Reanalysis
Total column water vapor	Surface	ERA5 Reanalysis
Precipitation	Surface	ERA5 Reanalysis, ENACTS-BMD

3. The precipitation climatology over Bangladesh

Bangladesh experiences a humid, tropical monsoon climate characterized by pronounced seasonal variability in precipitation. The majority of annual precipitation occurs during the monsoon season, typically from June to September, when moist air masses from the Bay of Bengal dominate the regional circulation. Annual precipitation ranges from approximately 1,200 mm in the western regions to more than 4,000 mm in the northeastern and southeastern parts of the country, reflecting strong spatial heterogeneity influenced by topography and proximity to moisture sources. Pre-monsoon (March–May) and post-monsoon (October–November) periods contribute smaller yet significant portions of the total precipitation, often associated with convective thunderstorms and tropical disturbances. In contrast, the winter season (December–February) remains relatively dry under the influence of continental high-pressure systems.

Figure 2 illustrates the monthly temporal distribution of precipitation over the study region. The data reveal a gradual increase in precipitation from the early months of the year, reaching its maximum in July, which records an average of approximately 488 mm of precipitation. The premonsoon season (March–May) contributes about 17% of the total annual precipitation, whereas the monsoon season (June–September) accounts for roughly 73%. This indicates that precipitation during the monsoon is more than four times greater than that of the pre-monsoon period. The post-monsoon season (October–November) contributes around 8.7% to the annual total. In contrast, the winter months (December–February) are notably dry, with minimal precipitation observed during this period.

Figure 3 illustrates the monthly spatial distribution of precipitation over the study region, highlighting distinct regional and seasonal contrasts. During the pre-monsoon period

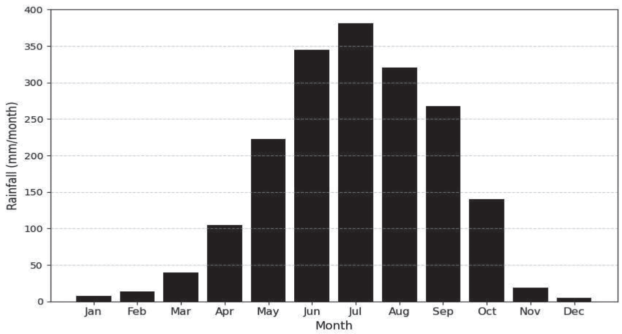

Figure 2. Monthly precipitation climatology over Bangladesh. The bar chart illustrates the mean daily precipitation intensity (mm/month) averaged for each month over the period 1981-2020 from ENACTS-BMD.

(March–May), precipitation is most pronounced in the northeastern part of the country, while the southeastern region also receives substantial amounts compared to the relatively drier southwestern areas. With the onset of the southwest monsoon in June, precipitation increases markedly, attaining its maximum intensity in July and August, when almost the entire country experiences extensive and extreme precipitation. Throughout this peak monsoon phase, the northeastern and southeastern regions consistently record the highest precipitation totals, whereas the western and northwestern zones remain relatively less affected. After the monsoon begins to withdraw in October, precipitation declines rapidly across all regions, giving rise to predominantly dry conditions during the winter months (December–February).

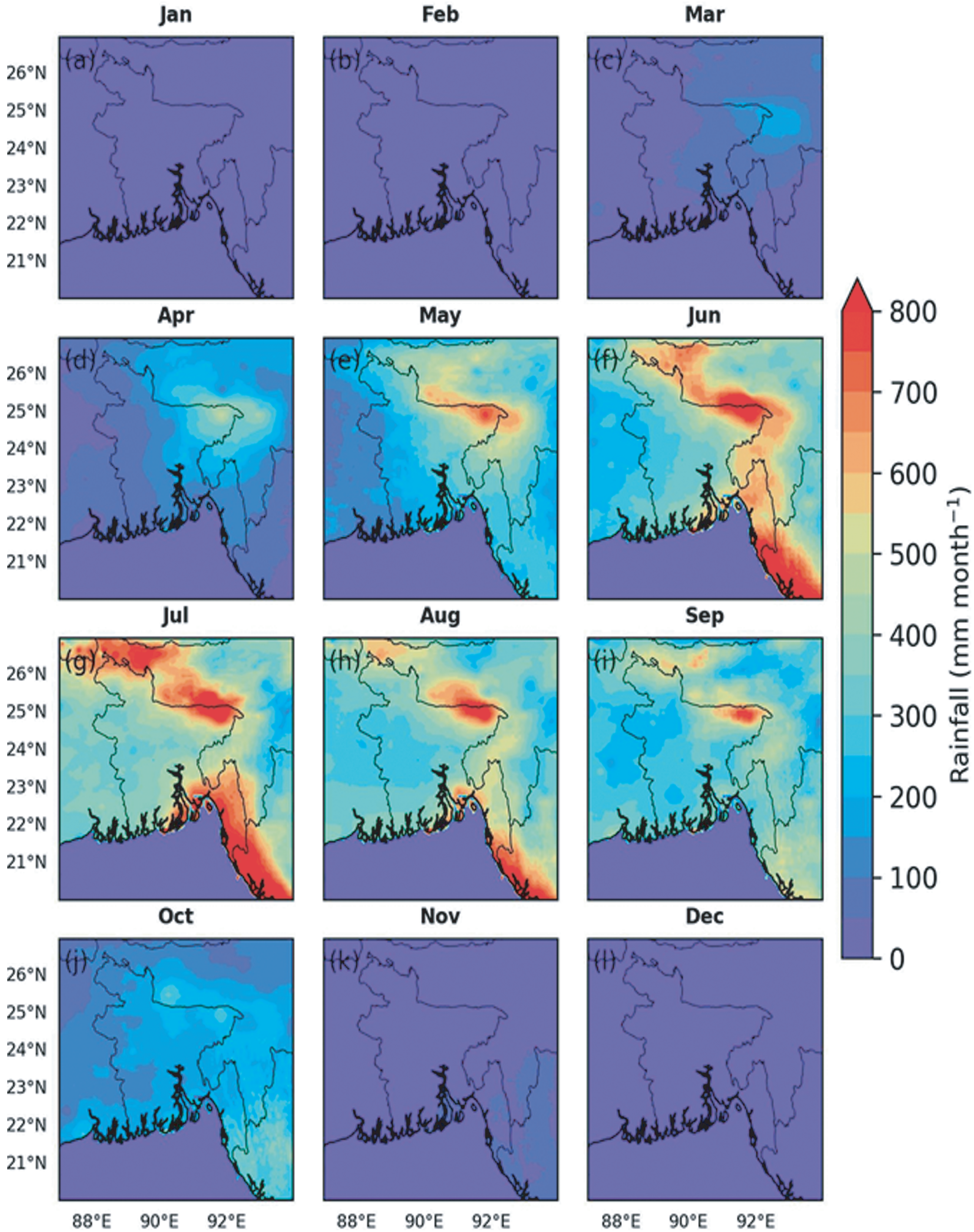

Figure 3: Monthly spatial distribution of precipitation climatology over Bangladesh from ENACTS-BMD. Each panel (a–l) represents the multi-year (1981-2020) mean precipitation for the respective month, from January to December. The color scale indicates the precipitation intensity in millimeters per month (mm month^{-1}).

4. Methodology

The Bangladesh Meteorological Department (BMD) applies the WMO/RA-II operational thresholds to classify precipitation intensity. According to this standard, moderate to extreme precipitation corresponds to daily precipitation amounts between approximately 65 mm and 125 mm within a 24-hour period. In this study, a precipitation event is classified as extreme when the maximum grid-scale precipitation exceeds 65 mm within a 24-hour period. For example, an extreme precipitation event on 21 June, 2017 in the southeastern regions of Bangladesh has been presented in Figure 4. The accumulated precipitation received within 24 hours was about 140 mm, occurring mainly over the Chittagong and Borisal division of Bangladesh.

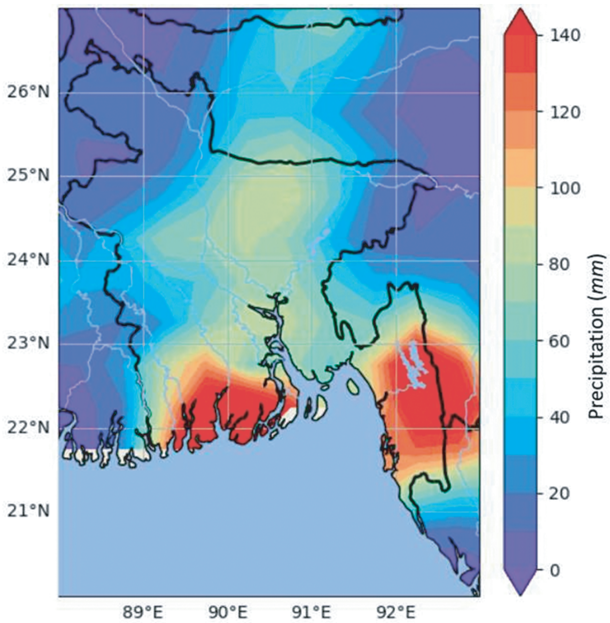

Figure 4. Spatial distribution of a representative extreme precipitation event over Bangladesh on June 21, 2017. The color scale indicates daily precipitation intensity in millimeters (mm).

ERA5 reanalysis data were used in this study. ERA5 is a globally recognized atmospheric dataset that offers high-resolution meteorological fields and has been extensively applied in climate and weather research. It contains all relevant variables required for our analysis. The binary target labels (extreme vs. non-extreme events) were defined using the precipitation data provided by the ERA5 dataset. Simultaneously, we leveraged ERA5's comprehensive atmospheric data including geopotential height, humidity, and wind components etc. as the physical predictors that allow the ANN and RFC models to forecast these events 24 hours in advance. The selection of input features was guided by the Pearson correlation matrix, presented in Figure 5.

Feature Scores method also used in this study. This technique quantifies the relative contribution of each predictor to the model output, enabling the identification of variables that provide the greatest benefit for prediction accuracy. Based on the Feature Scores analysis, the highest-ranking predictors included total precipitation, sector, date, geopotential height at 1000 hPa, mean surface direct short-wave radiation flux, relative humidity at 500 hPa and 800 hPa, and total column water vapor. Ultimately, the most influential atmospheric variables selected for model development were geopotential height at 1000 hPa, mean surface direct short-wave radiation flux, previous-day precipitation, and relative humidity at both 500 hPa and 800 hPa.

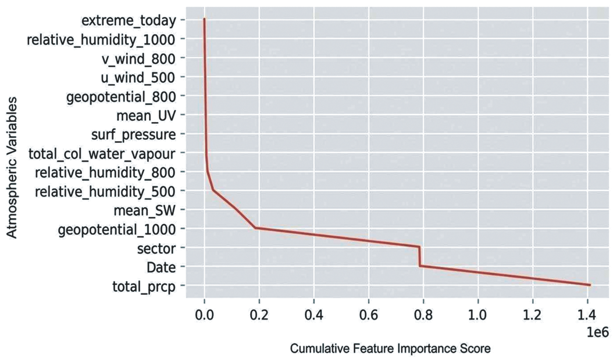

Figure 5: Cumulative feature importance scores for atmospheric input variables.

To optimize computation time, the original ERA5 grids (0.25° × 0.25°) were aggregated to a coarser resolution of 1.25° × 1.25°, defined as a 'sector'. Coarsening spatial resolution can influence representation of local-scale processes; however, given that Bangladesh has limited elevation variability, significant information loss is unlikely. This resolution was therefore considered sufficient to achieve efficient processing without compromising model performance.

In this study, an Artificial Neural Network (ANN) [26] and a Random Forest Classifier (RFC) [27] were developed to forecast extreme precipitation 24 hours in advance and to compare their predictive performance. ANNs represent a class of machine learning algorithms inspired by the interconnected neuron structure of the human brain. Multiple ANN algorithms were tested in this forecasting task and finally the best predicting algorithm was chosen. The final ANN configuration was implemented using the Keras Sequential API and consisted of multiple fully connected (dense) layers. The input layer was designed to accommodate the 5 selected predictors, followed by six hidden layers containing 128, 64, 48, 32, 16, and 8 neurons, respectively. Each hidden layer employed the Rectified Linear Unit (ReLU) activation function, defined as

$$f(x) = max(0, x) \qquad (1)$$

which introduces nonlinearity and mitigates the vanishing-gradient issue, facilitating faster convergence during training. Since the task involves binary classification (extreme vs. nonextreme precipitation), the output layer consists of a single neuron with a sigmoid activation function, which maps predictions to a probability value ranging between 0 and 1. To mitigate the risk of over-parameterization in the deep architecture, an L2 regularizer (λ= 0.002) was employed. The L2 or Ridge regression approach adds a penalty term to the loss function based on the squared magnitude of the coefficients, defined as:

$$Loss = \frac{1}{2m}\sum_{i=2}^{m}(Y_{predicted} - Y_{true})^2 + \frac{}{2m}\sum_{j=2}^{m} W_j^2 \qquad (2)$$

Here, the λ value represents the regularization parameter used to adjust the loss function of the network, balancing the tradeoff between bias and variance. This was used in conjunction with an Early Stopping callback to ensure the model maintained high generalization capability on the independent testing set. The model was trained using the Adam optimizer (learning rate = 0.001) with a binary cross-entropy loss function and a batch size of 32 over a maximum of 100 epochs. Moreover, a Random Forest Classifier (RFC) was also implemented to forecast extreme precipitation events. Random Forest is an ensemble learning technique that combines multiple decision trees to improve prediction stability and reduce model variance. In this study, the classifier was trained using an ensemble of 100 trees, with each tree constructed from a bootstrap sample of the dataset and a randomly selected subset of predictors. During inference, the final prediction was obtained through majority voting across all trees, resulting in a more reliable and generalizable classification. The use of multiple trees reduces the likelihood of overfitting and enhances predictive accuracy. The final optimized hyperparameter configurations for both models are summarized in Table II.

Table II. Optimized Hyperparameters for ANN and RFC Models.

Model	Hyperparameter	Final Configuration
ANN	Architecture	1 Input Layer, 6 Hidden Layers, 1 Output Layer
	Hidden Layer Units	128, 64, 48, 32, 16, 8 neurons
	Activation Function	ReLU (Hidden Layers), Sigmoid (Output Layer)
	Regularization	L2 Regularization (Ridge,
	Optimizer	Adam (Learning rate = 0.001)
	Batch Size	32
	Loss Function	Binary Cross-Entropy
	Framework	Keras Sequential API
	Objective	Binary Classification (Probability 0 to 1)
RFC	Ensemble Size	100 Decision Trees
	Sampling Method	Bootstrap Sampling
	Feature Selection	Randomly selected subset of predictors per tree
	Decision Logic	Majority Voting

In this study, a total of 10 years of data were used, of which seven years were used to train the model, while the remaining three years were used to evaluate the model's performance.

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To harmonize the influence of the predictor variables, Min–Max normalization was applied to the continuous input features, with the exception of temporal attributes (year, month, and day), spatial coordinates (latitude and longitude), and the prediction target. During the training phase, 20% of the training subset was randomly withheld as a validation set within the TensorFlow framework. This validation subset was utilized to track the model's performance throughout the training iterations (epochs) and to identify signs of overfitting by comparing the loss values between the training and validation subsets. The random selection process ensures that validation samples represent diverse atmospheric conditions, reducing the likelihood of temporal or spatial bias.

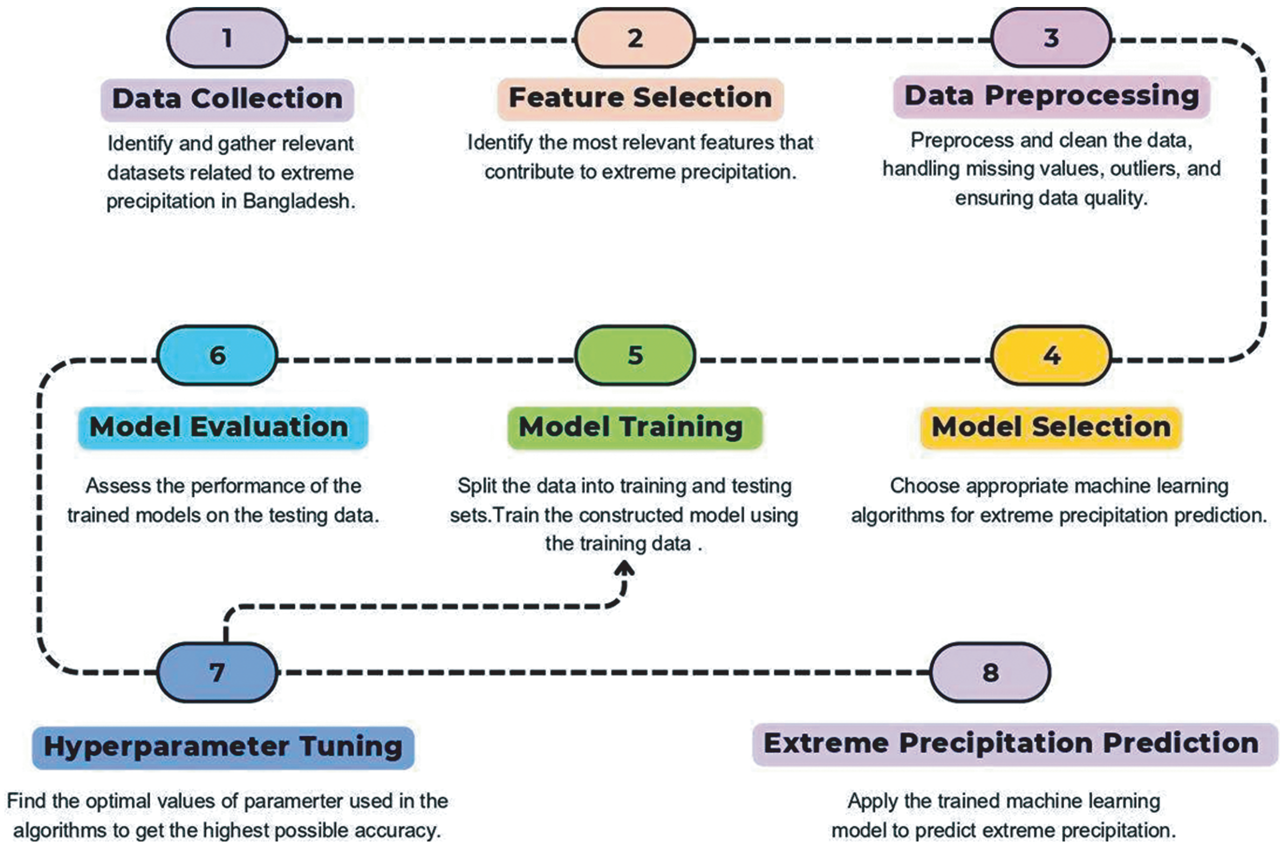

Figure 6 : Overall workflow used to develop the machine learning models.

After selecting and training an initial machine learning model, hyperparameter optimization is performed to enhance its predictive capability. Hyperparameter tuning aims to improve the model's generalization performance by identifying the optimal configuration of settings that govern the learning process. Once the optimal hyperparameters are determined, the model is retrained using these refined values.

Following model training and optimization, the final evaluation of the model was conducted using a strictly independent 3-year testing dataset to assess predictive performance of the model. In this study, model performance was quantified using accuracy, the Receiver Operating Characteristic (ROC) curve, and the Area Under the ROC Curve (AUC). By comparing model predictions with the corresponding observed values, we can evaluate the model's generalization ability and identify potential opportunities for further refinement. Figure 6 presents the general workflow outlining the key steps followed in this study

5. Results and discussions

The primary objective of this study was to incorporate machine learning techniques to extract predictive information from historical observations and apply this information to generate meaningful predictions of extreme precipitation. Model development followed an iterative workflow comprising performance evaluation and systematic hyperparameter optimization, resulting in the selection of the final configurations for the Artificial Neural Network (ANN) and Random Forest Classifier (RFC) models. To ensure methodological consistency and prevent data leakage, the testing dataset was subjected to the same pre-processing and normalization procedures used during training.

Figure 7 depicts the receiver operating characteristic (ROC) curve for the final Artificial Neural Network (ANN) model and Random Forest Classifier (RFC) in comparison with a random prediction. The ROC curve represents the relationship between the true positive rate (sensitivity) and the false positive rate, providing a visual assessment of the model's discriminative ability.The curves exhibit a sharp initial increase followed by a gradual plateau, indicating that the models attain high sensitivity while maintaining a relatively low rate of false positives. The dashed diagonal blue line corresponds to the expected performance of a random prediction (AUC = 0.50). The convex shape of the curves, bending toward the top-left corner, highlights that both the ANN (AUC = 0.797) and RFC (AUC = 0.798) substantially outperform random classification.

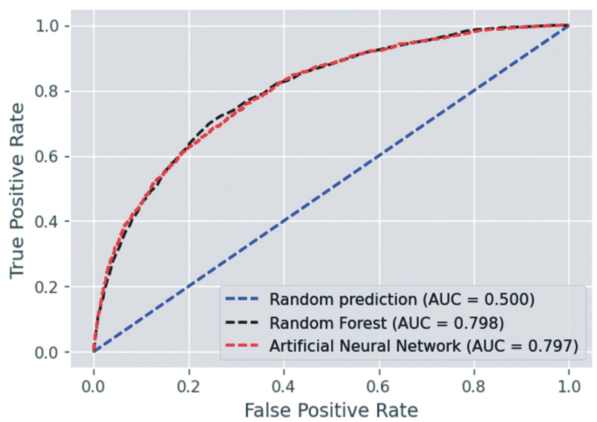

Figure 7: Comparison of model discriminative power using ROC curves. The plot illustrates the trade-off between the True Positive Rate (Sensitivity) and False Positive Rate for the ANN (red dashed line) and RFC (black dashed line).

Beyond the ROC curve, we analyzed the models using an independent testing dataset to calculate standard binary classification metrics such as precision, recall, F1-score, and accuracy. These results are summarized in Table III.

Table III. Performance Comparison of ANN and RFC Models.

Model	Precision	Recall (Sensitivity)	F1-Score	Accuracy
ANN	0.76	0.74	0.75	0.82
RFC	0.74	0.72	0.73	0.80

Precision (Positive Predictive Value) represents the model's reliability when it flags a potential extreme event. It is defined as (Eq. 2):

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

The ANN achieved a precision of 0.76, while the RFC model yielded a precision of 0.74. This indicates that when the ANN model predicts an extreme precipitation event, it is correct 76% of the time. Conversely, there is a 24% "false alarm" rate where the model predicts an extreme event that does not occur. Similarly, 74% of the "extreme" predictions made by the Random Forest Classifier were accurate observations of extreme rainfall. Recall, or Sensitivity, measures the model's ability to successfully detect all actual extreme precipitation events within the dataset. It is mathematically expressed as (Eq. 3):

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

As shown in Table III, the ANN achieved a recall of 0.74, while the RFC yielded 0.72. These results indicate that the ANN successfully identified 74% of all recorded extreme events during the testing period, slightly outperforming the RFC's detection rate of 72%. The F1-score provides a single harmonic mean of precision and recall, offering a comprehensive assessment of the model's performance on an imbalanced dataset. It is calculated as (Eq. 4):

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

According to the results in Table I, The ANN achieved a superior F1-score of 0.75 compared to the RFC's 0.73, indicating a better balance between minimizing false alarms and maximizing event detection. Accuracy represents the overall proportion of correct predictions (both extreme and non-extreme events) made by the model relative to the total number of cases. It is defined as (Eq. 5):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

The ANN and RFC achieved accuracies of 0.82 and 0.80, respectively. While high, these figures are interpreted alongside the F1-score to ensure the models are not simply favoring the majority non-extreme class.

Finally, a comparative analysis of the results indicates that both the Artificial Neural Network (ANN) and the Random Forest Classifier (RFC) are highly effective in forecasting extreme precipitation 24 hours in advance. While the RFC provided a competitive AUC-ROC of 0.798, the ANN demonstrated a slight edge in overall predictive reliability with an Accuracy of 0.82 and a superior F1-score of 0.75. The primary advantage of the ANN in this study lies in its higher Recall (0.74), which suggests a more robust capability to capture complex, non-linear atmospheric patterns associated with extreme events. Although the RFC is computationally more efficient to train, the ANN's superior balance of precision and sensitivity makes it the more reliable choice for an early warning system where minimizing missed events is critical.Ultimately, the high performance of both models confirms that incorporating machine learning with ERA5 reanalysis data significantly enhances the predictability of extreme weather events.

6. Summary and conclusion

In summary, the substantial risks posed by extreme precipitation—ranging from loss of life to damage across infrastructure, agriculture, and livestock—underscore the necessity of establishing an effective early warning system. This study explored the application of machinelearning approaches, specifically Artificial Neural Networks (ANN) and Random Forest Classifiers (RFC), to forecast extreme precipitation events using ERA5 reanalysis data. A broad suite of meteorological variables was employed as predictors, while the response variable was defined as a binary indicator distinguishing non-extreme from extreme precipitation events. The model development utilized a decade-long dataset, with seven years allocated for training and the remaining three years reserved for performance evaluation.

The results demonstrate that both machine-learning frameworks are highly effective for 24-hour advance forecasting. While both models achieved strong discriminative power with AUC-ROC values of approximately 0.80, the ANN model slightly outperformed the RFC in overall predictive reliability, achieving an accuracy of 0.82 and a superior F1-score of 0.75. Specifically, the ANN's higher recall (0.74) indicates a more robust capability to capture complex, non-linear atmospheric patterns, which is critical for minimizing missed extreme events in early warning contexts. These findings highlight the significant promise of machine-learning frameworks in supporting operational predictions of extreme rainfall in Bangladesh. The high performance achieved confirms that integrating these models with ERA5 reanalysis data can yield precise, regionally tailored forecasts. Future refinements of these models could further strengthen their applicability for early detection, providing stakeholders with reliable tools to mitigate the impacts of extreme precipitation events in the region.

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