ENHANCED PREDICTION OF RAINFALL USING A HYBRID MACHINE LEARNING APPROACH - A CASE STUDY IN KHULNA, BANGLADESH

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ABSTRACT

Rainfall is a significant non-linear element of the climate system that influences various domains. Rainfall forecasts hold a crucial significance in both climate research and environmental management, as they contribute to the comprehension of extended climate patterns, the assessment of economic implications, the formulation of infrastructure plans, the effective utilization of water resources, the enhancement of agricultural practices, and the facilitation of disaster preparedness strategies, while also shedding light on the health of ecosystems. Machine learning (ML) models offer substantial potential for understanding non-linear relations. Various machine learning models have been employed in previous attempts to forecast rainfall. Many of these studies have indicated that conventional machine learning models do not capture a significant level of forecasting accuracy. In this paper, a hybrid machine learning technique is employed to predict rainfall patterns. For hybridizing the machine learning model, a combination of Support Vector Machine (SVM) and Artificial Neural Network (ANN) models was employed. This hybrid model combines the forecast outputs of SVM and ANN using the SVM model. It combines the performance of the two conventional machine learning models. For this, a dataset containing 68 years' worth of historical rainfall data from the Khulna region of Bangladesh was employed. The study procedure entails dividing historical data into input and output features. To forecast rainfall patterns, the study considered the influences of temperature, humidity, and wind speed. These three climate components were used as input variables. The performance of the model was evaluated using various performance criteria, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The findings indicate that the hybrid machine learning approach yields promising forecasting results, surpassing the individual SVM and ANN outcomes. This model exhibits the capability to comprehend the nonlinear rainfall patterns in the Khulna region, and it also holds potential as a viable method for predicting rainfall in different geographical areas.

Keywords: *Rainfall prediction, ANN, SVM, SVM-ANN, Machine Learning*

1. INTRODUCTION

The hydrological cycle of the planet depends on rainfall. In many areas of human existence, including agriculture, water resource management, disaster preparedness, and urban planning, rainfall forecasting is significant. In locations like Khulna, the region's wealth and the livelihoods of its people are intrinsically linked to the predictable anticipation of rain. Furthermore, due to its geographical location, Khulna is susceptible to the continual threat of floods. Rainfall forecasting serves a dual purpose in this context: it not only supports agricultural planning for crop sustainability and food security, but it also plays an important role in disaster avoidance. In this setting, accurate rainfall projections act as a shield against flood hazards, protecting both people and property.

In this study, a hybrid machine learning approach is developed and used to anticipate rainfall rather than a single traditional model. Due to their considerable advancements, machine learning (ML) algorithms have attracted increasing interest in recent years for application in a variety of environmental processes, particularly hybrid processes. Researchers have looked at the potential of machine learning to forecast a variety of things, including sea surface temperature (de Mattos et al., 2022), flood prediction (Mosavi et al., 2018), daily soil temperature at multiple depths (Malik et al., 2022), solar power forecasting (Lim et al., 2022), annual rainfall forecasting (Diop et al., 2020), solar radiation predictions (Gala et al., 2016), water-level fluctuation forecasting (Barzegar et al., 2021), soil moisture (Breen et al., 2020), short-term wind speed prediction (Gupta et al., 2022), and so on. Taking into consideration the advantages of machine learning in the context of rainfall forecasting makes sense, considering the performance of conventional machine learning models in these many areas. Rainfall forecasts are becoming more precise and dependable since these traditional machine learning models have shown their ability to learn and predict rainfall patterns. The utilization of machine learning in this particular case holds great potential to provide significant advancements and insights into the changing pattern of rainfall and its effects on the environment.

Artificial neural networks (ANNs) (French et al., 1992; Hong, 2008) and support vector machines (SVM) (Pai et al., 2007) are two well-known models in the field of forecasting, particularly in the forecasting of rainfall, among the several ML methods for rainfall forecasting. These are well-known for their capacity to handle the complexities of rainfall patterns, which frequently display intricate and nonlinear interactions. ANNs are excellent at identifying these complex patterns, making use of past weather information, and changing with the weather. SVMs, on the other hand, are distinguished by their strong feature selection mechanism, which makes it easier to identify the most important meteorological factors. These traditional ML models have demonstrated their ability to learn and predict rainfall patterns effectively. However, in this study, a combined approach was adopted by utilizing an ANN-SVM-SVM hybrid model to enhance the performance of conventional ML methods. This model gives the combined strength in the case of predicting rainfall. Due to their capacity to incorporate the advantages of many forecasting techniques, hybrid forecasting systems have, in fact, grown in popularity in recent years. These strategies utilize the beneficial characteristics of many forecasting techniques in an effort to increase forecast accuracy (Citakoglu et al., 2022). The conventional model has some limitations, such as the need to find the best hypermeters manually (Mislan et al., 2015). It is very time-consuming, and it is not certain about the best result of the model. Otherwise, the hybrid model can find the best model parameters using different well-known optimizers such as the Generic Algorithm (GA), Particle Swarm Optimizer (PSO) (Wu et al., 2009), Sequential Minimal Optimization (SMO) (Dananjali et al., 2020) and so on. Consequently, the hybrid model can influence the forecast result. It may use the strengths of several conventional models (Xiang et al., 2018). These optimisation techniques can be used by hybrid models to significantly enhance forecasting outcomes. By combining the advantages of multiple traditional models, they are able to produce forecasts that are more reliable and accurate. This method increases the models' overall performance and dependability while also saving time.

The primary objective of this study is to develop and evaluate a rainfall forecasting model using a hybrid-combined technique. This approach aims to leverage the strengths of both SVM and ANN to create an integrated forecasting system that can provide more accurate and reliable predictions of rainfall patterns. By achieving this primary objective, the study aims to contribute to the advancement of rainfall forecasting techniques and provide a more accurate tool for addressing the challenges associated with predicting and managing rainfall in the target area.

2. STUDY AREA AND DATA USED

The study was performed for the Khulna station, Bangladesh, which is situated between 22°47'16" and 22°52' north latitude and 89°31'36" to 89°34'35" east longitude. Figure 1 shows the location map of the study area. Rainfall has a significant impact on this region, especially on its agriculture. Khulna District shares its borders with Jessore District to the north, Narail District to the northeast, Bagerhat District to the east, the Bay of Bengal to the south, and Satkhira District to the west. Its total land area is 4,389.11 square kilometers (1,694.64 square miles). With a daily maximum temperature of 32 degrees Celsius on average, Khulna is renowned as one of Bangladesh's rising cities. Khulna's climate is known for being warm, with an average yearly temperature of 32 degrees Celsius. But only a small portion of the year is genuinely tropical and humid. In Khulna, the wet season is characterized by oppressive and cloudy weather, whereas the dry season is muggy and largely clear, keeping scorching temperatures all year long. The annual average temperature varies between 57°F and 94°F, seldom falling below 52°F or rising over 100°F.

Figure 1: Location of the study area (Khulna district in Bangladesh)

The data used in this study was obtained from the Bangladesh Meteorological Department (BMD) and consisted of a comprehensive dataset spanning 66 years, documenting monthly observations of various meteorological parameters in the Khulna region, including rainfall, wind speed, humidity, and both maximum and minimum temperatures. Before analyzing the model, the data was normalized using the Z-score normalization technique. The z-score normalization process, also known as standardization, involves transforming the data to have a mean of 0 and a standard deviation of 1. The standardization of z-score is performed using Eq. (1) as follows:

$$z = (x_i - \mu) / \sigma \quad (1)$$

Where Z is the standardized value (z-score), X is the original data point, μ (mu) is the mean (average) of the data, and σ (sigma) is the standard deviation of the data.

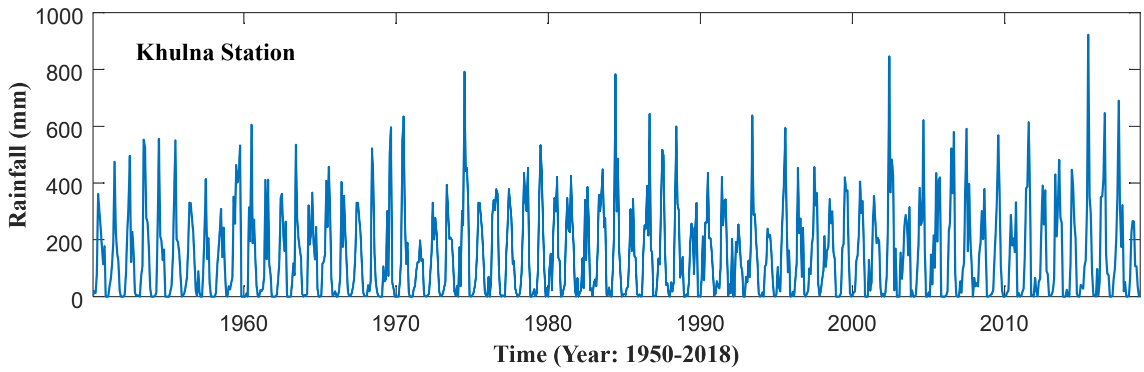

Figure 2: Monthly rainfall time series data in Khulna station

For model development, the dataset was separated into two parts: 70% was allocated and set up for training data, and 30% was set aside for testing data. At the first level, this divide served as the foundation for the development of two fundamental models: an artificial neural network (ANN) and a support vector machine (SVM). In order to improve predictive capabilities, the predicted results from the first-level models were effectively utilized as input for a second SVM model. The 80% and 20% data divide was taken during this second stage, maintaining consistency with the initial training and testing dataset division. Figure 2 shows the monthly rainfall time series data, which presents the yearly variation of rainfall patterns in the study area. The input variables' time series plot is shown in Figure 3, which makes it easier to observe precisely how these variables vary over time. Several meteorolgical variables are used to predict rainfall values. Table 1 provides the correlation matrix to determine the relationship between these meteorological variables and rainfall.

Table 1: Correlation matrix between input meteorological variables and rainfall

	Max. Temp. (ºC)	**Min. Temp. (ºC)**	**Humidity (%)**	**Wind speed (m/s)**	**Rainfall (mm)**
Max. Temp. (ºC)	1				
Min. Temp. (ºC)	0.831	1			
Humidity (%)	0.125	0.566	1		
Wind speed (m/s)	0.420	0.416	0.093	1	
Rainfall (mm)	0.321	0.652	0.688	0.303	1

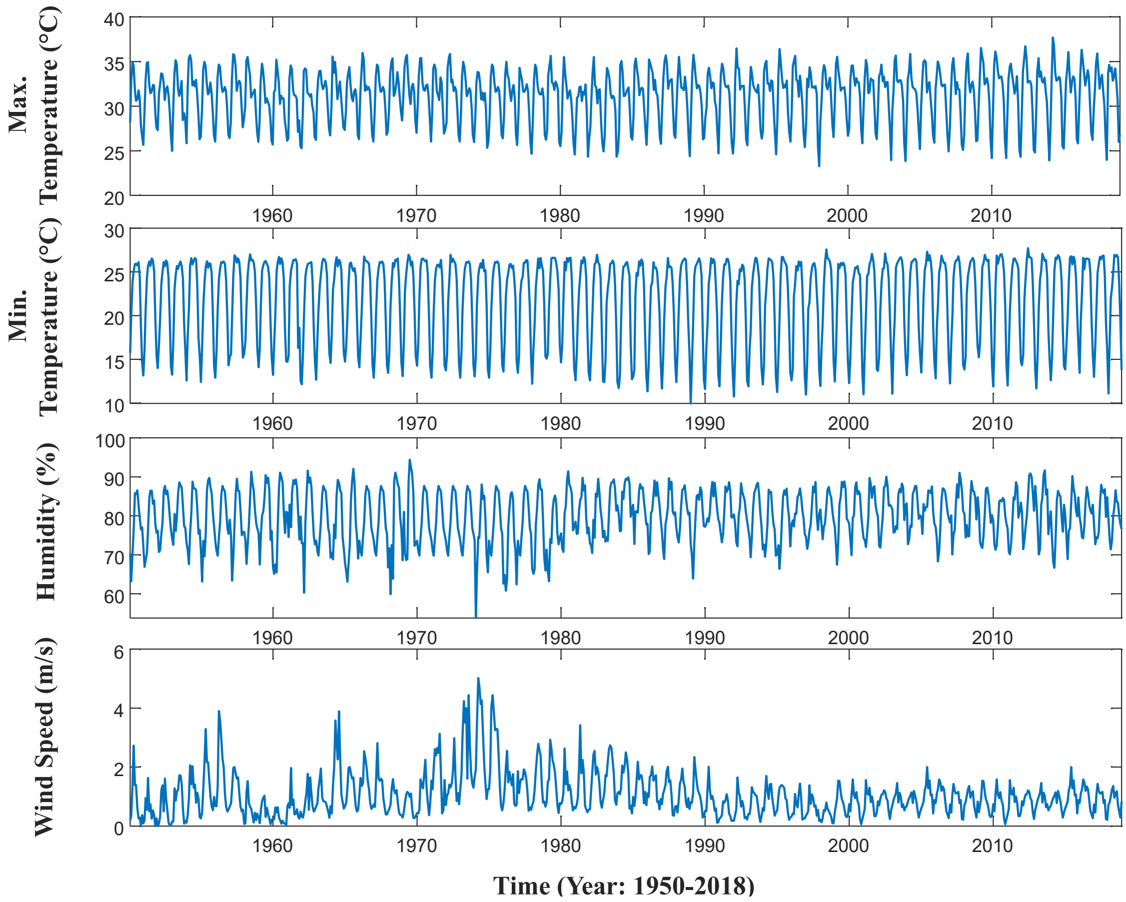

Figure 3: Time series plot of different input variables (maximum and minmum temperatures, relative humidity, wind speed in the current study) adopted for rainfall prediction

3. METHODOLOGY

3.1 ANN Model

The ability of artificial neural networks (ANNs) to simulate complex fluctuations in historical data is remarkable (Azad et al., 2022; Kandananond, 2012). It is a robust and adaptable data-modeling system that can capture and depict intricate input and output interactions (Mekanik et al., 2013). An ANN is a computational strategy that draws inspiration from studies relating to the nerve and brain systems of living things. The parallel, distributed processing capabilities of biological neurons have been implicated in the robust operation of a biological neural system. A neural network is a structure made up of multiple neurons, also known as unit nodes, which are small processing components. Direct communication lines with corresponding weights connect each neuron to the other neurons. The internal state of every neuron is termed the activation level, and it depends on the inputs the neuron has received. Multiple other neurons get a signal from a neuron when it is activated.

The input layer, the hidden layer, and the output layer are the network's three fundamental sub-sections. A model could have more than one hidden layer. The input signal moves towards the concealed layer after going through the transfer function and carrying a weight. After that, the weighted signal is transferred to the output layer via the transfer function. The idea behind this is to attempt to update the weight. The transfer function, hidden layer size, hidden layer count, etc. all affect the results significantly. The one hidden layer, N input nodes, feed-forward neural network, can be expressed by Eqs. (2)-(3):

$$y = S_1 \left(\sum_{h=1}^{H} O_h w_h + w_o \right) \quad (2)$$

$$O_h = S_2 \left(\sum_{n=1}^{N} X_n w_{nh} + w_{oh} \right) \quad (3)$$

where y is the ANN output and O_h is the hidden node output value. X_n are the FFNN's inputs, W_h are the connection weights between the hidden and output layers, W_{nh} are the connection weights between the hidden and input layers, and $x_0 = 1.0$ is a bias, w_0 and W_{oh} are bias weights (biases are employed to keep the error surface from passing through the origin forever), and S_1 and S_2 are activation or transfer functions.

3.2 SVM Model

Support vector machines (SVMs) are effective supervised machine learning algorithms used for regression and classification problems (Kazem et al., 2016). In the SVM model, A hyperplane in a two-dimensional feature space is a straight line that splits data points into two categories. It turns into a hyperplane in higher dimensions. An SVM's aim is to identify the hyperplane that maximizes the margin, or the distance between the hyperplane and the closest data points for each class. This is frequently known as the "maximum-margin hyperplane." Support vectors are utilized to locate the hyperplane since they are the data points that are closest to it. The margin must be determined using these data points.

The representation of the training data is $\{(xi, di)\}_i^N$, where xi is the input vector, di is the actual value, and N is the total number of data sequences. $y=f(x)=w\varphi(x_i)+b$ is the formula for SVM regression. The multidimensional feature space is denoted by $\varphi(x_i)$, and the weight and bisector factors are w and v, respectively. By limiting the error function in Eq. (4), w and b can be estimated (Wang et al., 2013).

$$\text{Minimize: } \frac{1}{2}\|w\|^2 + C\left(\sum_{i}^{N}(\xi_i + \xi_i^{¿})\right)$$

$$\text{Subjected to } \begin{cases} w\,i\,\varphi(xi) + b\,i - d\,i \le \in + \xi_i^{¿} \\ d_i - w_i\varphi(x_i) - b_i \le \in + \xi_i \\ \xi_i, \xi_i^{¿}, i = 1,2,3\ldots..N \end{cases} \quad (4)$$

Where $\frac{1}{2}\|w\|^2$ is the weight vector norm and C is referred to as the regularized constant determining the tradeoff between the empirical error and the regularized term. $\in$ represents the tube size.

By introducing Lagrange multipliers α_i and $\alpha_i^{¿}$, the above-mentioned optimization problem in Eq. (4) is transformed into the dual quadratic optimization problem. After the quadratic optimization problem with inequality constraints is solved, the parameter vector w can be obtained by Eq. (5):

$$w^{¿} = \sum_{i=1}^{N}\left(\alpha_i - \alpha_i^{i}\right)\varphi(x_i) \quad (5)$$

Thus, the obtained SVR regression function can be expressed by Eq. (6) as follows:

$$f(x, \alpha, \alpha^{¿}) = \sum_{i=1}^{N}\left(\alpha_i - \alpha_i^{i}\right)K(x, x_i¿)¿ + b \quad (6)$$

Here, $K(x, x_i)$ is called the Kernel function. The value of the Kernel is the inner product of the two vectors x and x_i in the feature space $\varphi(x)$ and $\varphi(x_i)$, so $K(x, x_i)= \varphi(x) \times \varphi(x_i)$, and a function that satisfies Mercer's condition can be used as the kernel functions. In general, there are several types of kernel function, namely linear, polynomial, and radial basis functions (RBF). The most commonly used kernel function is the RBF. The RBF kernel has been reported as the best choice over other kernel functions .It is not only capable of mapping the training data non-linearly into an infinite-dimensional space but also easier to implement. Therefore, the RBF kernel function is employed to deal with non-linear relationship problems in this study. The selection of the parameters C, ε and σ has a great influence on the forecasting accuracy of a SVR model.

3.3 Hybrid ANN-SVM Model

The prediction of rainfall in the study is a multi-level process, divided into two primary levels to enhance prediction accuracy. In the first level, artificial neural networks (ANN) and support vector machines (SVM) are used to make initial forecasts based on the available data. The base model was trained using historical climate data, where 70% of the initial data served as the training dataset, with the remaining portion designated for the testing phase of the base model, encompassing both ANN and SVM. In order to enhance the accuracy of rainfall prediction, simulated results from the level one base models are used as input features for another SVM model. This second-level model, known as a further SVM model, was created to include the insights and predictions given by the first-level models. The goal was to use the combined forecasting power of the ANN and SVM models to deliver a more sophisticated and accurate rainfall prediction. Figure 4 demonstrates the flowchart of the hybrid modeling framework that was adopted in the current study for the enhanced prediction of rainfall. The study employed a multi-level strategy to enhance the capabilities of multiple machine learning approaches and leverage insights learned from the base models to develop a more accurate rainfall prediction technique.

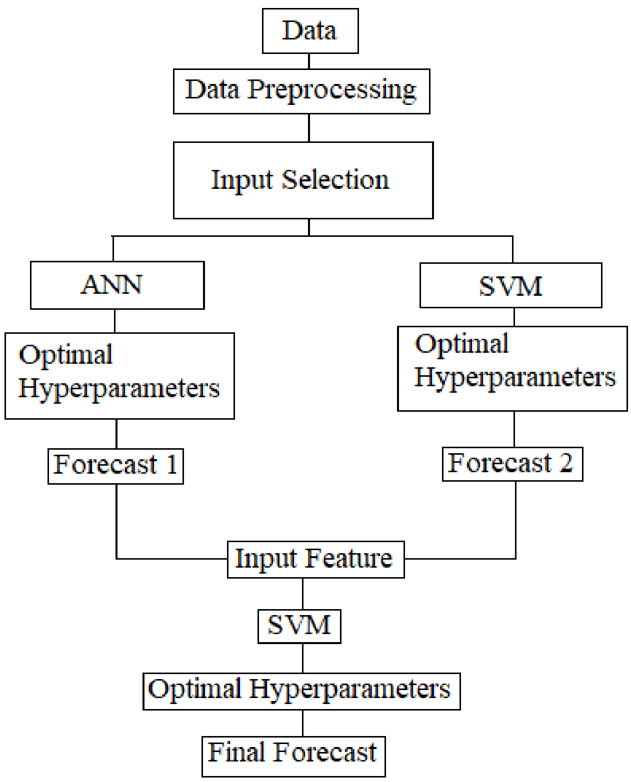

Figure 4: Proposed hybrid modeling framework for the enhanced prediction of rainfall

3.4 Performance Evaluation of Models

Several statistical indicators were adopted in the current study to evaluate the performance of each model. This increases the efficacy of the proposed hybrid model over the standard machine learning approaches, namely ANN and SVM techniques, for the enhanced estimation of rainfall. In the current study, mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) were used for model evaluation, which are given in Eqs. (7) – (10) in the following:

$$MSE=\frac{\sum\left(Y_i-\overline{Y}\right)^2}{N} \tag{7}$$

$$RMSE=\sqrt{\frac{\sum\left(Y_i-\overline{Y}\right)^2}{N}} \tag{8}$$

$$MAE=\frac{\sum\left(Y_I-\overline{Y}\right)}{N}$$
(9)

$$R^2=1-\frac{\sum\left(Y_I-\overline{Y}\right)^2}{\sum\left(Y_I-\hat{Y}\right)^2} \tag{10}$$

Where Y_i is observed rainfall values for i months, $\overline{Y}$ is the mean of the observed rainfall values, $\hat{Y}$ is the simulated rainfall values, N is the number of data points in the rainfall time series.

4. RESULTS AND DISCUSSION

The level-1 ANN prediction was performed employing the selected input structure. The attempt to optimize the ANN model required the use of a grid search hyperparameter tuning method, an intricate and systematic approach aimed at improving the key parameters that underlie the model's performance. These parameters included the number of neurons in the hidden layers as well as the learning rate, both of which were critical in determining the model's accuracy in forecasting. The hyperparameter search technique was successful in identifying the model's optimal hyperparameters, with the learning rate and number of hidden layers determined to be 0.5 and 11, respectively. In the current study, a single hidden layer architecture was used. The Levenberg-Marquardt algorithm was used as the training function, and the 'purelin' transfer function was employed for the hidden and output layers. The approach of hyperparameter optimization was quite effective in identifying the optimal model configuration. This thorough hyperparameter optimization could have a significant effect on the model's overall performance by enabling it to understand complex, non-linear data relationships. The monthly rainfall prediction result using the ANN model is illustrated in Figure 5.

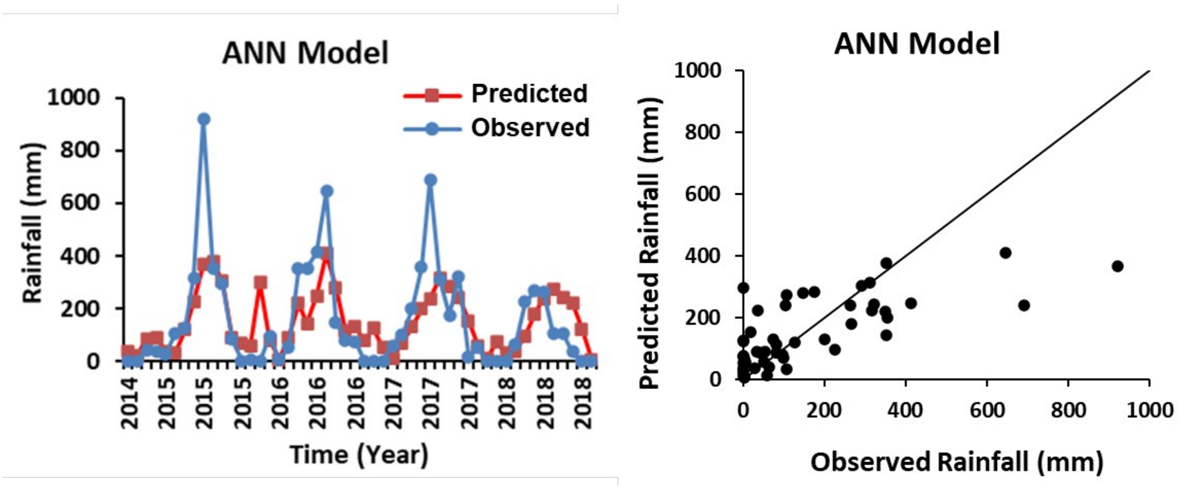

Figure 5: Comparison of the observed and predicted rainfall by the ANN model

The SVM model was trained using the same set of input features. This study used the adaptable Radial Basis Function (RBF) kernel for its predictive modeling, a common choice known for its accuracy. The RBF kernel, which is distinguished by its depth and complexity, was rigorously fine-tuned, with a focus on critical parameters such as C, Gamma, and Epsilon, which have a substantial impact on SVM performance. The study employed the Genetic Algorithm (GA), an effective optimization technique known for its capacity to methodically investigate and optimize hyperparameter configurations, ultimately improving prediction accuracy, to achieve optimal SVM model performance and identify the best hyperparameters. The predicted output of monthly rainfall by the level-1 SVM is illustrated in Figure 6.

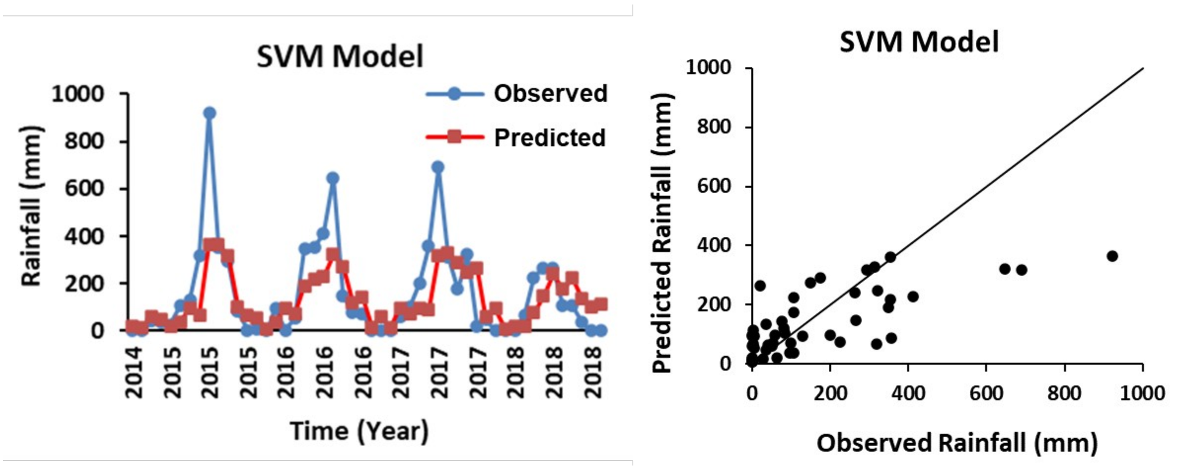

Figure 6: Comparison of the observed and predicted rainfall by the SVM model

The results of this study were significant, with optimal values for C, Gamma, and epsilon found to be 9.15, 8.07, and 0.39, respectively. These findings represent a substantial development in SVM modeling for the given task, providing an increased understanding of the factors necessary for achieving higher predicted performance. Finally, the hybrid SVM-ANN-SVM model was adopted to generate the rainfall prediction results. The predicted outcomes of the SVM model were used in conjunction with the ANN model to develop a hybrid model as a major extension of this study. This strategy involved using the conventional model's prediction outcomes as an input feature for an additional SVM model. The hybrid technique was developed to improve the coefficient of determination (R^2) value by lowering prediction errors. Figure 7 shows the results in the testing phase of the rainfall prediction results. As can be seen from the figure, the simulated or forecasted rainfall values have a reasonably close agreement with the lowest and highest values of monthly rainfall.

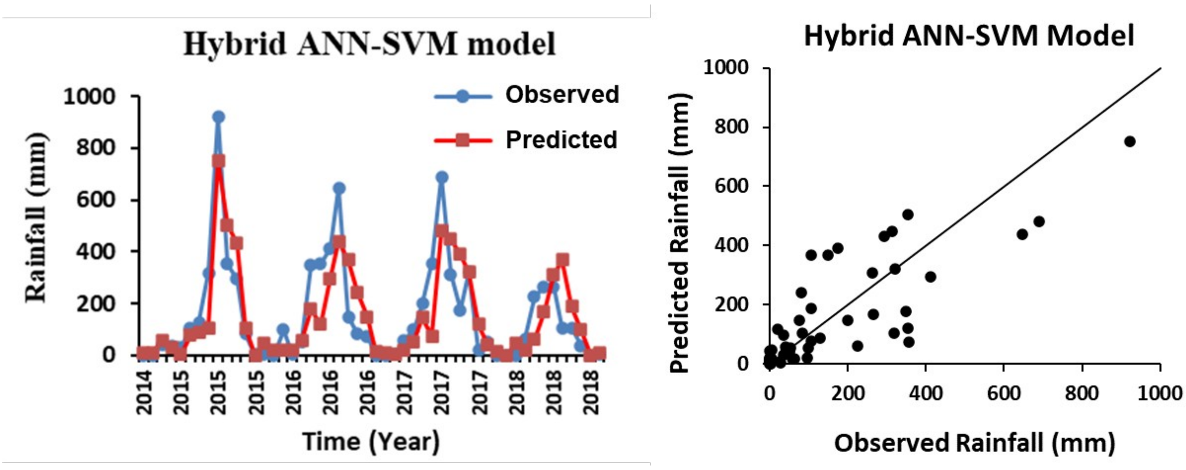

Figure 7: Comparison of the observed and predicted rainfall by the hybrid ANN-SVM model

The results of the performance evaluation of each rainfall prediction model are presented in Table 2. As can be observed from the table, the SVM model performs better than the ANN model for rainfall prediction. However, it is evident from the results that the proposed hybrid model outperforms both the ANN and SVM models. In comparison to the individual conventional model, the results strongly indicate that the hybrid model effectively captures non-linear patterns in rainfall, demonstrating its potential for improving rainfall prediction accuracy.

Table 2: Summary of the performance of different machine learning models

Models	Model Performance				Improvement by Hybrid Model (%)			
	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
ANN Model	0.72	0.85	0.54	0.51	31	18	19	30
SVM Model	0.7	0.83	0.5	0.53	29	16	12	25
Hybrid ANN-SVM Model	0.5	0.7	0.44	0.66	-	-	-	-

The reduction of error in rainfall prediction by adopting the proposed hybrid SVM-ANN-SVM model in the current study is presented in Table 3. The findings in Table 2 reveal the significant advantages of employing hybrid techniques. As can be seen from the table, a substantial reduction in estimation errors as well as a reasonable increase in the R^2 values are evident from the analysis. It can be seen that the proposed hybrid model reduces the MSE, RMSE, and MAE values by 31%, 18%, and 19%, respectively, compared to the ANN model. When it is compared to the SVM model, the reduction of errors is found to be 29%, 16%, and 12%, respectively. On the other hand, the R^2 value of the proposed hybrid model experiences a significant improvement of 30% with respect to the ANN model and 25% with respect to the SVM model. Thus, the findings overall demonstrate the efficacy of the hybrid ML technique over the conventional ML approach for the enhanced prediction of rainfall. The technique holds a significant amount of potential for rainfall analysis. Consider the fact that the study's scope was limited to a particular dataset, which might not represent all weather forecasting scenarios. Additionally, the study didn't go into more detail about things like hyperparameter tuning, which might affect the results. Nevertheless, the results should be used as inspiration for future research, especially when it comes to experimenting with different machine learning models—possibly more than two—and different preprocessing methods for input feature selection.

5. CONCLUSIONS

In the current study, a hybrid machine learning technique is proposed and demonstrated for the enhanced prediction of rainfall. Khulna station in Bangladesh is used as a case study area for the demonstration. For hybridizing the machine learning model, a combination of support vector machine (SVM) and artificial neural network (ANN) models was adopted. This hybrid model combines the forecast outputs of SVM and ANN using the SVM model. The proposed hybrid model significantly reduces errors in rainfall prediction and improves the coefficient of determination between the observed and simulated rainfall values. It was found that the proposed hybrid model outperforms both the ANN and SVM models. In comparison to conventional machine learning (ML) models such as ANN and SVM, the results of the proposed hybrid model demonstrate that it can effectively capture non-linear patterns in rainfall, demonstrating its potential for improving rainfall prediction accuracy. Thus, it can be concluded from the study that the proposed hybrid approach for predicting rainfall has the potential to improve on the performance of conventional ML models such as ANN and SVM. The proposed hybrid modeling framework demonstrated in the current study offers the advantages of combining several ML techniques together for the enhanced estimation of rainfall. This approach not only improves the accuracy of rainfall prediction but also highlights the value of using several ML approaches to achieve improved prediction of rainfall.

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