International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I6P103
Volume 73 Issue 6, 17-29, June 2025


*Original Article*

# Hybrid Machine Learning Model for Rainfall Prediction Using Time-Series Data

Abdikafi Elmi Abdishakur[1*], Abdihamid Mohamed Tahlil[1], Abdisalam Abdullahi Aden[1]

[1]*Department of Civil Engineering, Jamhriya University of Science and Technology, Mogadishu, Somlai.*

[*]*Corresponding Author : abdikafi.abdishakur@just.edu.so*

Received: 06 August 2024 Revised: 20 October 2024 Accepted: 29 May 2025 Published: 28 June 2025

***Abstract -*** *Weather forecasting is important in sectors ranging from farming to transport and disasters, to mention but a few. This paper discusses the effectiveness of three machine learning techniques: LSTM, GBM, and the combined LSTM-GBM model in rainfall prediction based on temperature and humidity data obtained from the chosen sites in Metro Manila and Rizal province. Also presented in the given dataset are data forecasted using simple linear regression, Gauss-Newton and Nernst-based non-linear, and a fourteen-gene-based genetic programming regression. This has been coupled with a high accuracy and low error rate based on the LSTM model data output. Another key model was the GBM model, which, despite its effectiveness, was also found to have a moderate accuracy with higher levels of FP and FN. This work, therefore, establishes LSTM-GBM as the model with the greatest effectiveness, perfect accuracy, precision, recall, and F1 score and the lowest error rates of all the models tested. More rigor was added by receiving operating characteristic analysis and precision-recall curve analysis, which all suggested that the hybrid model was an incredibly well-performing classifier. Thus, the effectiveness of the hybrid model again proves that the integration of various machine learning methods helps get accurate results and the reliability of predictions made by the model. The outcomes indicate that while using the presented dataset, the hybrid LSTM-GBM model performed much better than the individual LSTM and GBM models, affirming the possibility of utilizing the former structures in weather forecast-enunciated tasks. These results underscore the significance of applying various machine learning algorithms to improve weather prediction so that various entities and industries can make sound decisions.*

***Keywords -*** *Rain prediction, Machine learning, LSTM, GBM, Hybrid model.*

## 1. Introduction

The effects of climate change and global warming have continued to worsen, putting pressure on scholars to research environmental issues. Out of all the challenges associated with climate variability, the ability to forecast rainfall is among the most important, and it will help in water resource management, disaster risk reduction, and agriculture. While earlier approaches to rainfall predictions involved statistical models and physical measurements, modern approaches use machine learning algorithms. These innovations seek to improve the accuracy and certainty of the forecasts, building on the large volume of data collected by remote sensing and other instruments. Hybrid machine learning models combining two or more algorithms also show much potential. In the literature, various research works have been carried out with different purposes [1-4].

For example, Latif et al. [5] assessed to identify the benefits of machine learning and remote sensing in the development of rainfall estimating models. The statistical models, machine learning algorithms, and neural networks were compared to identify the most suitable model for prediction. Satellite data, radar information, and ground observation data were collected to obtain precipitation information for the region. The results depicted that the machine learning methods, particularly the LSTM models, were effective for various timescales, and the RMSE, the $R^2$, and MAE values were also higher in the study. These findings highlight the growing importance of integrating machine learning for more reliable rainfall forecasts. This goes to show the possibility of the use of complex, combined machine-learning models in this field.

The study recommended more research on RS and hybrid predictive models since they are not widely used. The same objective was used by Gomaa et al. [6], who examined the efficiency of the hybrid machine learning models for daily inflow forecast in Três Marias Reservoir, eastern Brazil, concerning the TRMM data. The current paper applied GRNN, GPR, and MLP-PSO modelling techniques to simulate and predict the rainfall-runoff for the discharge of runoff. The model used input vectors of auto-regression with daily TRMM rainfall and TMR inflow data. The conclusions also showed that the MLP-PSO model was the most effective since it had the least RMSE for the various combinations. The study also showed that the methodology of EMD-HHT combined with GRP and MLP-PSO improved the accuracy, so the authors proposed the use of the model based on MLP-PSO-EMD as the most appropriate one for streamflow forecasting due to its effectiveness in the RMSE indicators. The PSO-SVR has been applied in short-term rainfall forecasts by Aderyani et al. [7] and, in this paper, LSTM and CNN. The research compared PSO-optimized SVR, LSTM, and CNN for the 5-minute and 15-minute ahead rainfall depth predictions based on Niavaran station in Tehran. The findings also indicated that the PSO-SVR and LSTM are better than CNN. Based on the four classes of both severity and duration of the rainfall events, the K-nearest neighbor was used. There was a great improvement in the accuracy of the forecasts, and while comparing the two state-of-the-art models, PSO-SVR and LSTM, the accuracy of the two models was highest for 15-minute and 5-minute forecasts. Including the rainfall depth, predictors improved PSO-SVR's accuracy by up to 13%, while the overall improvements for the models were 3-15% for PSO-SVR and 2-10% for LSTM. From the study, it was evident that PSO-SVR and LSTM were more effective in short-term rainfall prediction. These results underscore the efficiency of hybrid and deep learning models for short-term rainfall predictions.

Another region-specific research by Huang et al. [8] proposed a machine-learning model that combines the best of two worlds to predict debris-flow volumes in China. This study used a database of debris-flow volumes of 60 catchments after the Wenchuan Earthquake and topographic and seismic parameters. The model used Extreme Learning Machine (ELM), Particle Swarm Optimization (PSO), and AdaBoost for debris-flow volume estimation. The findings showed a high level of prediction as indicated by the MAPE of less than 0. 35 for debris flows caused by the Wenchuan Earthquake and 0. 11-0. 16 for other earthquakes. The above study indicated that once this model is calibrated, it could be used to predict regional debris flows due to earthquakes with a lot of efficiency. Chen et al. [9] conducted another study in Iran that aimed at rainfall-runoff estimation using the TreeLSTM spatiotemporal machine learning model.

This study focused on the Jinsha River (JRB) and Han River Basins (HRB) in China and the issues concerning the neural network algorithms of hydrological runoff. The TreeLSTM model adopted historical and upstream rain and runoff data for temporal and spatial feature learning. The validation results of TreeLSTM were an RMSE of 0. 5375 and a MAPE of 8. 27% for JRB, an RMSE of 3. 3562, and a MAPE of 2. 91% for HRB. The accuracy of this proposed model is much higher than that of the standard BP and LSTM models, and it reaches 96.6% of the final correction accuracy. Considering the results of this study, it can be stated that, in general, TreeLSTM demonstrates better potential for obtaining better results in estimating runoff while, at the same time, offering more interpretable results on the given tasks. He et al. [10] applied STL and machine learning techniques for modeling and forecasting rainfall time series. This study employed STL-ML to model and forecast rainfall time series using historical and meteorological data. The approach included three steps: as individual steps of the proposed ETL methodology applied to the time series of rainfall and the models built to forecast the components (the GRU network, the multi-time-scale GRU, and LightGBM) and averaging of the forecasts. These models confirmed that the GRU network and LightGBM can understand trends and seasonal fluctuations; therefore, it is possible to get accurate forecasts for the one-step-ahead scheme.

Hence, the study showed that STL-ML is useful for precise rainfall prediction and can be helpful in flood prediction and hydrological disaster management. Tikhamarine et al. [11] studied rainfall-runoff modeling to enhance the possibilities of hydrological predictions by using modern machine-learning techniques, such as HHO and PSO. This work incorporated MLP and LSSVM-based approaches with HHO to improve the objective function's prediction. This paper considered five scenarios using ACF, CCF, and PACF. The study's findings showed that models developed with HHO had better results than those developed with PSO, and when HHO was integrated with LSSVM, the best prediction of runoff values was achieved. The study found that applying the enhanced HHO technique greatly enhances the efficiency of runoff prediction models. Nourani and Farboudfam [12] also investigated the rainfall time series disaggregation in the mountainous area by applying the hybrid wavelet artificial intelligence techniques.

The study's objectives were to decompose rainfall time series for Tabriz and Sahand rain gauges using WLSSVM and WANN models. Information was derived from six rain gauges in the Urmia Lake basin over 17 years. Analysis of the results indicated that the accuracy of the WANN model for the Tabriz rain gauge was improved. The accuracy of the models for the mentioned stations was 9.1%, 22%, 20%, and 50%; for the Sahand rain gauge, the optimized model led to enhancements of 4.5%, 21. 1%, 30. 2%, and 53. 3% in respective metrics. The study recommended these hybrid models due to their performance over the traditional data processing models. Short-term rainfall forecasting using cumulative precipitation fields from station data: a probabilistic machine learning approach was conducted by Pirone et al. [13]. The study presented a machine learning model for probabilistic rainfall nowcasting for the next 10 minutes for short lead times using cumulative rainfall fields from station data as inputs to a feed-forward neural network for 95 independent machine learning models trained and tested on 359 rain events in Southern Italy. The study proved that incorporating temporal and spatial information enhanced the model's prediction capability, making it possible to predict short-term rainfall with reasonable accuracy.

**Table 1. Comparative analysis of machine learning models for rainfall prediction**

| Study | Machine Learning Model | Performance Metrics | Applications |
|---|---|---|---|
| Study 1 [21] | Logistic Regression, Neural Network (MLP), Decision Tree, Random Forest | Logistic Regression: Accuracy: 82.80%, ROC: 82.45%, Cohen's Kappa: 65.05%<br>Neural Network (MLP): Accuracy: 82.59%, ROC: 81.94%, Cohen's Kappa: 64.40%<br>Decision Tree: Accuracy: 78.64%, ROC: 77.50%, Cohen's Kappa: 55.94%<br>Random Forest: Accuracy: 81.27%, ROC: 80.40%, Cohen's Kappa: 61.55% | Rainfall prediction |
| Study 2 [22] | CNN-LSTM, RNN-LSTM | CNN-LSTM: Loss: 0.012, RMSE: 0.107, MAE: 0.063<br>RNN-LSTM: Loss: 0.011, RMSE: 0.107, MAE: 0.062 | Daily rainfall forecasting |
| Study 3 [23] | XGBoost, LSTM, Random Forest, Gradient Boost, SVM, MLP, Linear Regression | XGBoost: Training CC: 0.88, Testing CC: 0.45<br>LSTM: Training CC: 0.68, Testing CC: 0.21<br>Random Forest: Training CC: 0.80, Testing CC: 0.30<br>Gradient Boost: Training CC: 0.75, Testing CC: 0.35<br>SVM: Training CC: 0.50, Testing CC: 0.25<br>MLP: Training CC: 0.70, Testing CC: 0.40<br>Linear Regression: Training CC: 0.45, Testing CC: 0.20 | Monthly rainfall prediction in hyper-arid environments |
| Study 4 [24] | ANFIS-ABC, ANFIS-GA, ANFIS-SA | ANFIS-ABC: RMSE: 7.60, MAE: 4.17, R: 0.82 (raw data)<br>RMSE: 3.08, MAE: 2.20, R: 0.92 (preprocessed data)<br>Gain: RMSE: 59.47%, MAE: 47.31%, R: 11.96%<br>ANFIS-GA: RMSE: 7.95, MAE: 4.62, R: 0.80 (raw data)<br>RMSE: 3.67, MAE: 2.71, R: 0.89 (preprocessed data)<br>Gain: RMSE: 53.78%, MAE: 41.49%, R: 10.19%<br>ANFIS-SA: RMSE: 8.58, MAE: 5.50, R: 0.78 (raw data)<br>RMSE: 4.16, MAE: 3.10, R: 0.85 (preprocessed data)<br>Gain: RMSE: 51.48%, MAE: 43.68%, R: 9.60% | Daily rainfall prediction |
| Study 5 [25] | Improved DBN, LSTM (Hybrid Model) | Improved DBN: MAE: 0.2435, MSE: 0.0838, RMSE: 0.2895<br>LSTM: MAE: 0.544, MSE: 0.4042, RMSE: 0.6439 | Long-term rainfall prediction in Indian regions |

| | | | |
|---|---|---|---|
| Study 6 [26] | BC-MODWT-DNNs (ConvLSTM, CNN-Bi-LSTM) | ConvLSTM: NSE: 0.988, RMSE: 0.008<br>CNN-Bi-LSTM: NSE: 0.990, RMSE: 0.006 | Real-time rainfall and runoff prediction in urban catchments |
| Study 7 [27] | SAELM, WSAELM | SAELM: NSE: 0.842, RMSE: 0.568, MAE: 0.439, R: 0.930<br>WSAELM: NSE: 0.973, RMSE: 0.245, MAE: 0.196, R: 0.988 | Monthly groundwater level prediction in Kermanshah, Iran |
| Study 8 [3] | MLP, SVR | MLP: RMSE: 0.162, MAE: 0.120, R: 0.990<br>SVR: RMSE: 0.191, MAE: 0.140, R: 0.980 | Hydro-power production capacity prediction in Northern Italy |
| Study 9 [28] | ELM-PSOGWO, ELM-PSO, ELM-GWO, ELM-PSOGSA | ELM-PSOGWO: RMSE: 55.14, MAE: 46.59, NSE: 0.919, R2: 0.925<br>ELM-PSO: RMSE: 71.59, MAE: 57.07, NSE: 0.864, R2: 0.866<br>ELM-GWO: RMSE: 69.69, MAE: 53.34, NSE: 0.866, R2: 0.871<br>ELM-PSOGSA: RMSE: 66.22, MAE: 51.55, NSE: 0.891, R2: 0.895 | Monthly runoff prediction in Mangla watershed, Northern Pakistan |
| Study 10 [1] | ANFIS, ANFIS-GA, ANFIS-DE, ANFIS-PSO | ANFIS: Training AUC: 0.807, Validation AUC: 0.768, Accuracy: 0.805<br>ANFIS-GA: Training AUC: 0.922, Validation AUC: 0.924, Accuracy: 0.883<br>ANFIS-DE: Training AUC: 0.901, Validation AUC: 0.919, Accuracy: 0.869<br>ANFIS-PSO: Training AUC: 0.915, Validation AUC: 0.921, Accuracy: 0.875 | Flood Susceptibility Prediction in the Middle Ganga Plain, India |
| Study 11 [29] | RVM-IGOA, RVM-GOA, RVM-PSO, ANN-IGOA, ANN-GOA, ANN-PSO | RVM-IGOA: NRMSE: 0.125, NSE: 0.986, MD: 0.953, KGE: 0.981<br>RVM-GOA: NRMSE: 0.167, NSE: 0.971, MD: 0.923, KGE: 0.908<br>RVM-PSO: NRMSE: 0.174, NSE: 0.969, MD: 0.911, KGE: 0.890<br><br>ANN-IGOA: NRMSE: 0.127, NSE: 0.981, MD: 0.941, KGE: 0.974<br>ANN-GOA: NRMSE: 0.172, NSE: 0.970, MD: 0.912, KGE: 0.891<br>ANN-PSO: NRMSE: 0.168, NSE: 0.971, MD: 0.924, KGE: 0.899 | River water level prediction in coastal catchments in Malaysia |

The study concluded that this approach is suitable for real-time forecasting and early warning systems because the method is fast and reproducible. Similarly, Qiao et al. [14] proposed a metaheuristic evolutionary deep learning model comprising TCN, IAO, and RF for rainfall-runoff simulation and multi-step runoff prediction. This study examined how different input variables affect prediction accuracy through the application of RF in eliminating input variables and parameter optimization of TCN through IAO. It is testified that the model was applied to five Jinsha River rainfall and runoff stations and the Panzhihua station runoff. Due to the results received, it was possible to conclude that the high efficiency of the offered model augmented the accuracy and speed of water resources and disaster prediction.

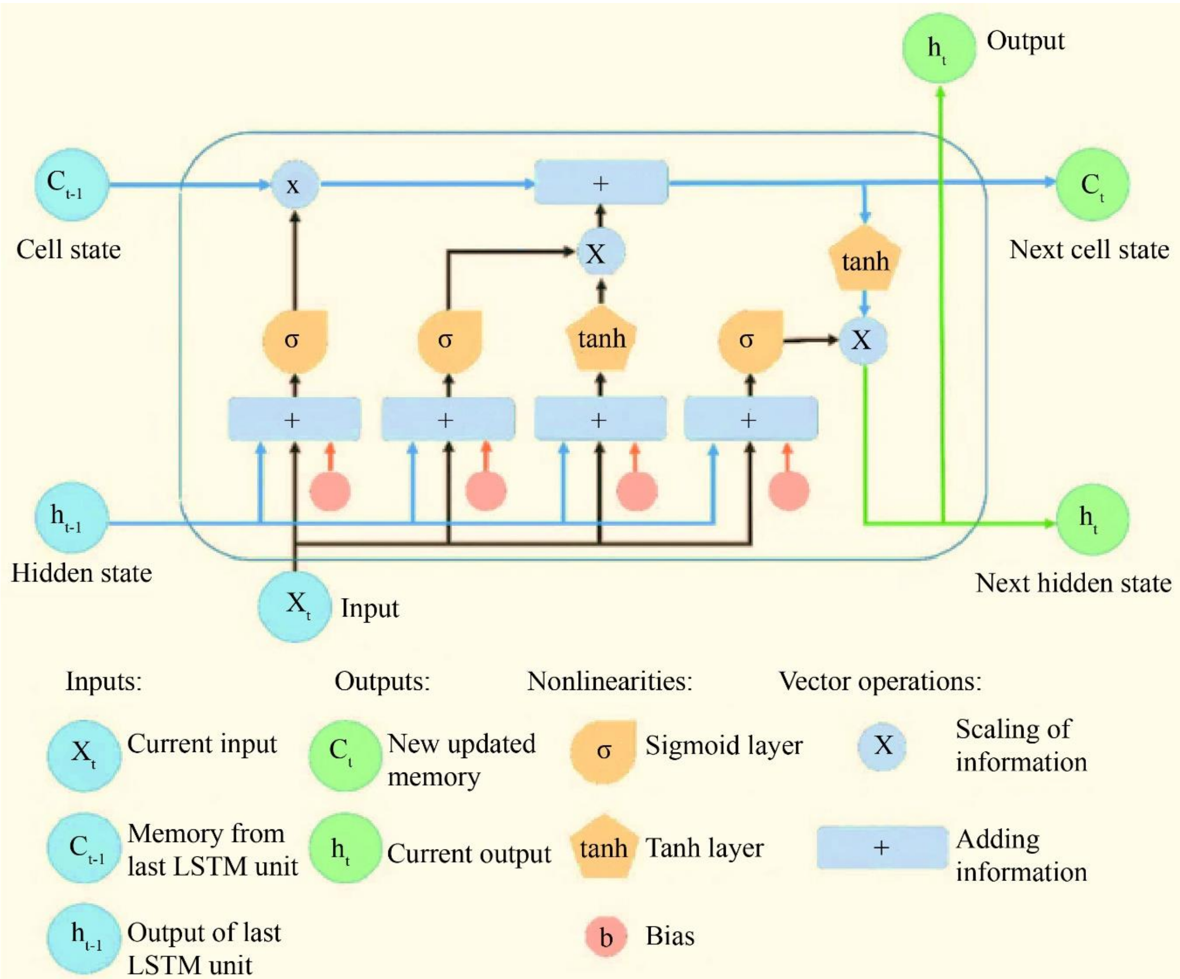


**Fig. 1 Structure of the LSTM model**

A comparative study with the modern machine learning algorithms for time-series forecasting was provided by Barrera-Animas et al. [15]. The objective of this study was to compare the machine learning and deep learning algorithms for rainfall prediction. Of applied models, LSTM is one, Stacked LSTM is another, and Bidirectional LSTM Networks, XGBoost, and regressors are some more models. The paper analyzed data obtained from the five major cities of the United Kingdom from 2000-2020. It was observed that bidirectional-LSTM Networks and stacked-LSTM Networks were the most accurate with lower error rates and suggested for economical-based rainfall prediction.

The study suggested the Bidirectional-LSTM Network for the budget-wise rainfall prediction applications. In addition, Bui et al. [16] also conducted a study to confirm the reliability of a new hybrid model with swarm intelligence-optimized ELM for mapping flash flood susceptibility. This research implemented Extreme Learning Machine (ELM) and Particle Swarm Optimization (PSO) in flash flood prediction. The model was applied in a high-frequency tropical typhoon area in northwest Vietnam with 654 flash flood locations and 12 factors. It was also established that the proposed results exhibited high prediction performance with kappa statistics of 0. 801, RMSE of 0. 281, MAE of 0. 079, $R^2$ of 0. 829, and AUC-ROC of 0. 954, better than other machine learning models. This hybrid approach reveals that using more than one technique is likely to yield better prediction results.

Also, Ridwan et al. [17] have proposed a rainfall prediction model based on machine learning techniques for Terengganu, Malaysia. The research work concerned forecasting the rainfall data in Tasik Kenyir using different ML algorithms, including BLR, BDTR, DFR, and NNR. Two forecasting methods were evaluated: There are two methods to check the convergence of the model, namely Method 1 (M1) with Autocorrelation Function (ACF) and Method 2 (M2) with Projected Error.

It has been found that BDTR offered the highest regression performance for ACF with high $R^2$ values ranging from 0. 5 and 0. 9 across different scenarios. It was established that method M1 was more accurate than M2; this proved the model's efficiency in predicting rainfall and water management. Fijani et al. [18] developed a novel two-layer decomposition method with extreme learning machines for real-time monitoring of water quality parameters in the environment. The study applied CEEMDAN and VMD with ELM and LSSVM for daily chlorophyll-a (Chl-a) and Dissolved Oxygen (DO) records of a lake reservoir. What has been achieved in the second hypothesis is the ability of the ELM algorithm to achieve higher accuracy than the LSSVM algorithm and the positive impact of the multi-layer structure of the model, which was divided into high-frequency oscillations and low-frequency oscillations.

Therefore, employing this research, it can be concluded that the proposed hybrid model can be applied for real-time water quality control and, therefore, enhance ecological/environmental sustainability. In the same way, the authors Nigam and Srivastava [19] also employed hybrid deep learning models for the elements of traffic stream variables in the rainy environment. Concerning the research goal, the task of the seminal study was to predict the macroscopic traffic stream parameters, including speed and density, under adverse weather conditions.

Therefore, the models were named CNN-LSTM for the spatiotemporal features extraction and LSTM-LSTM for the memory part. The studies also showed that the model trained with traffic and rainfall data gave better accuracy than the model that was not trained with rainfall data. This is because the LSTM-LSTM model was able to determine longer dependency patterns between the traffic stream variables and the weather data in traffic control during rainy weather.

Ahmed et al. [2] employed a deep-learning hybrid model with a Boruta-Random forest optimizer algorithm for streamflow prediction using climate mode indices, rainfall, and periodicity. The study aimed to enhance streamflow prediction by employing a feature selection method with two distinct deep-learning models.

To increase the accuracy, lagged inputs from climate mode indices, rainfall, and periodicity were accumulated as predictor variables. The findings showed that the proposed hybrid LSTM method, namely the BRF-LSTM model, achieved more than 98% of predictive errors within an acceptable error range (RRMSE ≈1.30%).

Therefore, the BRF-LSTM model enhanced the forecasting performance and should be implemented in strategic water resource management. Likewise, Shahani et al. [20] evaluated the climate change effect on river flow extreme events in various climates of Iran employing LARS-WG6 and rainfall-runoff modeling of deep learning. The study was intended to estimate future weather changes based on climate change for emission scenarios RCP2. The meteorological data from LARS-WG6 (2021-2040) forecasted was used as inputs to the CNN model to estimate runoff. The results showed that rainfall enhanced in CSA, HT, and CA climates under RCP8. Five would be +14%, +11%, and +6%, respectively, while maximum discharge in CA would increase by 18%, and runoff in HT would reduce by about 5% under RCP2. This study revealed that there was a dire need to adapt to regional differences in the management of water resources.

In the existing literature, several studies emphasize the critical role of accurate weather prediction, which is crucial for sectors from agriculture to disaster management, as shown in Table 1. While individual models like LSTM and GBM have demonstrated promise, a significant research gap remains regarding their combined potential. Previous studies have rarely leveraged a direct hybrid integration of LSTM and GBM for rainfall forecasting using time-series data, limiting forecast accuracy under varying conditions.

This study addresses that gap by proposing and evaluating a Hybrid Machine Learning Model for Rainfall Prediction Using Time-Series Data. The hybrid framework integrates the Long Short-Term Memory (LSTM) and Gradient Boosting Machine (GBM) models, harnessing LSTM's capability to capture temporal dependencies and GBM's robust classification and regression performance.

Unlike previous studies, the hybridization presented here is specifically designed to maximize predictive accuracy across short-term and long-term rainfall patterns, with rigorous validation to demonstrate its superiority over single models.

This research establishes a new level of forecast precision, critical for agriculture, transportation, logistics, and disaster management applications. Combining LSTM and GBM, the proposed approach provides decision-makers with enhanced, reliable weather predictions, supporting better operational planning and sustainable management of environmental resources.

## 2. Problem Identifications

This section compares the analyzed models employed for rainfall prediction, describes each model's architecture, and outlines the evaluation criteria used. The data preprocessing steps, model parameterization, validation techniques, and justification for model selection are provided to enhance the study's reproducibility and credibility. Table 1 below compares eleven studies undertaken in this research [4].

These studies explore different models, datasets, performance metrics, and significant findings conducted by researchers globally. The architectures of the Logistic Regression, Neural Network (MLP), Decision Tree, Random Forest, CNN-LSTM, RNN-LSTM, and hybrid models such as ANFIS-ABC, ANFIS-GA, and ANFIS-SA are depicted in Figures 1 to 3, respectively.

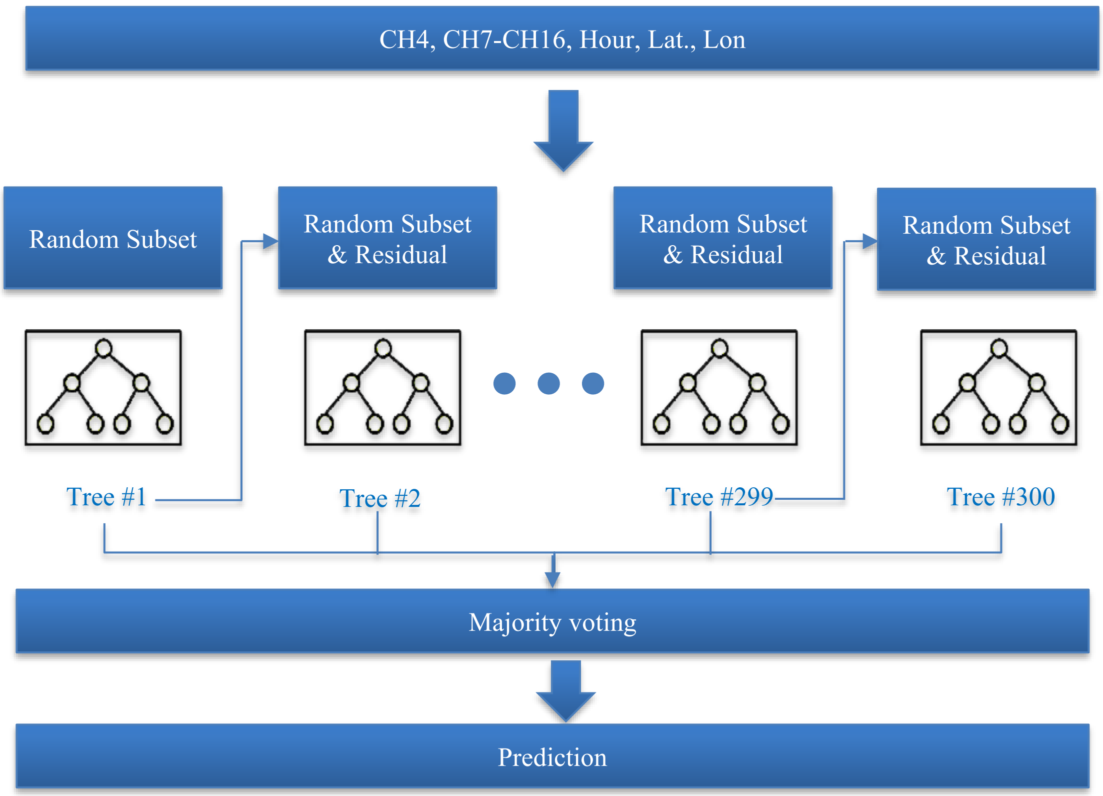


**Fig. 2 Structure of the GBM model**

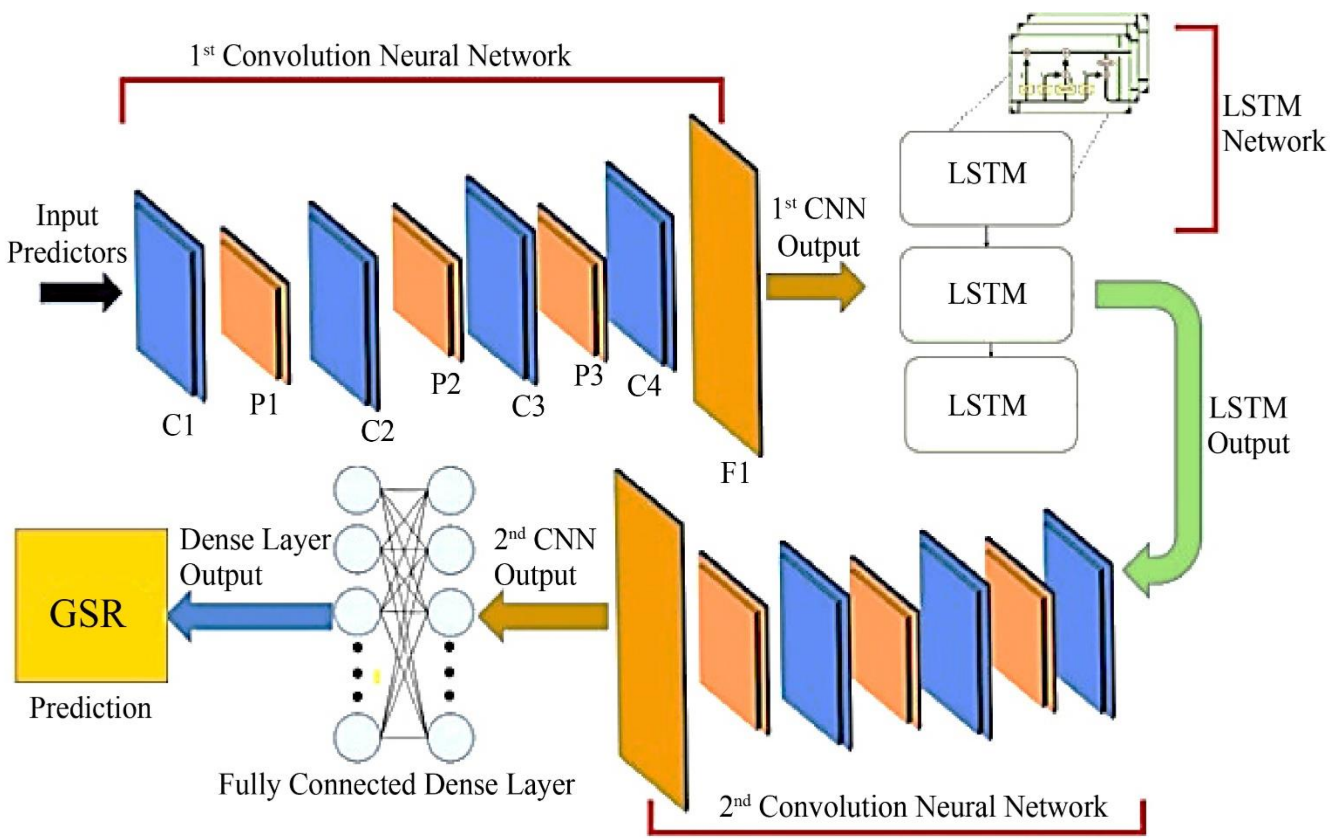


**Fig. 3 Structure of the hybrid LSTM-GBM model**

### 2.1. Mathematical Models for LSTM, GBM, and Hybrid Architectures

#### 2.1.1. Formulation of LSTM Model

LSTM networks are a variant of RNNs designed to capture long-term dependencies and mitigate the vanishing gradient problem [30]. The LSTM model uses a series of gates to control the flow of information. The detailed equations governing the LSTM network are:

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t &= f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\ h_t &= o_t \odot \tanh(C_t) \end{aligned} \tag{1}$$

The LSTM model uses several components to control the flow of information. The input gate $i_t$ Manages the incorporation of new information, while the forget gate $f_t$ Determines what information from the previous state should be discarded.

The output gate $o_t$ Regulates the output of the current cell state. The cell input activation $\tilde{C}_t$ Is a candidate value for the new cell state, and the cell state $C_t$ Holds the long-term memory.

The hidden state $h_t$ Represents the output based on the cell state. Activation functions, such as the sigmoid $\sigma$ and hyperbolic tangent tanh, introduce non-linearity into the model. The weight matrices $W$ and bias terms $b$ are parameters learned during training. The element-wise multiplication $\odot$ operation ensures that cell and hidden state updates are applied correctly.

#### 2.1.2. Formulation of the GBM Model

GBM is an ensemble technique that builds models iteratively to minimize a loss function. The model combines weak learners (typically decision trees) to form a strong predictive model. The mathematical formulation of the GBM model is given by Equation (2):

$$F_m(x) = F_{m-1}(x) + \lambda \cdot h_m(x) \tag{2}$$

where:
$F_m(x)$ Is the model prediction at the m-th stage.
$F_{m-1}(x)$ It is the prediction from the previous stage.
$\lambda$ is the learning rate.
$h_m(x)$ The new base learner was added at stage m.

The objective at each stage is to minimize the loss function L:

$$h_m(x) = \arg\min_h \sum_{i=1}^{n} L\big(y_i, F_{m-1}(x_i) + h(x_i)\big) \tag{3}$$

Where:

| | | |
|---|---|---|
| $L$ | - | is the loss function. |
| $y_i$ | - | is the actual values. |
| $x_i$ | - | is the input feature. |

#### 2.1.3. Formulation of Hybrid LSTM-GBM Model

These weaknesses are avoided in the hybrid LSTM-GBM model since LSTM and GBM are combined for data analysis. LSTM captures the complex temporal relationships in the weather data, while GBM enhances the predictive performance by addressing model bias and reducing prediction error. This hybrid design capitalizes on the strengths of both architectures.

- LSTM Component:
  $$h_t = \mathrm{LSTM}(x_t, h_{t-1}, C_{t-1}) \tag{4}$$
- GBM Component:
  $$F_m(x) = F_{m-1}(x) + \lambda \cdot h_m(x) \tag{5}$$
- Final Prediction:
  $$\hat{y} = F_M(h_t) \tag{6}$$

Where:
LSTM represents the LSTM network.
$h_t$ It is the hidden state from the LSTM network.
$F_m(x)$ Is the prediction from the GBM at stage m.
$\hat{y}$ is the final prediction.

This hybrid model aims to improve prediction accuracy by combining the temporal learning capabilities of LSTM with the optimization strengths of GBM.

## 3. Working Structure

### 3.1. Model Setup

The working structure of this study has some basic steps: data collection and preliminary data analysis, introduction of and selection of the model, model estimation, and analysis of results. This systematic approach implies a thorough and well-structured analysis of the possibility of using various machine learning algorithms in the given context of weather prediction.

#### 3.1.1. Model Development

Three models were developed and evaluated in this study:

- LSTM Model: To predict the weather status, LSTM model sequences of temperature and humidity data were used to train the model.
- GBM Model: It can be seen, therefore, that GBM is an ensemble learning technique that constructs the model invented stage-wise and generalizes it in a way that optimizes a differentiable loss function. Like the LSTM model, GBM model training was based on the same input features as what has been identified above.

- Hybrid LSTM-GBM Model: This model is the extension of the LSTM model, and the GBM model integrates the features of both models. The components of this model are the LSTM network – which computes temporal features of input data, and the GBM model – which computes the final weather status.

*3.1.2. Model Evaluation*

The effectiveness of the proposed models was analyzed based on nine measurements: Accuracy, Precision, Recall, F1-Score, MSE, MAE, and RMSE. Furthermore, to doubly ensure confusion matrices for a better understanding of the models' classification capabilities, ROC curves and Precision-Recall curves were also computed.

*3.1.3. Analysis and Interpretation*

The last step in the process is the identification and comparison of the performances of all three models. This consists of analyzing the assessment criteria and charts to identify the results and accuracy of each created model. The last one, which employed a combined model LSTM-GBM that unites LSTM' temporal learning and GBM's classification ability, was mentioned as more accurate and with less error than the single models.

This is especially useful when analyzing the application flow; it aids in understanding the utilization of additional complex machine-learning algorithms in making weather forecasts. The findings show the possibility of applying hybrid models to enhance the efficiency of WRF weather predictions that are essential to industries, depending on accurate weather data.

### 3.2. Data Description

The data source used in this investigation involves essential climate parameters obtained from four chosen stations in Metro Manila and Rizal province. The authors clearly include temperature and humidity as other main aspects already presented are weather conditions encoded with 0 if it is not raining and 1 if it is instead. These variables are crucial for models intended for the construction of weather-predicting systems.

## 4. Results and Discussion

To compare the findings of this study with previous studies and to check the efficacy of the models, the performance of the three models, the LSTM, GBM, as well as the mixed model LSTM-GBM, was measured against the following parameters: Accuracy, Precision, Recall, and F1 Score, MSE, MAE, as well as, RMSE. The three models were evaluated on a dataset generated from temperature and humidity to provide a binary target parameter for weather, as illustrated in Table 2. The measure of accuracy shows the ratio of the total number of cases classified correctly to the total number of cases. The measure of the accuracy of the LSTM model was 0.998341, implying that 99% of the numbers with that ID were categorized properly. Based on the above analysis, it can be concluded that the availability of AC is very high, with 83% of the instances coming from this source. From this study, the GBM model, with an accuracy of 0.977404, also gives good results but is slightly less reliable than the LSTM model. The proposed LSTM-GBM model achieved the best accuracy of 0.999585, correctly classifying 99 percent of the samples. Total accuracy stood at 96% on the occasions and illustrated the kind of synergy that exists between LSTM and GBM models. Among all the positive predictions the model generates, precision gauges the percentage of true positive predictions. With a precision of 0.96478, the LSTM model made a few false positive mistakes. With a far lower precision of 0.61194, the GBM model indicated a larger false positive rate. Reflecting its great capacity to reduce false positives relative to both individual models, the hybrid LSTM-GBM model attained an amazing precision of 0.99285.

Sensitivity, sometimes referred to as recall, gauges the model's accurate identification of true positives. With a recall of 0.97857, the LSTM model proved rather successful in spotting the most positive examples. With a recall of 0.33064, the GBM model could not clearly capture true positives adequately. Reaching a recall of 0.99285, the hybrid LSTM-GBM model exceeded both single models in terms of almost all positive instance identification. The harmonic mean of recall and precision, the F1 Score, offers a fair assessment of a model's performance. With an F1 Score of 0.97 163, the LSTM model showed a decent mix of recall and precision. With an F1 Score of 0.42931, the GBM model reflected its difficulty in striking recall against precision properly with an amazing F1 Score of 0.99285.

The hybrid LSTM-GBM model proved to be quite balanced and generally efficient. Between expected and actual values, MAE and MSE, respectively, are used to gauge the average absolute and squared deviations. With an MSE of 0.00127 and an MAE of 0.00179, the LSTM model proved highly accurate in forecasts. Reflecting more significant mistakes in its predictions, the GBM model had an MSE of 0.01594 and an MAE of 0.03326. With an MSE of 0.00044 and an MAE of 0.00193, the hybrid LSTM-GBM model shows its improved prediction accuracy by greatly lowering these mistakes.

**Table 2. A comparison of the model performance**

| Model | Accuracy | Precision | Recall | F1 Score | MSE | MAE | RMSE |
|---|---|---|---|---|---|---|---|
| LSTM | 0.998341 | 0.96478 | 0.97857 | 0.97163 | 0.00127 | 0.00179 | 0.03574 |
| GBM | 0.977404 | 0.61194 | 0.33064 | 0.42931 | 0.01594 | 0.03326 | 0.12626 |
| LSTM-GBM | 0.999585 | 0.99285 | 0.99285 | 0.99285 | 0.00044 | 0.00193 | 0.02114 |

RMSE offers a standard deviation of prediction error metric. With an RMSE of 0.03574, the LSTM model showed remarkably minimal prediction errors. Reflecting greater variation in its prediction mistakes, the GBM model had an RMSE of 0.12626. With an RMSE of 0.02114, the hybrid LSTM-GBM model proved to be the most consistent and accurate in forecasts. Ultimately, across all evaluation criteria, the hybrid LSTM-GBM model outperformed the separate LSTM and GBM models. By combining the best features of both models, this hybrid technique produces lower error rates (MSE, MAE, RMSE) and enhanced accuracy, precision, recall, and F1 Score.

These findings draw attention to the possible advantages of integrating several machine learning methods to improve classification task predicting performance. The performance of the models in terms of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) is thoroughly broken out in the confusion matrix as in Figure 4. Examining the confusion matrices for the LSTM, GBM, and hybrid LSTM-GBM models provides an important new understanding of their classification capacity. Based on the confusion matrix, the LSTM model, the accuracy of the model in forecasting both classes is extremely high. It classifies rather few incorrectly while correctly identifying 4678 cases of class 0 (no-rain) and 137 cases of class 1 (rain). Also, at just five erroneous positives and three false negatives, there is vast potential for the LSTM model to align the two classes accurately. This is a great advantage of the LSTM model; the model performs rather stably and robustly, partly due to such great precision and recall. The GBM model, on the other hand, gives a reasonable number of correct predictions or true positives, with significantly higher false positives and false negatives than the LSTM model. In the confusion matrix result for the GBM model, class 1 is predicted as 26 instances, while class 0 is correctly predicted as 4674. Moreover, the model wrongly labels 83 occurrences as class 0 while accurately identifying just 41 examples of class 1. Particularly in determining the positive class (rain), these results show that the GBM model suffers from accuracy and recall, which reduces general dependability and accuracy. But as its confusion matrix shows, the hybrid LSTM-GBM model performs close to flawlessly. With only one mistake in each category, it appropriately labels practically all cases, noting 4682 instances of class 0 and 139 instances of class 1. The very low false negatives (1) and false positives (1) emphasize the remarkable accuracy and recall of the model.

This model minimizes errors in classification by efficiently aggregating the strengths of LSTM and GBM. The analysis of the forecast results indicates that Li, Le, and Ma's hybrid LSTM-GBM model has less mean absolute percentage error than the individual LSTM and GBM models. Generally, the score achieved by the LSTM model is high with a few mistakes, while, on the other hand, the GBM model has many false positive and false negative cases. The virtues of both models are fully utilized to attain a near-perfect classification; therefore, it is evident that the hybrid model increases the overall effectiveness. This superior performance involves measures like accuracy, precision, recall, and a low error rate, which makes the hybrid model show high performance on binary classification.

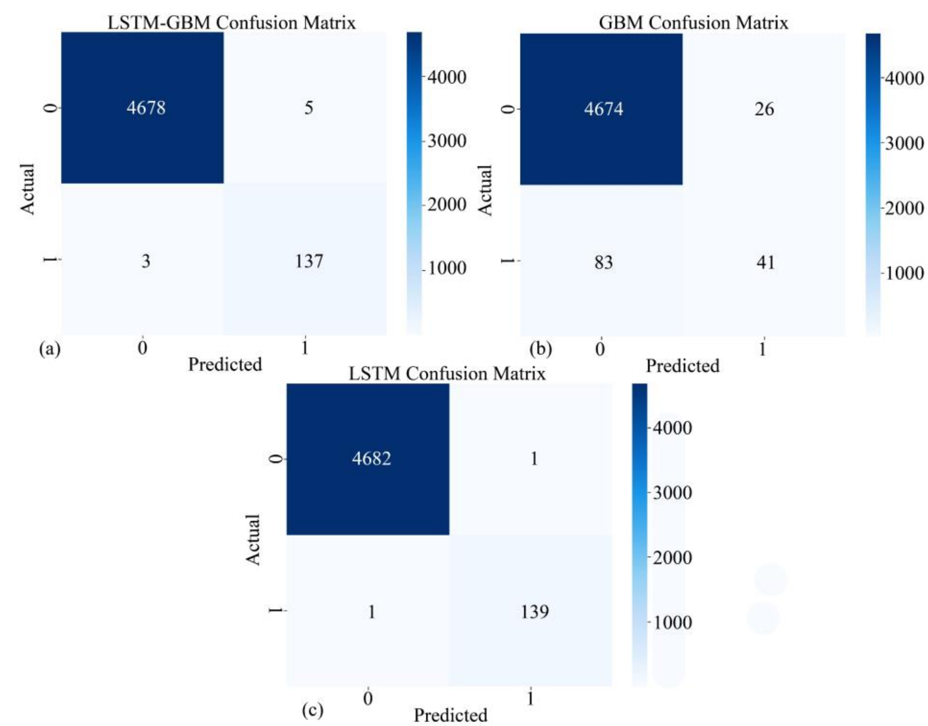


**Fig. 4 Confusion matrices of (a) LSTM, (b) GBM, and (c) Hybrid LSTM-GBM models**

Figure 5 shows the performance of the LSTM model component inside the hybrid LSTM-GBM model, highlighting how the accuracy and loss measures change after 500 training cycles. Subfigure (a) shows the number of epochs against the accuracy of the training and validation datasets. The training accuracy first rises quickly and, in the first few epochs, approaches almost ideal levels. This trend suggests that the model quickly picks the fundamental patterns in the training data. Rising quickly and stabilizing near 1.0, the validation accuracy also shows the great generalizing capacity of the model to unprocessed data. Following the first learning phase, the near-constant accuracy for training and validation datasets points to the model preserving good performance free from major overfitting. Placed against the number of epochs, Subfigure (b) shows the loss values for training and validation datasets. The training loss first declines significantly, showing the model's rapid adaptation to minimize errors. Effective learning is shown by the identical downward tendency of the validation loss. Training and validation losses are steady at low values across the next epochs, indicating that the model keeps performing effectively and free from significant swings. The rather modest and steady loss values across the training procedure support, even more, the resilience of the model and its capacity to preserve constant performance. These charts, taken together, show that the LSTM component of the hybrid model has outstanding learning and generalizing properties. The low loss and great accuracy across both training and validation sets point to the hybrid LSTM-GBM model's great efficacy for the particular classification problem, so balancing stability over long training cycles with precision. Two important evaluation measures-the Precision-Recall Curve (PRC) and the Receiver Operating Characteristic (ROC) curve- are used, as shown in Figure 6, to show the performance of the hybrid LSTM-GBM model. Such visuals assist one in comprehending the model's performance in terms of accuracy, recall, and discriminability of different classes.

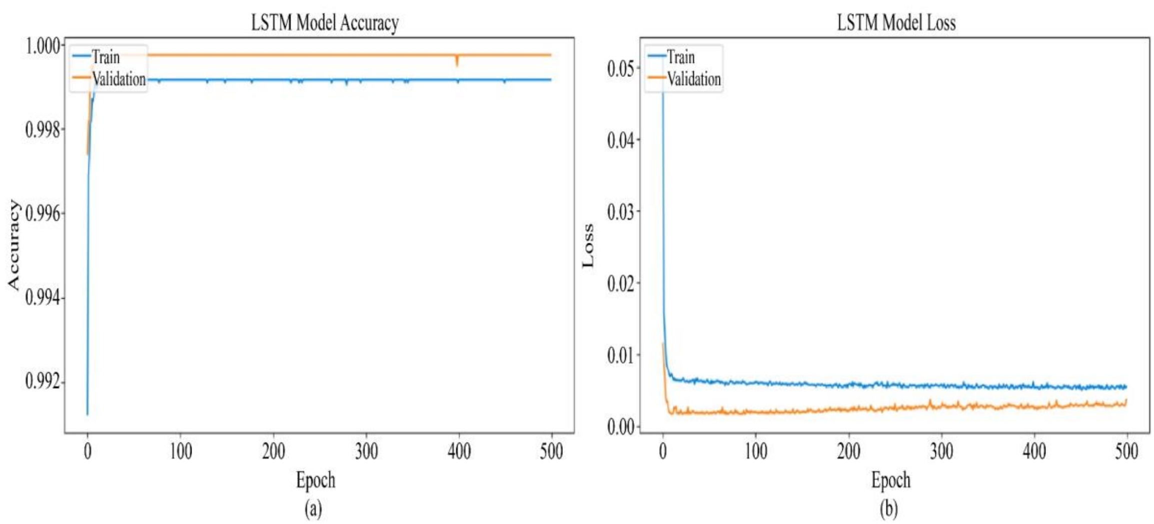


**Fig. 5 The hybrid LSTM-GBM models performance (a) Accuracy, and (b) Loss Vs Epochs**

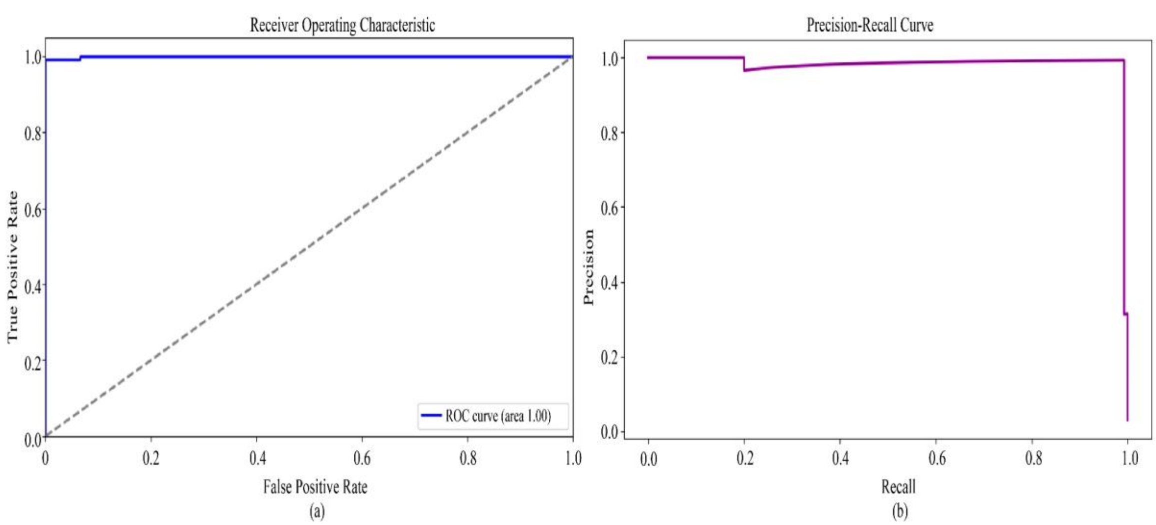


**Fig. 6 The performance of the hybrid LSTM-GBM model was measured by (a) ROC, and (b) PRC**

As seen in Subfigure (a), the ROC curve of the proposed system depicts the trade-off between the false positive rate and the area under the curve–genuine positive rate or sensitivity. A very good curve performance is observed by the hybrid LSTM-GBM model, whose curve is close to the top left corner. One has flawless classification capacity with a 1.00 area under the ROC curve (AUC). This suggests that free from false positives or false negatives, the model is quite good at differentiating between positive and negative classes. Such a high AUC captures the dependability and resilience of the model in target variable prediction.

Subfigure (b)'s Precision-Recall curve emphasizes the link between recall-the fraction of true positive predictions among all positive predictions-and precision-the proportion of true positive predictions among all positive predictions. For most of the recall values, the curve stays near 1.0, meaning that the hybrid LSTM-GBM model preserves great accuracy over a range of recall levels. This performance implies that even with varying recalls, the model can efficiently find genuine positives while minimizing false positives. The minor dip near the end of the curve reflects the few misclassifications of the model but does not appreciably reduce its general excellent performance.

## 5. Conclusion

This work uses temperature and humidity data to evaluate three machine learning models-LSTM, GBM, and a hybrid LSTM-GBM-forecasting weather. Accuracy, precision, recall, F1 score, MSE, Mean MAE, RMSE, and confusion matrices were used to evaluate each model. With 0.983991 accuracy, 0.96478 precision, 0.97857 recall, and 0.97 163 F1 score, the LSTM model performed admisitely. Its low error rates are seen from MSE 0.00127, MAE 0.00179, and RMSE 0.03574. The durability of the confusion matrix was demonstrated by minimal misclassifications. The GBM model scored 0.977404 accuracy, 0.61194 recall, and 0.42931 F1 score; hence, it performed poorly. With 0.01597, 0.03326, and 0.12626, its MSE, MAE, and RMSE were higher. The confusing matrix's classification accuracy was limited by more false positives and negatives. With 0. 999585, 0.99285, and 0.99285 F1 scores, the hybrid LSTM-GBM model came out top. With 0.00044 MSE, 0.00193 MAE, and 0.02 114 RMSE, it likewise had the lowest error rates.

The confusion matrix of the hybrid model revealed almost flawless classification with only one false positive and one false negative. Verifying its better performance, the hybrid model's ROC and Precision-Recall curves Perfect categorization was shown by the 1.00 AUC of the ROC curve. The Precision-Recall curve demonstrated that the model minimized false positives while identifying true positives at all recall levels. At all evaluation measures, the hybrid LSTM-GBM model finally outperformed the LSTM and GBM models. Combining LSTM and GBM this hybrid method enhances predictive accuracy, precision, recall, and error rates. Integrating machine learning techniques enhances model performance for difficult categorization issues. Hence, the hybrid LSTM-GBM model presents a potential weather prediction solution.

## References


[1] Aman Arora et al., "Optimization of State-of-the-Art Fuzzy-Metaheuristic ANFIS-Based Machine Learning Models for Flood Susceptibility Prediction Mapping in the Middle Ganga Plain, India," *Science of The Total Environment*, vol. 750, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] A.A. Masrur Ahmed et al., "Deep Learning Hybrid Model with Boruta-Random Forest Optimiser Algorithm for Streamflow Forecasting with Climate Mode Indices, Rainfall, and Periodicity," *Journal of Hydrology*, vol. 599, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] C. Condemi et al., "Hydro-Power Production Capacity Prediction based on Machine Learning Regression Techniques," *Knowledge-Based Systems*, vol. 222, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Diaa Salman et al., "Hybrid Deep Learning Models for Time Series Forecasting of Solar Power," *Neural Computing and Applications*, vol. 36, no. 16, pp. 9095-9112, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Sarmad Dashti Latif et al., "Assessing Rainfall Prediction Models : Exploring the Advantages of Machine Learning and Remote Sensing Approaches," *Alexandria Engineering Journal*, vol. 82, pp. 16-25, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Ehab Gomaa et al., "Assessment of Hybrid Machine Learning Algorithms Using TRMM Rainfall Data for Daily Inflow Forecasting in Três Marias Reservoir, Eastern Brazil," *Heliyon*, vol. 9, no. 8, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Fatemeh Rezaei Aderyani, S. Jamshid Mousavi, and Fatemeh Jafari, "Short-Term Rainfall Forecasting Using Machine Learning-Based Approaches of PSO-SVR, LSTM and CNN," *Journal of Hydrology*, vol. 614, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Jian Huang et al., "A Hybrid Machine-Learning Model to Estimate Potential Debris-Flow Volumes," *Geomorphology*, vol. 367, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Zeqiang Chen, Hui Lin, and Gaoyun Shen, "TreeLSTM: A Spatiotemporal Machine Learning Model for Rainfall-Runoff Estimation," *Journal of Hydrology: Regional Studies*, vol. 48, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Renfei He, Limao Zhang, and Alvin Wei Ze Chew, "Modeling and Predicting Rainfall Time Series Using Seasonal-Trend Decomposition and Machine Learning," *Knowledge-Based Systems*, vol. 251, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Yazid Tikhamarine et al., “Rainfall-Runoff Modelling Using Improved Machine Learning Methods: Harris Hawks Optimizer vs. Particle Swarm Optimization,” *Journal of Hydrology*, vol. 589, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] Vahid Nourani, and Nima Farboudfam, “Rainfall Time Series Disaggregation in Mountainous Regions Using Hybrid Wavelet-Artificial Intelligence Methods,” *Environmental Research*, vol. 168, pp. 306-318, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] Dina Pirone et al., “Short-Term Rainfall Forecasting Using Cumulative Precipitation Fields from Station Data: A Probabilistic Machine Learning Approach,” *Journal of Hydrology*, vol. 617, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Xiujie Qiao et al., “Metaheuristic Evolutionary Deep Learning Model Based on Temporal Convolutional Network, Improved Aquila Optimizer and Random Forest for Rainfall-Runoff Simulation and Multi-Step Runoff Prediction,” *Expert Systems with Applications*, vol. 229, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Ari Yair Barrera-Animas et al., “Rainfall Prediction: A Comparative Analysis of Modern Machine Learning Algorithms for Time-Series Forecasting,” *Machine Learning with Applications*, vol. 7, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] Dieu Tien Bui et al., “A Novel Hybrid Approach Based on a Swarm Intelligence Optimized Extreme Learning Machine for Flash Flood Susceptibility Mapping,” *Catena*, vol. 179, pp. 184-196, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[17] Wanie M. Ridwan et al., “Rainfall Forecasting Model Using Machine Learning Methods: Case Study Terengganu, Malaysia,” *Ain Shams Engineering Journal*, vol. 12, no. 2, pp. 1651-1663, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Elham Fijani et al., “Design and Implementation of a Hybrid Model Based on Two-Layer Decomposition Method Coupled with Extreme Learning Machines to Support Real-Time Environmental Monitoring of Water Quality Parameters,” *Science of The Total Environment*, vol. 648, pp. 839-853, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[19] Archana Nigam, and Sanjay Srivastava, “Hybrid Deep Learning Models for Traffic Stream Variables Prediction During Rainfall,” *Multimodal Transportation*, vol. 2, no. 1, pp. 1-23, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Mohammad Hossein Shahani et al., “Assessing Climate Change Impact on River Flow Extreme Events in Different Climates of Iran Using Hybrid Application of LARS-WG6 and Rainfall-Runoff Modeling of Deep Learning,” *Ecohydrology & Hydrobiology*, vol. 23, no. 2, pp. 224-239, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Mohd Usman Saeed Khan et al., “Comparative Analysis of Different Rainfall Prediction Models: A Case Study of Aligarh City, India,” *Results in Engineering*, vol. 22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Geethu Thottungal Harilal, Aniket Dixit, and Giovanni Quattrone, “Establishing Hybrid Deep Learning Models For Regional Daily Rainfall Time Series Forecasting in the United Kingdom,” *Engineering Applications of Artificial Intelligence*, vol. 133, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Faisal Baig et al., “How Accurate are the Machine Learning Models in Improving Monthly Rainfall Prediction in Hyper Arid Environment?,” *Journal of Hydrology*, vol. 633, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[24] Binh Thai Pham et al., “Hybrid Artificial Intelligence Models Based on Adaptive Neuro Fuzzy Inference System and Metaheuristic Optimization Algorithms for Prediction of Daily Rainfall,” *Physics and Chemistry of the Earth, Parts A/B/C*, vol. 134, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] T. Anuradha, P.S.G. Aruna Sri Formal, and J. RamaDevi, “Hybrid Model for Rainfall Prediction with Statistical and Technical Indicator Feature Set,” *Expert Systems with Applications*, vol. 249, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Amirmasoud Amini, Mehri Dolatshahi, and Reza Kerachian, “Real-Time Rainfall and Runoff Prediction by Integrating BC-MODWT and Automatically-Tuned DNNs: Comparing Different Deep Learning Models,” *Journal of Hydrology*, vol. 631, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] Ali Azizpour et al., “Estimation of Water Level Fluctuations in Groundwater through a Hybrid Learning Machine,” *Groundwater for Sustainable Development*, vol. 15, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[28] Rana Muhammad Adnan et al., “Improving Streamflow Prediction Using a New Hybrid ELM Model Combined with Hybrid Particle Swarm Optimization and Grey Wolf Optimization,” *Knowledge-Based Systems*, vol. 230, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[29] Hai Tao et al., “River Water Level Prediction in Coastal Catchment Using Hybridized Relevance Vector Machine Model with Improved Grasshopper Optimization,” *Journal of Hydrology*, vol. 598, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[30] Diaa Salman et al., “Integration of Electric Vehicle Charging Stations Into the Unit Commitment Modeling,” *2022 11$^{th}$ International Conference on Power Science and Engineering*, Eskisehir, Turkey, pp. 79-83, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[31] Joyce Cai et al., “Data for Rain Prediction,” *Mendeley Data*, 2022. [CrossRef] [Publisher Link]