An Automatic Data-Driven Long-term Rainfall Prediction using Humboldt Squid Optimized Convolutional Residual Attentive Gated Circulation Model in India

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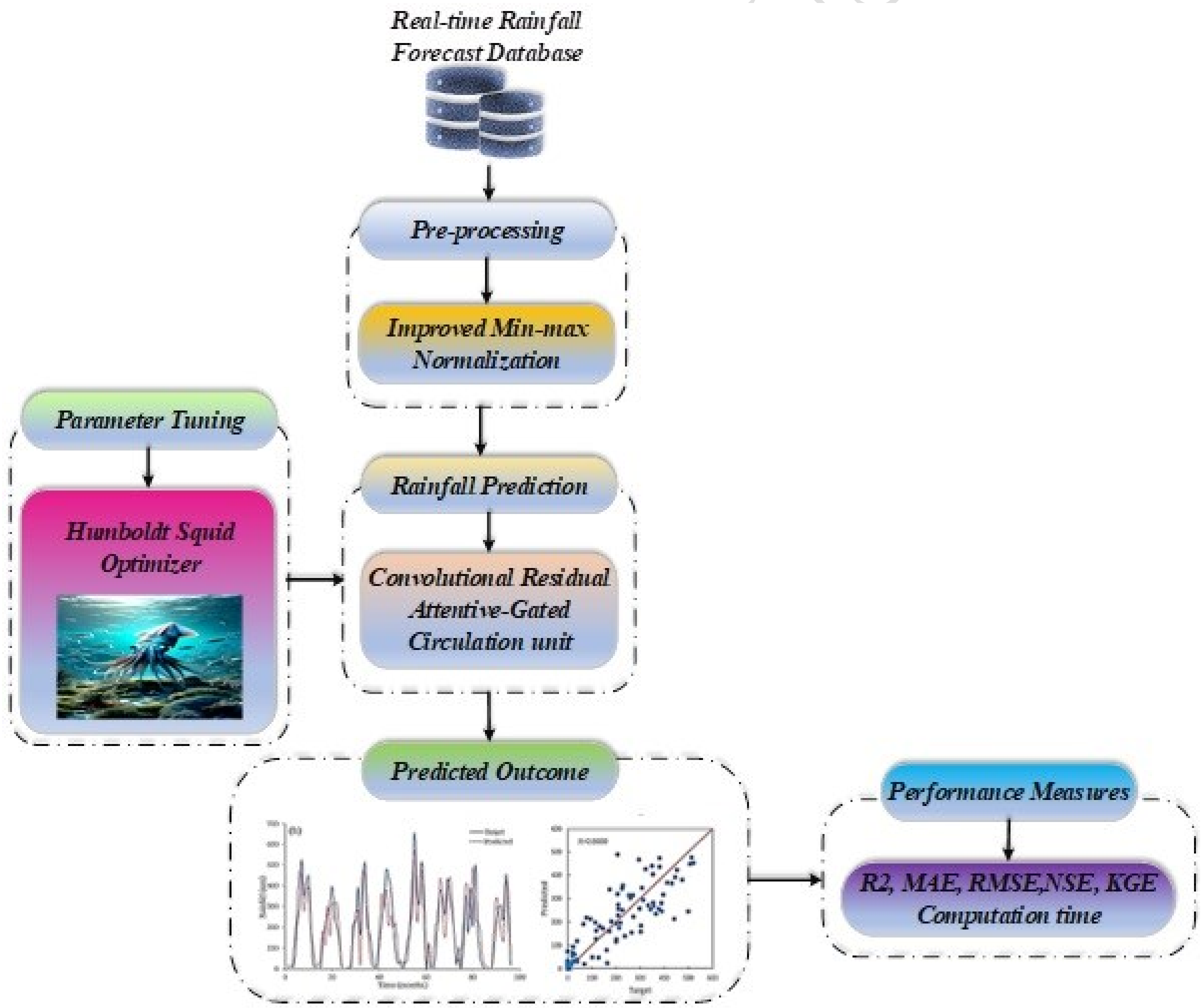
GRAPHICAL ABSTRACT



ABSTRACT

Precise long-term rainfall forecasting is becoming progressively significant, predominantly in periods of fluctuating weather circumstances. These prophecies are indispensable for several areas, including agronomy, water resource supervision, flood attentiveness, and effluence monitoring. This framework investigates the composite association between climatological data, with an emphasis on the precise estimating of rainfall by finding the effect of temperature disparities on rainfall outlines in diverse states of India. The developed framework undergoes two phases: pre-processing and rainfall forecasting. At first, the Improved min-max normalization (I-MMN) technique is highlighted in the preprocessing stage to eliminate unsolicited missing values from the database. Then, the convolutional residual attentive gated circulation unit (CResAtt-GCU) technique is presented to envisage the amount of rainfall that occurs in various Indian states. Finally, the Humboldt squid optimizer (HBSO) technique is presented to tune the parameters of the developed model to minimize network complications during the training process. The developed framework is processed under the Python platform and the real-time rainfall prediction database collected between 2000-2023 is utilized for the experimentation process. Various computational measures like R2, root mean square error (RMSE), Kling-Gupta Efficiency (KGE), Nash-Sutcliffe Efficiency (NSE), mean absolute error (MAE), and computation time are evaluated and distinguished from different studies. The overall R2 of 0.993, RMSE of 0.84, KGE of 0.96, NSE of 0.992, MAE of 0.53, and overall CT of 86.66s are obtained by the developed technique against various conventional studies on forecasting the rainfall in different regions of India.

Keywords: Rainfall Prediction, Monthly Forecasting, Indian Monsoon Climate, Time-Series Data, Deep Learning, Convolutional Residual Attentive Gated Circulation Model, Humboldt Squid Optimizer.

1. Introduction

Rainfall is an essential climatological aspect, and India is notorious for its recurrent and often disproportionate rain. These climatic conditions provocatively challenge India's economy and agro-farming, since they may impact overwhelming blizzards or devastating insufficiencies [1, 2]. These surfactant backwaters embrace a lot of inclement days in excess of 200 per annum in several Indian counties, thereby embracing above quasi of the itinerary, while thirstier districts statement an annual typical value of 150 to 200 rainy days. Across the ancient era, India has seen a surge in the number of generous rain days, unresolved the thresholds set at 95% and 99% of the typical precipitation from 2000 to 2023 [3, 4]. Besides, events of precipitation beyond 50 mm have turned out to be more conjoint, a fact that denotes consolidation and enlarged manifestation of precipitation diagonally over India. The influence of human-induced conservatory gas discharges on worldwide temperatures is generally recognized, subsequent in substantial temperature upsurges in India over the ancient years, predominantly in the preceding 20 years [5, 6].

As humanoid happenings subsidize to environment revolution, it develops domineering to inspect the association between temperature vagaries and precipitation in diverse counties in India for efficient reworking and adversity moderation stratagems [7]. Precipitation is a multifaceted progression predisposed by various atmospheric reasons and circumstances over diverse time gauges, ranging from one month to several months. A wide-ranging empathy of these features is perilous for handling and envisaging rainfall precisely. The forecast of precipitation is a decisive component of climate prognostication [8, 9]. In previous works, this has been contemplated by scientific practices that challenge associating precipitation with topographical synchronization and innumerable atmospheric influences. However, these procedures frequently fail to precisely envisage rainfall outlines because of their intrinsic complication and irregularities [10, 11]. In the current centuries, enlightened practices like Empirical Mode Putrefaction, Wavelet investigation, and Singular Spectrum Scrutiny are revealed to give solution to these issues. However, these processes could be computationally widespread and at times yield only derisory developments in prognosis precision [12, 13].

Several previous elucidations directed to envisage precipitation in India have mainly concentrated on explicit estimates and have not adequately investigated the provincial multiplicity of the nation [14, 15]. This downside emphasizes the inevitability of additional comprehensive practice, taken to justify the distinct topographical and climatological characteristics contemporary in diverse countries transversely India [16, 17]. The advent of ANNs has transfigured rainfall prognostication by contributing a suppler and malleable method. Among several ANNs, RNNs have become prevalent due to their capability to discourse chronological undercurrents that are contemporary in climatological time-series data. Nevertheless, outdated RNNs have been confined to elucidating and making accurate long-term forecasts [18, 19]. Adaptations of RNNs, including Long Short-Term Memory Networks, have been industrialized to get rid of their restrictions. The LSTM setups are basically strengthened with the memory cells holding onto information over a prolonged era, having publicized better performance in multi-step forward prognosis as associated with the conventionalized RNNs, which many studies recognize [20].

Prognosticating rainfall efficaciously is unsafe in abundant fields, comprising food production, water preservation, and scheduling desolations. Deep Learning (DL), a part of Machine Learning (ML), has recognized comforting outcomes in envisaging weather encounters owing to its capability to accomplish huge capacities of statistics and embrace problematical inferences. Prevailing investigation has presented that DL systems can be used to prognosis precipitation. Neural Networks deliberated to estimate chronological data and prognosis disparities in precipitation with exceptional precision. RNNs are furthermore utilized to exemplar the periodic outlines in climatological interpretations and engender prognoses practically. Although the effectiveness of DL in precipitation estimation, various limitations must be rectified.

1.1 The Motivation

The Motivation of the work initiated with from a certain problem is the requirement for enormous quantities of classified information while retraining DL models. Gathering and classifying such information can be laborious and expensive, particularly in areas with few weather observatories. Another problem is interpreting DL models, which, unlike typical mathematical models, tend to be seen as black boxes, rendering it impossible to articulate where they turned up at a particular forecast. This lack of accessibility may undermine optimism regarding the algorithm and its findings. Additionally, DL models are susceptible to distortions and discrepancies in training data. However, when the training sample does not reflect the genuine variation in the precipitation, the model may generate premature projections, resulting in erroneous outcomes. Motivated by these concerns, this study planned to put forth an effective optimized DL framework for precipitation forecasts in different regions of India.

Forecasting long-term precipitation patterns is an extremely challenging task in the hydrological scenario because of the arbitrary landscape of precipitation conditions. Conventional studies rely on statistical and numerical approaches, which restricts reliability and precision, especially in extreme weather conditions. Presently, artificial intelligence (AI)--based ML and DL techniques have deliberated promising results in various fields like financial prediction, image recognition, and NLP applications. However, ML models are not effective while processing with a larger rainfall distribution that maximizes the overfitting complications. In today's scenario, DL models are highly capable of predicting the precipitation level even under extreme weather events. Moreover, the DL technique trains an extensive amount of data and efficiently learns the complicated patterns and relationships across various regions of different countries. Hence, this study aimed to put forth an innovative optimized DL framework for predicting precipitation across various stations in India.

1.2 Contributions

The main contributions of the developed framework are encompassed as follows:

To propose an innovative optimized DL model with CResAtt-GCU and HBSO for forecasting the rainfall across various regions in India. The convolutional residual attentive gated circulation unit (CResAtt-GCU) technique is introduced to predict the amount of rainfall that occurs in various Indian states. Finally, the Humboldt squid optimizer (HBSO) technique is presented to tune the parameters of the developed model to minimize network complications during the training process.

To introduce an improved min-max normalization (I-MMN) technique to eliminate unwanted missing values present in the rainfall data. Initially, the improved min-max (I-MMN) normalization technique is emphasized in the pre-processing stage to eliminate unwanted missing values from the database. I-MMN that correlates the null features using the Pearson coefficient (PC) and MM normalization to eliminate null values.

To elucidate an effective convolutional residual attentive gated circulation unit (CResAtt-GCU) technique to forecast the amount of precipitation that occurs in various Indian regions. To conquer a meta-heuristic-aided Humboldt squid optimizer (HBSO) to tune the model parameters for minimizing the overfitting complications during the training process. The proposed CResAtt-GCU technique causes high complexity while training with larger data. This may lead to the loss of essential features and subject to increased error. To overcome this issue, parameters like batch size, learning rate, epochs, and dropout rates are tuned before providing the data into the proposed network model. To perform this, metaheuristic optimizers update the model parameters with a globally optimal solution.

To test the performance of the developed model with different evaluation measures of performance assessment, including R2, RMSE, Kling-Gupta Efficiency, Nash-Sutcliffe Efficiency, mean absolute error, and computation time, with reference to various conventional studies. Performance indicators like R2, root mean square error (RMSE), Kling-Gupta Efficiency (KGE), Nash-Sutcliffe Efficiency (NSE), and mean absolute error (MAE) are scrutinized to understand the developed method better.

The following sections are organized in this manner: Section 2 outlays the related work, Section 3 deliberates over the approaches suggested, Section 4 presents results and discussion, and Section 5 represents the conclusion of the proposed framework.

2. Related Works

The author [21] proposed a multi-module based approach for explainable DL-based monthly rainfall prediction. The study composed of four different modules such as attention mechanism, GRU-based decoder and encoder modules, and expected-gradient module. Initially, climate and weather features were given as input to the encoder to produce associated hidden states. Next, based on the decoder and encoder hidden states, a series of attention values were generated by the attention mechanism module. In the third step, each attention values were integrated with the rainfall predicted value in the decoder module at the final time stamp. Then, the obtained values were provided to the GRU cell to generate recent hidden state. This hidden state was passed through fully connected layer of the model to achieve associated rainfall prediction value. Finally, the expected gradient was used to quantify the significance of input feature to the output feature. The introduced model struggle in capturing long-term dependencies.

The researcher [22] suggested RfGanNet (Rainfall Generative Adversarial Networks) model for efficient prediction of rainfall particularly in India. Rainfall data from 36 regions was considered as the dataset. As an initial stage, this data was pre-processed using min-max scaling method in which the data were finalized from -1 to 1 respectively. Next, important features were predicted using ANOVA F-Test, Ordinary Least Square Linear Regression, and Mutual information. For better data analysis a heat map known as pearson correlation coefficient was utilized. Finally, to classify regions of India, k-means clustering technique which was popularly known as a supervised technique was employed. The suggested model requires additional data to learn the underlying distribution.

The author [23] recommended a hybrid model employing ML and DL in predicting rainfall at the district scale. A model known as WRF (Weather Research Forecast) which was a non-hydrostatic mesoscale used in predicting numerical value of weather. Two satellite gauges were merged such as dual-frequency precipitation Radar and Global Precipitation Measurement (GPM) to produce effective rainfall prediction over ocean and land. These initially predicated values were again estimated by merging with other two satellite gauge. Finally, the intensity of the rainfall was predicted using hybrid ANN models such as CNN and MLP. MLP was used to simulate non-linear function whereas, CNN was used to capture multi-scale spatial patterns. The suggested hybrid model struggle to produce accurate uncertainty estimates.

The author [24] contemplated a hybrid DL model to predict rainfall and weather forecast using weather bigdata analytics. To remove unwanted artifacts Modified Planet Optimization (MPO) algorithm was utilized as a part of data pre-processing. To select optimized features by avoiding data dimensionality errors, an algorithm known as Improved Tuna Optimization (ITO) was utilized. Finally, to enhance rainfall prediction and weather forecast a hybrid DL technique known as Memory-augmented Artificial Neural Network (MA-ANN) was employed. The effectiveness of the proposed model was validated using climate forecast system reanalysis (CFSR) dataset. ITO can be computationally intensive, especially when dealing with large datasets or complex feature spaces.

The work [25] suggested a novel classification technique for rainfall prediction using adaptive dynamic algorithms. Two algorithms were integrated in predicting rainfall such as Guided Whale Optimization (GWO) and Adaptive Dynamic Puma Optimizer (AD-PO) algorithms for effective rainfall classification. To enhance the predictive performance AD-PO-GWOA was combined with voting ensemble approach. The efficiency of the proposed model in predicting rainfall was evaluated using PME MET dataset known as Presidency of

Meteorology and Environment. The dataset was analyzed using an effective technique called copule analysis which was considered as a statistical method utilized in modeling the dependence structure between multiple variables randomly. The utilization of two optimization techniques in classifying rainfall consumes more training time.

The framework [26] put forth a model to forecast rainfall patterns using XGBoost with time series analysis particularly in India. The model which was known as a statistical model named Autoregressive Integrated Moving Average (ARIMA) and ML models such as SVM, ANN, and RF were developed to compare the proposed model in forecasting rainfall patterns. To forecast time series data, the proposed approach used ARIMA framework. SSM refers to State Space Model was used for analysis of time series which uses a filter known as Kalman was utilized in effective smoothing, filtering, and prediction. The research showed that the proposed XGBoost algorithm performed well than the existing models. The method ARIMA achieves perfect in sample accuracy but poor in out-of-sample.

The researcher [27] introduced an optimized cascaded-based CNN model for rainfall prediction. The main aim of the proposed framework was to reduce cross entropy loss function and to achieve better prediction rate. The initial step used was data pre-processing which was handled using data normalization and augmentation. To optimize CNN model, an adaptive searched scaling factor-based elephant herding optimization (ASS-EHO) was utilized thereby to perform hyperparameter tuning of the model. The parameters such as hidden neuron count, cascaded CNN count, and activation function were optimized for better prediction. The main drawback of the proposed approach was due to the complexity of the model it produces low prediction accuracy.

The work [28] suggested TVF-EMD known as time-varying filter-based empirical mode decomposition with Bi-LSTM-encoder-decoder to forecast monthly rainfall. Initially, the rainfall signals were considered as the dataset in which it was decomposed into intrinsic mode decomposition functions (IMFs) using TVF-EMD technique. Next, the IMF's decomposed values were computed using partial autocorrelation function (PACF). Again, the PACFs decomposed values were decomposed using singular valued decomposition (SVD). This was done to improve forecasting accuracy and to reduce the dimensionality. Finally, Bi-LSTM-encoder-decoder was utilized for accurate weather and rainfall forecasting. The model becomes more complex when integrated with encoder and decoder.

3. The Proposed Model

This framework investigates the composite association between climatological data, with an emphasis on the precise estimating of rainfall by finding the effect of temperature disparities on rainfall outlines in diverse states of India. The developed framework undergoes two phases: pre-processing and rainfall forecasting. Initially, the Improved min-max (I-MMN) normalization technique is emphasized in the pre-processing stage to eliminate unwanted missing values from the database. Then, the convolutional residual attentive gated circulation unit (CResAtt-GCU) technique is introduced to predict the amount of rainfall that occurs in various Indian states. Finally, the Humboldt squid optimizer (HBSO) technique is presented to tune the parameters of the developed model to minimize network complications during the training process. The developed framework is processed under the Python platform and the real-time rainfall prediction database collected between 2000-2023 is utilized for the experimentation process. Figure 1 indicates the Workflow of the developed Method.

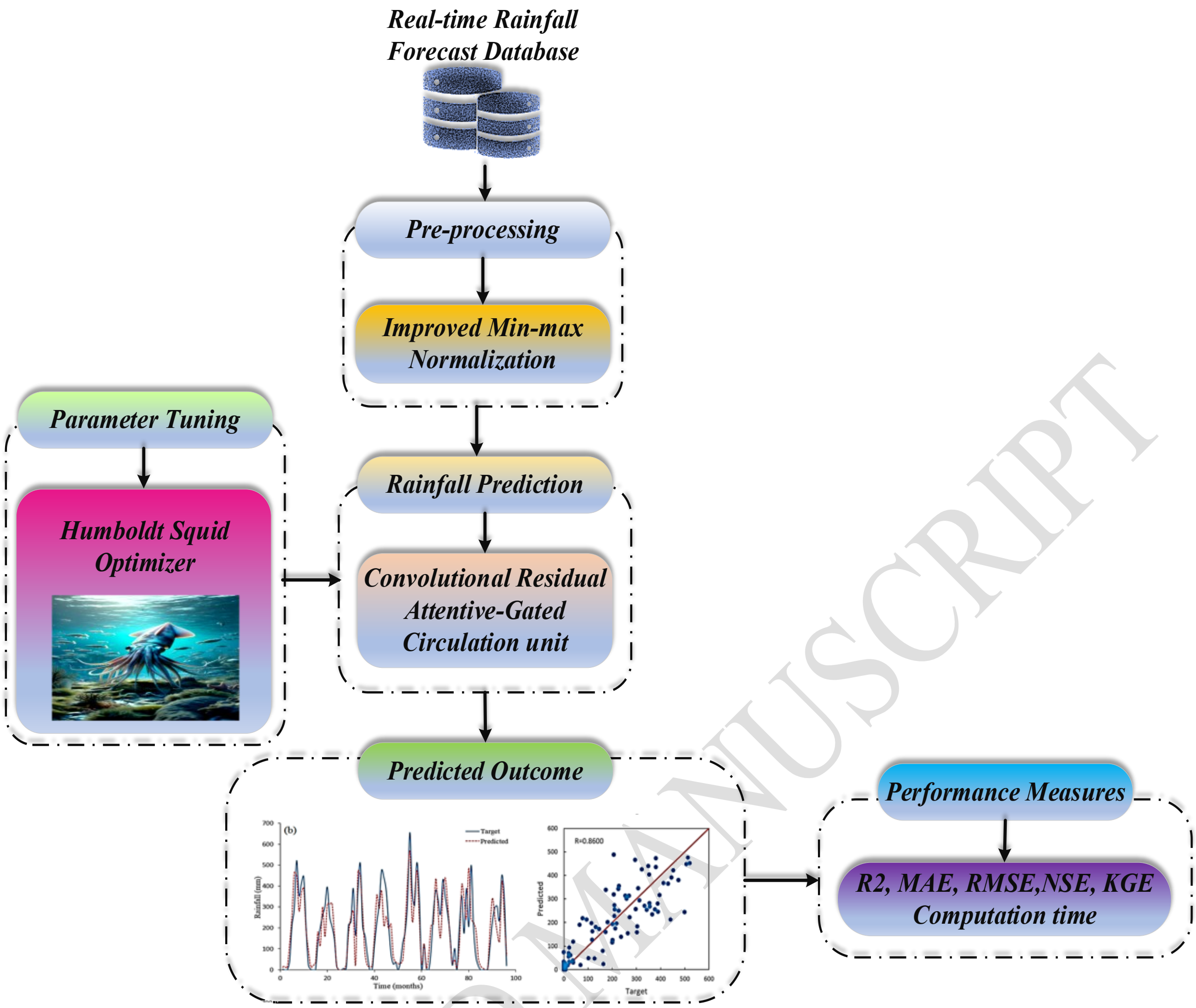


Figure 1. Workflow of the developed Method

3.1. Preprocessing Stage

Initially, the raw samples collected from the public source database are preprocessed by performing a normalization process to remove the null values. Recently, the min-max normalization technique [29] has provided better normalization performance but it may not be suitable when processing with non-linear attacked data. Hence, this framework proposes an Improved Min-Max normalization (I-MMN) that correlates the null features using the Pearson coefficient (PC) and MM normalization to eliminate null values. The updated range of feature vectors is indicated as, $U_{min}$and U_{max}having the values 0 and 1 respectively. The mathematical formulation of updated weighted values is encompassed in equations (1-3),

$$K = \frac{\sum_{x=1}^{n}(y_x-\bar{y})(v_x-\bar{v})}{\sqrt{\sum_{x=1}^{n}(y_x-\bar{y})^2(v_x-\bar{v})^2}} \tag{1}$$

$$MMNz'_{x,m} = \frac{z_{x,m}-min(z_x)}{max(z_x)-min(z_x)}(Umin_{max}+U_{min}) \tag{2}$$

$$W_{value}p' = \left(\frac{P_{x,y}-nx_y}{nk_y-nx_y}(Umin_{max} + U_{min}())\middle| C\left(\frac{P_{x,y}-nx_y}{nk_y-nx_y}\left(Umin_{max} + \beta\left(P_y, P_{final}\right)\right)\right)\right) \quad (3)$$

Here, $W_{value}p'$indicates the adaptive weighted value, $P_{x,y}$indicates the actual value, Cmanipulates the parameter to stabilize the updated range, and $\beta\left(P_y, P_{final}\right)$indicates the correlation coefficient between column y and labeled columns using PC. Moreover, nx_yindicates the minimum value of y^{th}column, nk_yrepresents the maximum value of y^{th}column, $U_{max}$and U_{min}represents the updated minimum and maximum value.

3.2. Rainfall Prediction using CResAtt-GCU Technique

After data normalization, the rainfall forecasting process is performed for various agricultural purposes, water resource management, disaster preparedness, urban planning, and weather forecasting. Nowadays, the bidirectional gated recurrent unit (Bi-GRU) technique [30] effectively predicts the precipitation by capturing the data and assists in alleviating vanishing gradient problems. However, traditional Bi-GRU models tend to overfit the training data, leading to poor generalization performance on unseen data. Hence, the proposed framework introduces an innovative convolutional residual attentive gated circulation unit (CResAtt-GCU) technique for effectively forecasting the amount of rainfall in various states in India. The proposed CResAtt-GCU technique helps reduce the impact of noise and outliers in the data, making the model more robust and reliable. A brief analysis of the proposed CResAtt-GCU technique is encompassed below:

3.2.1. Gated Circulation Unit (GCU)

The GRU is the abridged form of LSTM and every GRU unit has a dual threshold and single-time outcome. Hence, the GRU can accurately transfer time-series and it has lesser parameters. The mathematical expression for the unit structure is depicted below:

$$x_k = (w_x y_k + r_x h_{k-1} + P_x)\sigma \quad (4)$$

$$z_k = (w_z y_k + r_z h_{k-1} + P_z)\sigma \quad (5)$$

$$c_k = tanh(w_c r_c (h_{k-1} \times z_k) + P_c) \quad (6)$$

$$h_{k-1} = (1 - x_k) \times (h_{k-1} + x_k \times c_k) \quad (7)$$

Here, $y_k$indicates the input of the present layer at a time k, h_{k-1}represents the outcome at a time $k-1$, x_k and $z_k$indicates the update and reset gates at a time k, σ deliberates the sigmoid activation function (AF), c_k signifies the hidden candidate state at a time k, tanh signifies the hyperbolic tangential AF. Moreover, w_x, w_z, w_c, r_x, r_z and r_c indicates the weight parameters and P_x, P_z and P_c signifies the bias vectors. Figure 2 encompasses the Architecture of the CResAtt-GCU model.

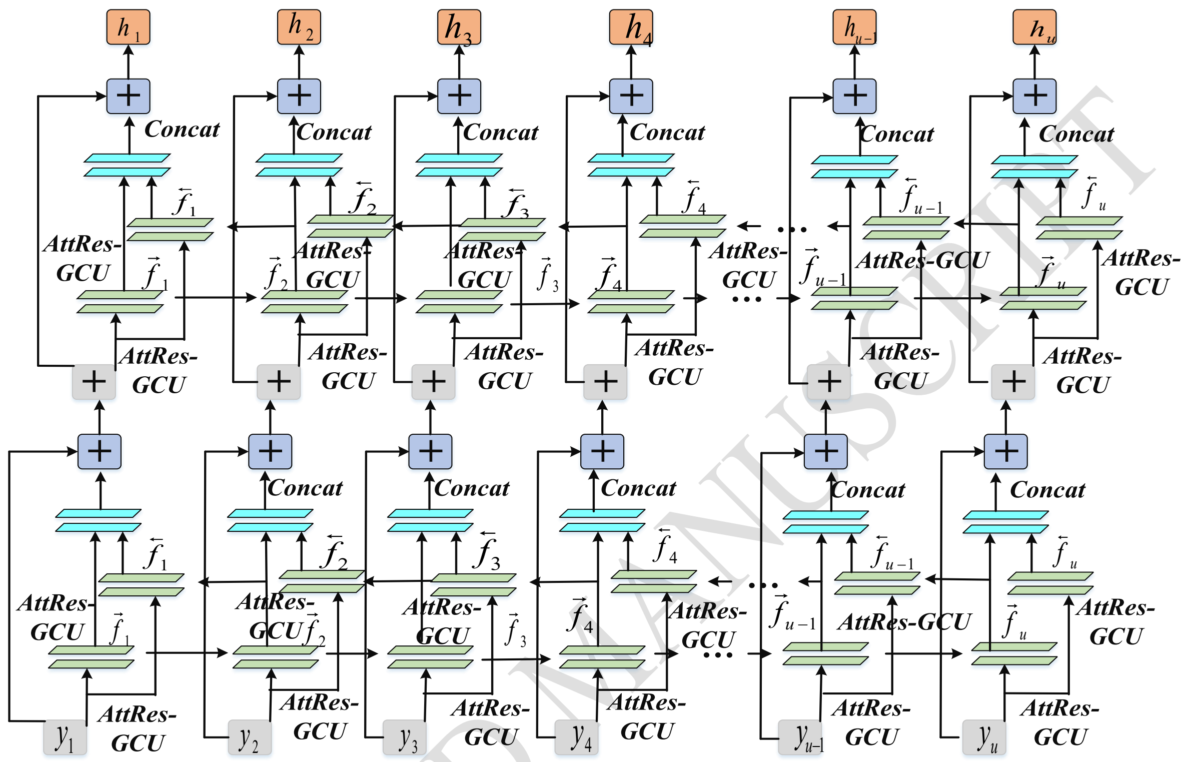


Figure 2. Architecture of CResAtt-GCU Model

3.2.2. Residual Operation

In the GRU network, vanishing gradient and model degradation are quite high and in GRU, the most essential formulation is the hidden candidate state that jointly defines the outcome values. Hence, the hidden candidate state is enhanced, and it is split up into three sections:

Unsaturated AF - The hidden candidate state of the GCU is changed using a linear rectifier unit (ReLU) and prevents gradient explosion problems. Finally, it can be managed with deep model training and the use of transmitting data is obtained using ReLU. Hence, it does not contain a gradient explosion problem caused by the saturated AF. It can equalize residual data transmission and is modified using the formulation as,

$$c_k = ReLU(w_c y_k + r_c(h_{k-1} \times z_k) + P_c) \tag{8}$$

Accumulation Residual Connection - The residual connection in GCU enhances the accuracy performance and reduces the overfitting issues. The residual connection assists in optimizing the outcome of c_k and the enhanced hidden state can be formulated mathematically as,

$$c_k^l = Re\,L\,U(\lambda_c^{l-1}) \tag{9}$$

$$\lambda_c^l = \left(w_c^l c y_k^l + r_c^l\left(h_{k-1}^l \times z_c^l\right) + P_c^l + V^l \lambda_c^{l-1}\right) \tag{10}$$

Here, c_k^l indicates the outcome of the hidden candidate state in l^{th} layer, λ_c^{l-1} signifies the outcome of a disabled hidden candidate state in $l-1$ layer, h_{k-1}^l encompasses the vector state of l^{th} layer at a time $k-1$, λ_c^l signifies the outcome of a disabled hidden candidate state in l^{th} layer, V^l signifies the extent equalization matrix of l^{th} layer. If the upper and lower extents of the network are similar, then the extent equalization matrix is not necessary.

Attention Module - The different rainfall data from various Indian regions contain the inheritance and inconsistent distribution. Such inconsistencies are often extracted in three consecutive features X_{k-1}, X_k, and X_{k+1} are fed as input into the three-stream Attention module enabling the network to deliberate into the adaptive learning model. In this module, a single Convolution (Conv) layer and quadruple residual blocks (RBs) are present under each stream, and features are extracted in an increasing order separately under each stream. The features extracted from the Conv layers are fused and fed into the RBs to extract the depth-level features from the diseased images. Using the Parallel streams, the interaction between the adjacent features can be determined effectively. Figure 3 illustrates the Architecture of Proposed Attention module.

Three stream Parallel Attentive module

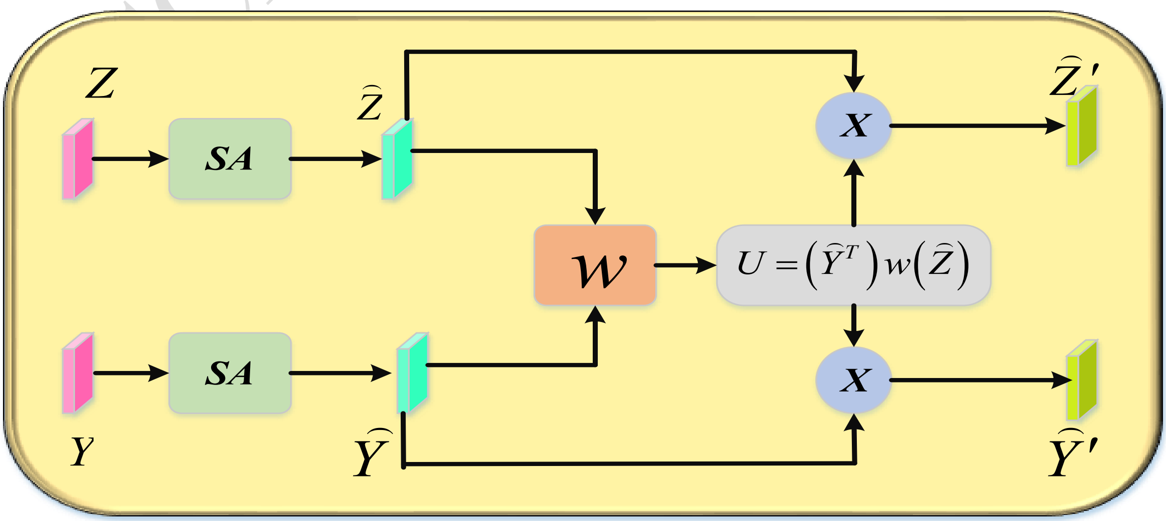


Figure 3. Architecture of Proposed Attention module

The in-between features of the nearby streams $Z \in \Re^{w\times h\times c}$and $Y \in \Re^{w\times h\times c}$are modified to improve the primary attentive features $\hat{Z}$and $\hat{Y}$using the soft attentive mechanism. The Parallel attentive (PAtt) module helps to determine a correlation matrix $P \in \Re^{wh\times wh}$for generating joint improvements and fusion between two feature subsets. The mathematical expression from the PAtt module is encompassed as follows:

$$U = \lambda(\hat{Y}^T)w\lambda(\hat{Z}) \tag{11}$$

$$\hat{Z}' = \hat{Z}M_{row}(U) \tag{12}$$

$$\hat{Y}' = \hat{Y}M_{col}(U) \tag{13}$$

Here, λindicates the linear transformation that subsets to lower-dimensional features, $w$indicates the learnable weight matrices, $M_{row}$and M_{col}indicates the normalized row and column-wise feature vectors obtained by soft attentive mechanism.

Batch Normalization - The earlier activation of the mean and variance of the minimum training batch are regularized and hence, the vanishing gradient problems is minimized. The outcome of Res-GCU can be mathematically formulated as,

$$x_k^l = \sigma\left(BN\left(w_c^l y_k^l\right) + r_x^l h_{k-1}^l\right) \tag{14}$$

$$z_k^l = \sigma\left(BN\left(\left(w_z^l y_k^l\right) + r_z^l h_{k-1}^l\right)\right) \tag{15}$$

$$c_k^l = Re\,L\,U(\lambda_c^l) \tag{16}$$

$$\lambda_c^l = \left(BN\left(w_c^l y_k^l\right) + r_c^l\left(h_{k-1}^l * z_c^l\right) + V^l \lambda_c^{l-1}\right) \tag{17}$$

$$h_k^l = (1 - x_z^l) * x_z^l * c_k^l \tag{18}$$

Finally, from the SoftMax layer, the amount of rainfall is forecasted accurately. However, the parameters present in the network model still lack the effectiveness of the prediction performance. To tackle this problem, the parameters are enhanced using the novel meta-heuristic technique.

3.3. Parameter Tuning using HBSO Technique

The proposed CResAtt-GCU technique causes high complexity while training with larger data. This may lead to the loss of essential features and subject to increased error. To overcome this issue, parameters like batch size, learning rate, epochs, and dropout rates are tuned before providing the data into the proposed network model. To perform this, metaheuristic optimizers update the model parameters with a globally optimal solution.

The proposed study introduced a Humboldt Squid Optimizer (HBSO) to tune the weight parameters of the network model. The Humboldt squid (HBS) are bigger and found in the eastern Pacific Ocean. They have excellent biological and economic importance that grows up to 1.5m long and are considered the largest candidate among their family. The velocity of swimming ranges to 24km/h and encompasses the fastest growing species that grows from 1mm to 1 m at 1 to 2 years of age. Their common prey species are shrimps, red crabs, mollusks, tiny squids, pelagic octopuses, amphipods, copepods, etc. Normally, HBS is capable of flying in multimodal strategies like jetting, roaming, accelerating, gliding, and diving. The other factors of HBS are mating performing internal fertilization and laying millions of eggs over a short lifetime.

The HBS are unique predators and the process of attacking, mating and movement are highly the same for determining the global optimal solution for an optimization problem. Here, the weaker squids and school fishes are deliberated as the optimal solution, and inspired by this behavior, the model problem constraints are solved using the HBSO technique. The behavior of the HBSO technique is illustrated in mathematical expression and it is depicted briefly below:

3.3.1. Initialization Phase

In the HBSO algorithm, the best individuals are considered the HS, and the remaining are fish. This problem is reliable due to the large body structure and finest fitness compared to school fish.

3.3.2. Hunting of Fish schools

The hunting of fish schools is simulated using the mathematical expression determined below:

$$YS_{new,u}^{d} = Y_{best} + J_{jet}\left(-Yf_{new,r1}^{d} - TP_{r2}^{d}\right) \tag{19}$$

Here, $YS_{new,u}^{d}$ indicates the new location of u^{th} HBS in d^{th} dimension, J_{jet} deliberates the locomotive velocity variable, $Yf_{new,r1}^{d}$ signifies the location of $r1^{th}$ fish in d^{th} dimension, and

TP_{r2}^{d}defines the stored $r2^{th}$location in the HBSO memory. Moreover, $r1$symbolizes the arbitrary integer between fish population and 1, $r2$signifies the arbitrary integer between 1 and the size of TP.

3.3.3. Fitness Function

The HBSO technique utilized fitness function (FF) for analyzing the optimality of the proposed classifier model and it is formulated as,

$$f = min(RMSE) \tag{20}$$

3.3.4. Successful Attack

After changing the updated location, the present position is updated with the new location for HBS YS_uas,

$$YS_u^v = \begin{cases} YS_u = YS_{new,u} if fS_{new,u} < fS_u \\ successful escape otherwise \end{cases} \tag{21}$$

Here, $fS_{new,u}$and fS_usignifies the FF and present FF of the u^{th}HBS.

3.3.5. Successful Escape

After the fish school is attacked by squids, the fish escapes to an arbitrarily positioned location. At this stage, the fish's location and velocity are updated using the expression given below:

$$fS_{new,u} = \begin{cases} Yf_u + \vec{r}_n \times (m_{best} - Yf_u) f_w, if f_e < 0.1 \times max_{f_e} \\ Yf_u + \vec{r}_n \times (AX_{r1} - TP_{r2}) f_{w,} else \end{cases} \tag{22}$$

Here, $f_e$deliberates the number of present function estimations, max_{f_e} denotes the number of maximum function estimations, $fS_{new,u}$indicates the updated location of u^{th}fish, Xf_uencompasses the present location of u^{th}fish, m_{best}signifies the best location, AX_{r1}indicates r_1^{th}location in the archived best outcome, $\vec{r}_n$deliberates the arbitrary random vector, $f_w = \frac{f_{best}}{f_u}$whereas, f_{best}encompasses the best FF, and $f_u$indicates u^{th}fish.

3.3.6. Hunting of larger squids to tiny squids

When the HBS and fish fail to determine a better location at the existing stage, it is considered that there are no more fish to attack. However, the larger HBS hunts the tiny squids and in this phase, the position of HBS is derived mathematically as,

$$YS^{d}_{new,u} = YS^{d}_{new,u} + J_{jet2}\left(-Yf^{d}_{new,u} - Y^{d}_{best}\right) \tag{23}$$

Here, J_{jet2}deliberates the second locomotive velocity variable. To define all the best solutions, it is considered that the HBS is in the best location and according to the relationship, the larger squid's movement takes place. Hence, it is assumed that the best location Y_{best}as the tiny HBS.

3.3.7. HBS Mating

The generated egg location of HBSO is deliberated by improving the differential evolution mechanism. It can be mathematically formulated as,

$$\lambda_{eggs} = \left(\theta \times Yf + (1 - \theta m_{best})\right) \times \chi + (1 - \chi) \times P(r1,:) + w\left(P(r3,:) - TP(r2,:)\right) \tag{24}$$

Here, λ_{eggs}indicates the location of HBS egg masses, θ, $\chi$and $w$deliberates the improved weights for the control search mechanism ranges between 0 and 1. The parameter $w$can be mathematically formulated as,

$$w = max(\theta \times \chi(1 - \theta) \times \chi, 1 - \chi) \tag{25}$$

The mathematical expression for the parameter $\theta$and χcan be represented as given below:

$$\theta = \lambda_{\theta} + x_1 \times z \tag{26}$$

$$\chi = \lambda_{\chi} + x_2 \times \vec{r}_n \tag{27}$$

Here, $x_1$and $x_2$represent the constant variables considered during the simulation process. Furthermore, $\lambda_{\theta}$and λ_{χ}defines the vectors having the value 0.5 and it can be mathematically formulated as,

$$\lambda_{\theta} = \frac{\left(D_f(Q)\right)\left(\theta(Q)^2\right)}{\left(D_f(Q)\right)\left(\theta(Q)\right)} \tag{28}$$

$$\lambda_{\chi} = \frac{\left(D_f(Q)\right)\left(\chi(Q)^2\right)}{\left(D_f(Q)\right)\left(\chi(Q)\right)} \tag{29}$$

Here, Q indicates the HBS index that provides a more optimal solution than λ_{eggs}, D_f represents the difference between the fitness of HBS and their λ_{eggs}. However, HBS mate multiple times in their lifetime, the iteration is done several times for the HBSO technique.

Moreover, the parameter χ must be more than zero, and finally, if χ attains zero it can be adjusted using the formulation depicted below:

$$\chi = \lambda_{\chi} + 0.1 \times tan(\pi \div rand) \tag{30}$$

Here, $rand$ symbolizes the general arbitrary number ranges between 0 and 1. Finally, the parameter z can be mathematically formulated as,

$$z = \frac{f_e}{Max_{f_e}} \vec{rand}^{10r} \tag{31}$$

Here, $\vec{rand}$ and r defines the general random vector and general random vector ranges between 0 and 1.

3.3.8. Control search Mechanism

The HBSO technique is controlled by different variables such as, J_{jet}, J_{jet2}, z, f_w, θ, χ and w. The parameter J_{jet} and J_{jet2} are contemplated to excite the locomotive shape of HBS and hence, a polynomial function is utilized. The polynomial power function for J_{jet} and J_{jet2} are considered the third and fourth degree respectively. The mathematical expression for J_{jet} and J_{jet2} is depicted below:

$$J_{jet} = (Y - i_1) \times (Y - i_2) \times (Y - i_3) \tag{32}$$

$$J_{jet2} = (Y - i_1) \times (Y - i_2) \times (Y - i_3) \times (Y - i_4) \tag{33}$$

Here, i_1, i_2, i_3 and i_4 indicates the polynomial function that determines the locomotive shape, and Y can be formulated as,

$$Y = \frac{f_e}{Max_{f_e}} \tag{34}$$

Here, f_e indicates the radius of escaped fish and it is the ratio between the best fitness value and the present fish's fitness value.

3.3.9. Termination Criteria

The proposed HBSO technique further iterates into the next stage and the HBSO updating process is repeated from equations (21) to (24) until the termination criteria are satisfied. Subsequently implementing the HBSO algorithm, the best global optimal solution is chosen during repetitive iteration which is utilized as the solution to the problem. Algorithm 1 depicts the pseudocode of the HBSO technique.

Algorithm 1: Pseudocode of HBSO technique

Determine initial variables: M, N_{cycle}, Y_{best}, AX_{r1}, and $Memory_{size}$

Result: Optimally tuned CResAtt-GCU technique using updated HBS location

while $N < N_{cycle}$ **do**

$N \leftarrow N + 1$

Arrange population based on fitness function;

$Memory_{index,rand} \leftarrow [d, \vec{r}_{nd}]$

$\lambda_\theta = Memory_\theta(Memory_{index,rand})$

$\lambda_\chi = Memory_\chi(Memory_{index,rand})$

Evaluate $z$using equation (30);

Evaluate $\theta$and χusing equation (26) and (27);

Create three arbitrary integers (r_1, r_2, r_3);

Select Y_{best}%of the best location and store it on Y_{best};

Evaluate $w$using equation (24);

Determine the egg's location using equation (23);

Determine the egg's location;

if $f_{eggs} < f_{pop}$ **then**

$pop = \lambda_{egg}$% when eggs have a better location than a parent, the egg's location is considered as the parent's location;

end if

Update the archive to eliminate repetitive solutions to maintain the size of the archive;

Update $\lambda_\theta$and λ_χ

if $\chi < 0$ **then**

χupdated using equation (30);

end if

Combine $pop$and the archive and store it in TP;

$YS_u \leftarrow LB + (UB - LB)\vec{rand}$

Calculate the fitness function using equation (20);

end while

Return the best optimal solution

4. Results and Discussion

The developed framework is processed and experimented with via the Python platform. Real-time rainfall data collected from the Indian Institute of Tropical Meteorology [31] that covers the entire Indian Region (2000 to 2023) is utilized in this study. This database rainfall distribution of 36 meteorological sub-regions in India. Various computational measures like R2, root mean square error (RMSE), Kling-Gupta Efficiency (KGE), Nash-Sutcliffe Efficiency (NSE), mean absolute error (MAE), and computation time are scrutinized and distinguished from conventional studies. 80% and 20% of the data are considered for the training and testing process respectively in the ratio of 8:2. Totally 100 epochs are considered and the dropout rate of 0.2, batch size of 32, and learning rate of 0.1 are encompassed for the execution process.

4.1. Assessment Measures

Performance indicators like R2, root mean square error (RMSE), Kling-Gupta Efficiency (KGE), Nash-Sutcliffe Efficiency (NSE), and mean absolute error (MAE) are scrutinized to understand the developed method better.

4.1.1. R2 Analysis

It is the statistical measure that indicates the ratio of the variance of a reliant variable that's enlightened by a self-governing variable in a regression model. It can be mathematically formulated as,

$$R^2 = \frac{\sum_{x=1}^{z}(u_x - u')(v_x - v')}{\sqrt{\sum_{x=1}^{z}(u_x - u')^2}\sqrt{\sum_{x=1}^{z}(v_x - v')^2}} \tag{35}$$

Here, $u_x$indicates the actual values, u'_xindicates the predicted value, and $\hat{u}_x$represents the mean of all the values.

4.1.2. MAE Analysis

It is defined as the measure of the average absolute difference between actual and forecasted values and it can be formulated as depicted below:

$$MAE = \frac{\sum_{x=1}^{z}|u_x - u'_x|}{z} \tag{36}$$

Here, $z$indicates the total data points.

4.1.3. RMSE Analysis

It is defined as the sum of the square difference between the observed value and the forecasted value that divides the total observations. It can be expressed as given below:

$$RMSE = \sqrt{\frac{\sum_{x=1}^{z}\left(u_x - u_x^{'}\right)^2}{z}} \tag{37}$$

4.1.4. NSE Analysis

It is the measure used in hydrological modeling to evaluate the efficacy of the developed model similar to the observed value. It can be formulated as,

$$NSE = 1 - \frac{\sum_{x=1}^{z}\left(u_x^{'} - u_x\right)^2}{\sum_{x=1}^{z}(u_x - \hat{u}_x)^2} \tag{38}$$

4.1.5. KGE Analysis

It is defined as the measure to determine the effectiveness of the developed model between forecasted and modeled hydrological data points. It can be formulated as,

$$KGE = 1 - \sqrt{(x-1)^2(\lambda-1)^2(\beta-1)^2} \tag{39}$$

Here, $x$indicates the correlation coefficient between forecasted and modeled data, λsignifies the standard deviation of predicted and actual values, and βsignifies the ratio of the mean of predicted and actual values.

4.2. Computational Analysis of Developed Scheme over Conventional Studies

In this section, the performance obtained by the proposed method is analyzed via the graphical illustration. Various conventional techniques like convolutional neural network (CNN), Genetic algorithm-generative adversarial network (GA-GAN), particle swarm optimizer-Bidirectional Long short-term memory (PSO-BiLSTM), and heuristic search optimizer (HSO-GRU) are scrutinized and compared with other existing techniques. The detailed analysis of the obtained outcomes is encompassed as given below:

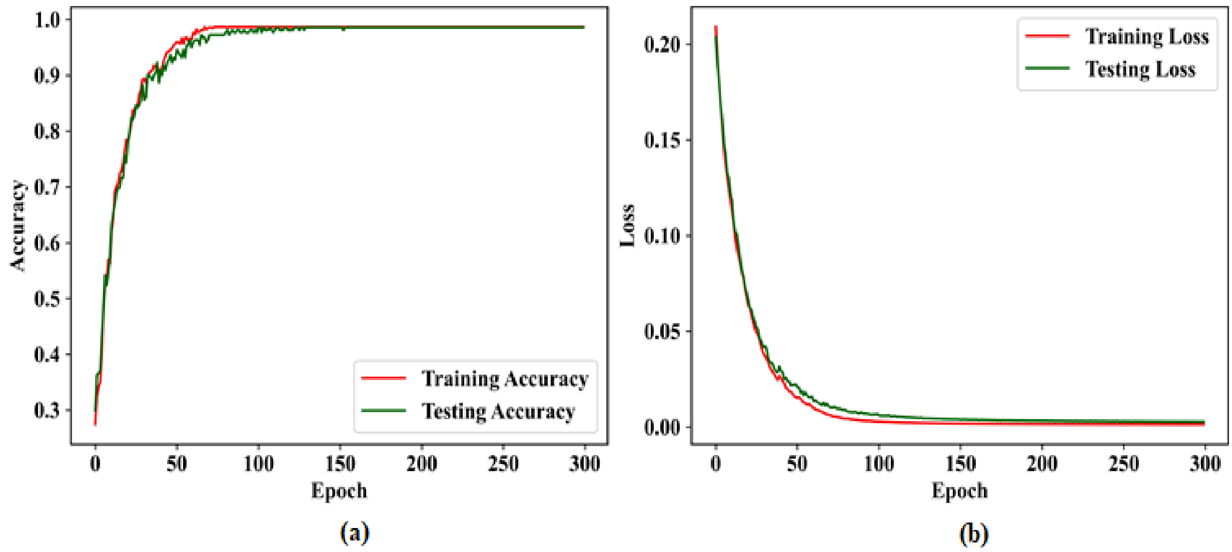


Figure 4. Accuracy and Loss analysis by altering epochs

Figure 4 signifies the Accuracy and Loss analysis by altering epochs. The graphical manifestation is analyzed for training and testing data with 300 epochs. Under 300 epochs, the training and testing accuracies achieved the value of 99% and 98.7% respectively. In addition to this, the training and testing losses under 300 epochs are achieved at about 0.02 and 0.031 respectively.

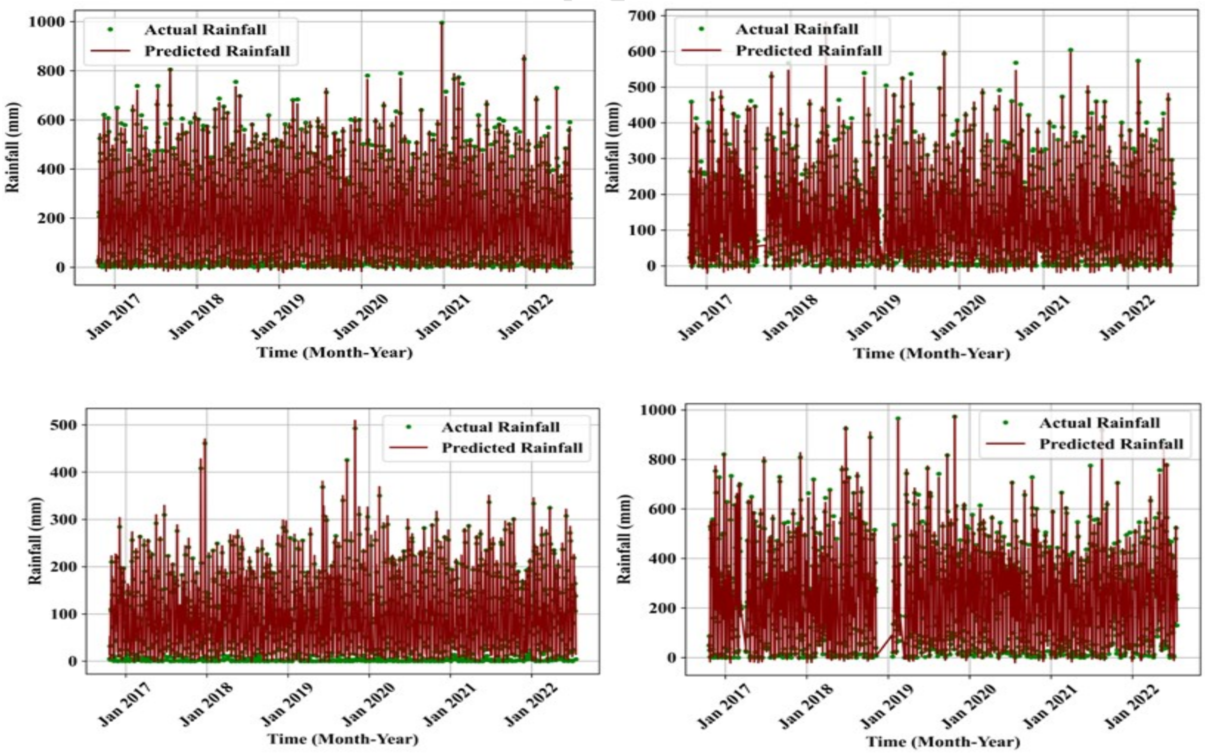


Figure 5. Actual and Predicted Rainfall for various regions, **(a)** Assam, **(b)** Lakshadweep, **(c)** Tamil Nadu, and **(d)** Andaman

Figure 5(a-d) depicts the actual and predicted rainfall in Assam, Lakshadweep, Tamil Nadu and Andaman regions in India. The analysis is made for the developed CResAtt-GCU technique to analyze the efficacy of the prediction performance. In the graphical manifestation, it is clear that the model provides almost similar performance compared to the actual data. The developed method proved that the model deliberately outperforms even larger rainfall data is considered for the training process.

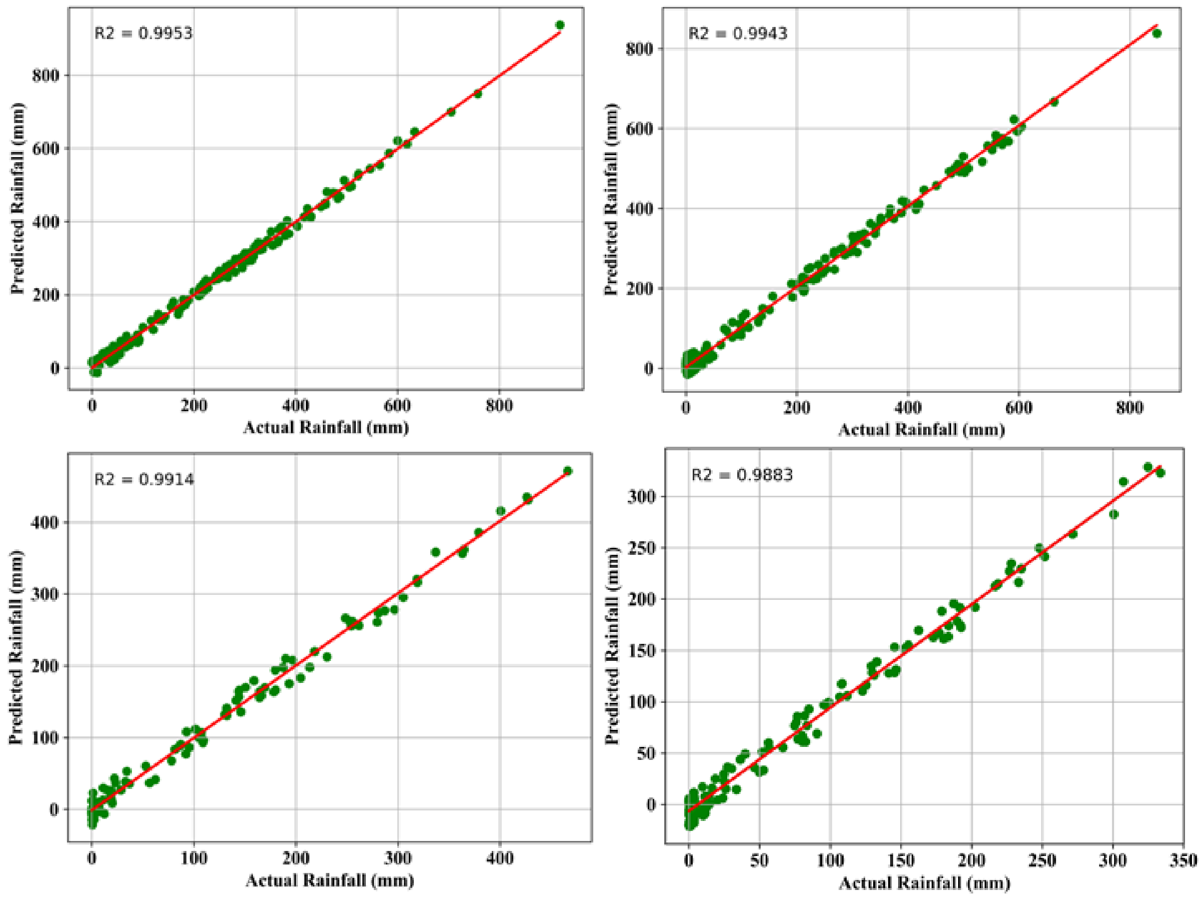


Figure 6. R^2 analysis on Rainfall forecasts for various regions, **(a)** Assam, **(b)** Lakshadweep, **(c)** Tamil Nadu, and **(d)** Andaman

Figure 6(a-d) depicts the R^2 analysis on Rainfall forecasts in Assam, Lakshadweep, Tamil Nadu and Andaman regions in India. The analysis is made for the developed CResAtt-GCU technique to analyze the efficacy of the prediction performance in regression plot. In the graphical manifestation, it is clear that the model provides almost similar performance compared to the actual data. The developed method proved that the model deliberately outperforms even larger rainfall data is considered for the training process with an R^2 of more than 98.8%.

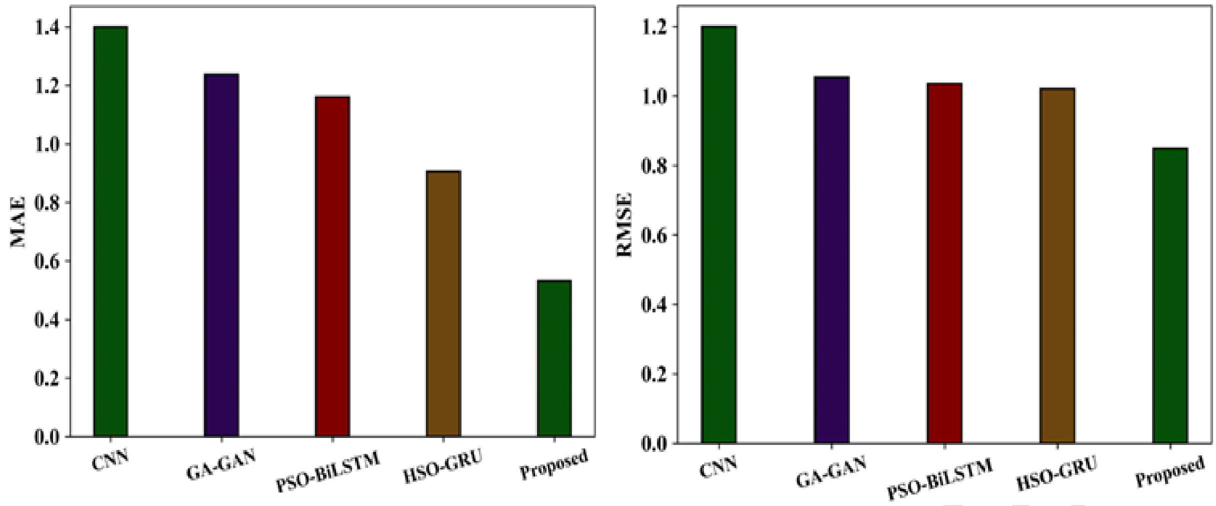


Figure 7. MAE and RMSE analysis under different traditional frameworks

Figure 7 illustrates the MAE and RMSE analysis under different traditional frameworks. The graphical interpretation shows that the developed CResAtt-GCU technique obtained minimal error compared to conventional schemes making them capable of upcoming weather prediction processes. For MAE, the existing CNN, GA-GAN, PSO-LSTM, HSO-GRU, and developed CResAtt-GCU technique obtained the values of 1.4, 1.23, 1.16, 0.90, and 0.532 respectively. For RMSE, the existing CNN, GA-GAN, PSO-LSTM, HSO-GRU, and developed CResAtt-GCU technique obtained the values of 1.2, 1.05, 1.036, 1.020, and 0.84 respectively.

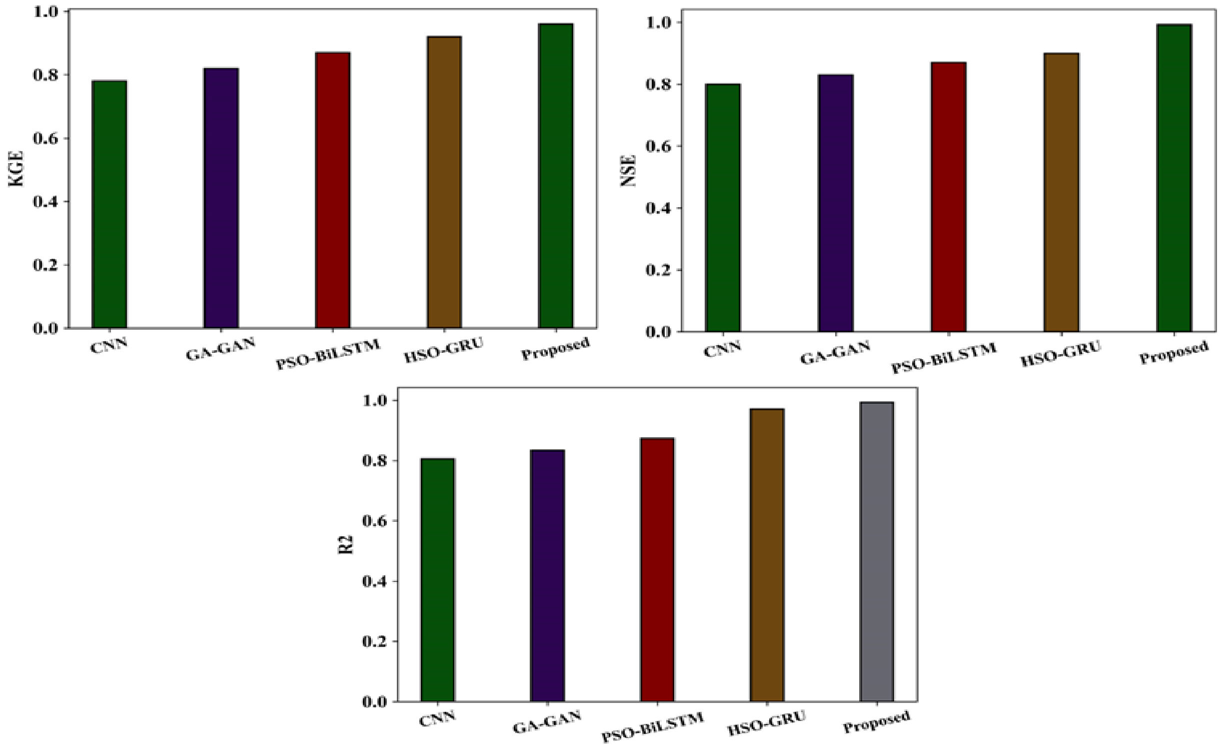


Figure 8. KGE, NSE, and R^2 analysis under different traditional frameworks

Figure 8 illustrates the KGE, NSE, and R2 analysis under different traditional frameworks. The graphical interpretation shows that the developed CResAtt-GCU technique obtained minimal error and enhanced efficacy compared to conventional schemes making them capable of upcoming weather prediction processes. For KGE, the existing CNN, GA-GAN, PSO-LSTM, HSO-GRU, and developed CResAtt-GCU technique obtained the values of 0.78, 0.82, 0.87, 0.92, and 0.96 respectively. For NSE, the existing CNN, GA-GAN, PSO-LSTM, HSO-GRU, and developed CResAtt-GCU technique obtained the values of 0.8, 0.83, 0.87, 0.9, and 0.992 respectively. For R2, the existing CNN, GA-GAN, PSO-LSTM, HSO-GRU, and developed CResAtt-GCU technique obtained the values of 0.80, 0.83, 0.87, 0.97, and 0.993 respectively.

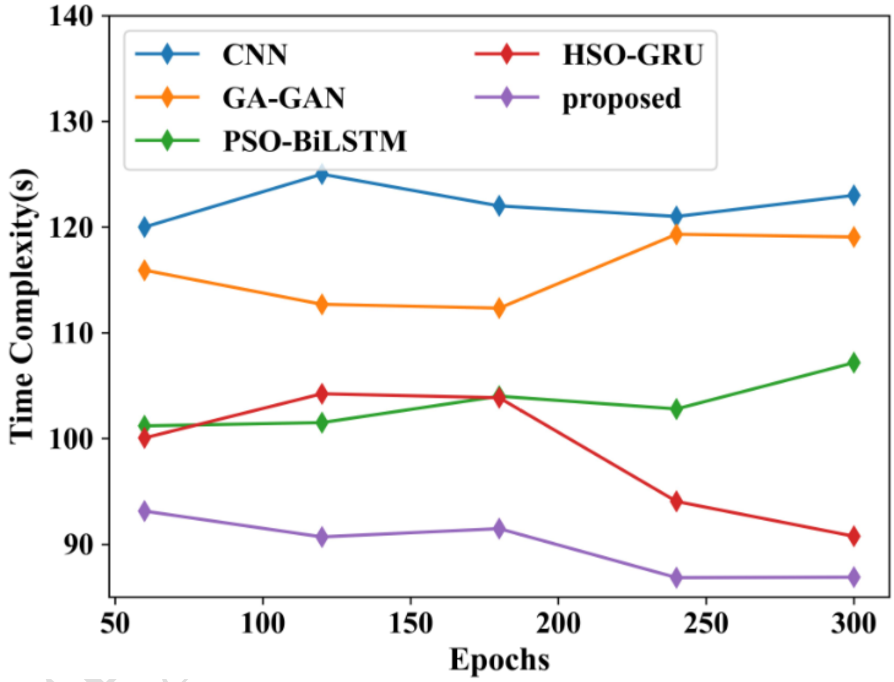


Figure 9. Computational Time analysis by altering epochs

Figure 9 depicts the Time complexity Analysis for varying Epochs under different Techniques. The graphical interpretation shows that the developed method attains lesser complexities compared to traditional studies. The traditional techniques consume increased time while training with complex rainfall data that increases the model's error due to unknown data distribution. The developed method overcomes all the issues faced by the existing studies thereby providing accurate results with minimal training time. For 300 epochs, the existing CNN, GA-GAN, PSO-LSTM, HSO-GRU, and developed CResAtt-GCU technique consumed an overall time of 123s, 119.06s, 107.16s, 90.75s, and 86.88s. For 50 epochs, the existing CNN, GA-GAN, PSO-LSTM, HSO-GRU, and developed CResAtt-GCU technique consumed an overall time of 120s, 115.91s, 101.19s, 100.05s, and 93.13s respectively.

5. Conclusion

The developed framework introduced and investigated the novel Humboldt squid optimizer (HBSO) with convolutional residual attentive gated circulation unit (CResAtt-GCU) technique to predict the amount of rainfall that occurs in various Indian states. The proposed optimizer effectively tuned the model parameters with minimal computation time and with enhanced global optimal solutions. Moreover, the CResAtt-GCU technique effectively forecasts the precipitation level by utilizing the adaptive and optimal feature learning mechanism with minimal computational complications. To enhance the effectiveness of precipitation prediction and the classification process more effective, an improved Min-max normalization (I-MMN) technique is introduced that normalizes the medical data by eliminating unwanted missing values. The proposed framework is tested on the Python platform and real-time rainfall data distribution datasets are collected and processed in this study. To prove the proposed efficacy, various computational measures like R^2, RMSE, KGE, NSE, MAE, and CT are scrutinized with different conventional frameworks. The overall R^2 of 0.993, RMSE of 0.84, KGE of 0.96, NSE of 0.992, MAE of 0.53, and overall CT of 86.66s are obtained by the developed technique against various conventional studies on forecasting the rainfall level. However, the developed framework highly relies on historical climatological data, which may not always accurately reflect current weather patterns due to the effects of climate change. Additionally, the accuracy of rainfall forecasts may be affected by factors such as unexpected weather events or changes in local environmental conditions. In the future, the present research work will be extended by incorporating the impact of other environmental factors, such as humidity and wind patterns, on rainfall patterns in different regions. Moreover, the upcoming studies will be encompassed by exploring other regions or countries to develop a more comprehensive understanding of the relationship between temperature disparities and rainfall.

Ethics Declarations.

Funding statement:
No funding was received for this study.

Data Availability Statement

The datasets generated and or analyzed during the current study is publicly available of the submitted research work.

https://www.data.gov.in/catalog/departure-rainfall-data

https://www.kaggle.com/datasets/harinkl/rainfall-of-india

Conflict of Interest

The authors declare they have no conflicts of interest to report regarding the present study.

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