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Establish An Advanced River Flow Prediction Model Using An Artificial Intelligence Approach

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Abstract

Accurate river flow predictions are essential for effective management of water resources, flood control, and environmental protection due to the increasing frequency of extreme weather events and shifting hydrological tendencies. An improved river flow prediction method utilizing artificial intelligence (AI) approaches is presented in this research. To advance the method's accuracy and rate of convergence, the raw river flow data is first normalized to decrease the impact of outliers and guarantee consistency across different scales. To raise the convergence speed and predictive performance, the Refined Northern Goshawk Optimized Deep Neural Network (RNGO-DNN), a novel hybrid method, incorporates optimized optimization methods that were influenced by the hunting tactics of the northern goshawk. When associated with conventional prediction approaches, the method's performance shows greater accuracy and dependability. The proposed method is measured against existing approaches, demonstrating larger performance in forecasting river flow by using metrics such as R-squared (R^2) of 0.98, Root Mean Square Error (RMSE) of 0.20, and Mean Absolute Error (MAE) of 0.08 in River flow forecast. The outcomes illustrate that the suggested technique achieves significantly better than conventional prediction methods, providing a reliable tool for forecasting river flow and improving resource management and environmental sustainability.

Keywords: River Flow Prediction, Refined Northern Goshawk Optimized Deep Neural Network (RNGO-DNN), Resource Management, Environmental Protection.

Introduction to River Flow Prediction

One of the most vital issues for scientific management and planning of the river flow system over the last couple of decades has been forecasting river flows. River forecasting is crucial to sustaining human culture growth, the environment, and subsequently the economy. Accurate river flow forecasts are also useful in protecting ecosystems and planning infrastructures such as dams and bridges (Lan et al., 2021). Prediction of river flow is crucial for water management and environmental protection since it depends on a number of variables, including climate and rainfall, and also it helps to group better strategies for natural disasters like droughts and floods. The rivers are pretentious by rainfall, evaporation, water stage, groundwater, and other variables. These factors are characteristically complicated, abrupt, and nonlinear, and they depend on a wide range of variables, including temporal and spatial variations (Rajabi et al., 2023).

Decisions on the management of water resources can be directly impacted by the proficiency of flow forecasts. A number of conceptual and statistical streamflow forecasts have been contributed to contribution policymakers, administrators, and urban planners in creating more informed decisions. Understanding how much water will flow in rivers and streams at various periods needs the ability to anticipate river flow. This aids in flood prevention and the management of water resources for uses such as agriculture, drinking water, and then electricity production (Tripathy and Mishra 2023). A high degree of nonlinearity is typically present in a river basin's rainfall-runoff process. To protect water resources, one of the most important components of the hydrological cycle, the process necessitates accurate modeling. Prediction is one of the critical roles played for effective water management tasks like planning irrigation, food, and hydroelectricity generation. Forecasts of stream flow with the help of a time series of stream flow continue to be among the greatest challenging problems in hydrology (Fang et al., 2020).

Flooding is ranked as one of the most common and natural hazards that affect property and human life globally. All flood disaster victims were comprised of all-natural disaster-affected persons, making it the highest number of persons affected in all disasters. The reason for floods being an almost very uncontrolled disaster up to now is their burstiness and unpredictability; more sophisticated control techniques are greatly in demand (Echendu 2020). Inflow of a river into a reservoir at any point in time should be forecasted with minimum error to manage water resources efficiently. Inflow forecasts support the water policy makers and managers in making decisions concerning the management of reservoirs, flood control, drought alleviation, and water distribution. Precise predictions allow the effective utilization of water resources as they provide information regarding the distribution and availability of water (Mohammadi et al., 2020)

Precise inflow predictions that consider ecological considerations, flood control, and downstream demands in reservoir operations are helpful in making informed judgments about water release and storage. AI-based river flow prediction uses intelligent processer systems that can learn from historical data to predict how much water will flow in rivers (Tan et al., 2022). Because AI is able to evaluate vast information such as rainfall and patterns of weather and reveal some hidden patterns that the more aged methodologies would have definitely missed, it contributes much to the creation of more accurate forecasts. It contributes to planning extreme weather events, floods, and helps in water management. This way, AI will be able to inform us better on how the rivers will perform and, importantly predict river performance, which will make the communities safer and more resilient to the change in the flow of water (Abdulla et al., 2022).

This objective of the study to exactly forecast river flow patterns to facilitate improved management of water resources and the avoidance of flooding. This led to better decision-making and enlarged readiness for environmental variations.

This paper is organized into several sections: Section 2 covers the literature review, Section 3 and 4 methodology and outcomes, and Section 5 and 6 provides the study's discussion and conclusion.

Survey on Related Works

Liu et al., (2020) suggested that river flow of the Yangtze River at the Hankou Hydrological Station was predicted using a DNN. The Empirical Mode Decomposition (EMD) algorithm was used in this technique. The outcomes established the method's reliability in years with catastrophic flooding and in continuous rolling forecast over a protracted period. Hussain et al., (2020) demonstrated a DNN, namely a extreme learning machine (ELM), then an one-dimensional convolutional neural network (1D-CNN) to advance streamflow forecast for three-time horizons. Based on programmed three-time scale statistical procedures, the outcomes presented that the ELM method outperformed the 1D-CNN method. Numerically, the ELM was larger than the 1D-CNN method.

Parisouj et al., (2020) examined this for their ability to forecast the monthly and daily stream flows of four US rivers. Three primary forecaster variables and their antecedent values were taken into account when developing the model. The study demonstrated that support vector regression (SVR) performs best at monthly and daily scales, ELM has superior simplification, all methods are unable to estimate the Carson River's streamflow as a basin conquered by snowmelt, and the accuracy of all models declines at daily scales. Ghimire et al., (2021) combined the long-short-term memory network (LSTM) and the convolution neural network (CNN) to advance a new CNN-LSTM hybrid method. A number of traditional artificial intelligence (AI) methods as well as the Deep Neural Network (DNN), LSTM, and CNN standalone approaches were associated with recommending the CNN-LSTM technique. The results showed that forecasts made by the CNN-LSTM technique, which is created on the innovative outline, were accurate. As an outcome, the CNN-LSTM technique offered important predictive utility.

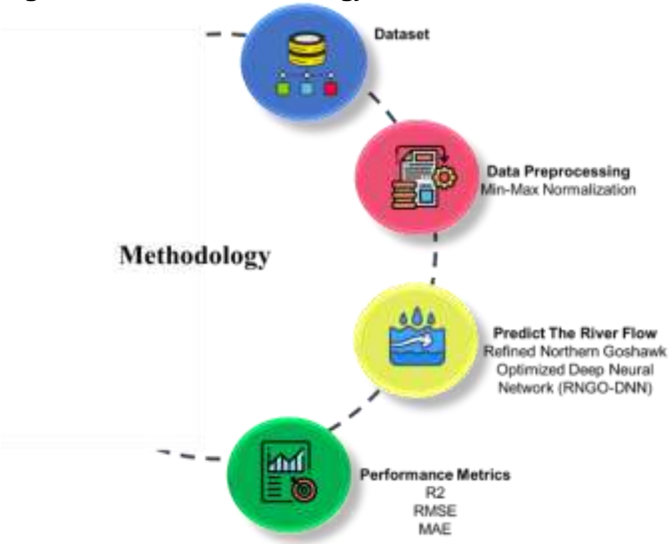
Hussain and Khan (2020) suggested anticipating Hunza River flow using in-situ for the years 1962–2008; they inspect the possibility of information-driven Machine Learning (ML) methods, with multilayer perceptron (MLP), random forests (RF) and SVR, The outcomes support the claim that algorithms and ML approaches, in specific the RF technique, can be used to precisely anticipate river flow, which improves water then hazard management even further. Hu et al., (2020) attempted to present a novel method of prediction using the LSTM deep learning method, which focused on time-series data. They used three criteria to measure the forecast results. They established that LSTM achieved better, with an R^2 of 0.970, an RMSE of 82.007, and an MAE of 27.752.

Lin et al., (2021) suggested a hybrid method for hourly streamflow forecast, called the Differential feedforward neural network long short-term memory (DIFF-FFNN-LSTM) technique. According to their results, the DIFF-FFNN-LSTM method was very good for the hourly streamflow prediction. The study proved effective in showing the application of integrating several driven analytics methods and then promoting possible hybrid techniques for water-related prediction. Jia et al., (2021) improved the prediction of the water flow and temperature of river networks, this study presented a physical ML method that combines ML methods with physical methods. In an effort to capture the interactions among several river network segments, the first construct a recurrent graph network method was built. Furthermore, it has also been established that the proposed method performs better when applied to numerous river segments with varying streamflow ranges or seasons.

Methodology

To advance river flow prediction using Refined Northern Goshawk optimized Deep Neural Network (RNGO-DNN) approaches, which combine the DNN algorithm and improve the RNGO technique. Fig. 1 depicts the methodology flow.

Figure 1. Flow of Methodology



Data collection

This study gathers river flow observations for predicting the river flow. In addition to dates, timings, and environmental variables like temperature and precipitation, this collection includes historical river flow observations from multiple monitoring sites. Date, time, station ID, river name, discharge, temperature, precipitation, catchment area, and land use type are all included.

Pre-processing using Min-Max Normalization

Pre-processing utilizes min-max normalization for the gathered river flow data. Min-max normalization is a preprocessing technique used to scale data to a specific range, typically between 0 and 1. It alters the information by deducting the minimum value and then dividing by the range. This technique defends that all features donate equally to the method and advances the overall performance of ML algorithms. A balance of contrast values among the information before and after processing is produced by the linear transformation of the original information using the Min-Max normalization method. The following is the formula to determine Min-Max Normalization by Equation (1):

$$W_{new} = \frac{W - Min(W)}{max(W) - Min(W)} \quad (1)$$

W_{new} is the early normalization original by the new W value, W shows the value that needs to be adjusted, max(W) signifies the highest number that a quality in the dataset can have and Min(W) is the dataset's minimal value for a certain attribute.

Refined northern goshawk optimized Deep Neural Network (RNGO-DNN)

In improving the accuracy of river flow prediction, an RNGO-DNN was integrated. The DNN was optimized by the NGO, assuring that it functions perfectly and professionally.

Deep Neural Network (DNN)

DNN advances river flow prediction accuracy by professionally extracting complicated patterns from past information. This technique makes prediction more accurate, which is water resource management than planning. $w_{nj'i,l'}$ $s_{nj'i,l}$ and $f_{nj'i,l}$ at each time step is regarded as one training sample for the n^{th} DNN sub model, and $Z_{n,i} = \{w_{n,j'i,l} | j' = 1,2,\ldots, M_n; i = 1,2,\ldots,24\}, Z_{n,i+3} = \{s_{n,j'i,l} | j' = 1,2,\ldots, M_n; i = 1,2,3,4; l = 1,2,\ldots,24\}$. Three basic layers typically make up DNN models: an input layer, many hidden layers, and the exit layer. The depth of the architecture is determined using equation (2) with a number of concealed layers. In contrast, the i_l^{th} neuron in the l^{th} $(m \geq l \geq 2)$ hidden layer can be found as follows by equation (3): The output layer's neuron z is identified as follows by equation (4):

$$y_{n,1,g_1} = e\left(\sum_{i=1}^{i=7}(x_{n,0,i,g_1} Z_{n,i})\right) \quad (2)$$

$$y_{n,j,g_j} = e\left(\sum_{g_{j-1}=1}^{g_{j-1}=M_{g_{j-1}}-1} (x_{n,j}, g_{j-1}, g_j . y_{n,j,g_j})\right) \quad (3)$$

$$F_n = e\left(\sum_{gm=1}^{gm=M_{g\,m}} \left(x_{n,m,gm} . Y_{n,m,M_{gm}}\right)\right) \quad (4)$$

The training DNN model aims to minimize the mean absolute percentage error (MAPE) between the expected river flow $\hat{F}_n$ and the measured river flow F_n by altering the set of weighting parameters. Thus, using equation (5), the yearly river flow may be predicted as follows: $\{\hat{f}_{n,j'} | n = 1,2,\ldots, M_{opt}; j' = 1,2,\ldots,24\}$

$$MAPE = \frac{1}{M_n \times 24} \sum_{j'=1}^{j'=M_n} \sum_{l=1}^{l=24} \frac{|f_{n,j,l} - \hat{f}_{n,j,l}|}{f_{n,j'}l} \times 100\% \quad (5)$$

The impacts of architecture on the DNN model's prediction performance are examined by varying the number of hidden layers, and the number of neurons in each layer (i.e. $M, M_2, \ldots, M_n$), activation functions (e), and training methodologies. The sigmoid, tanh, exponential linear (elu), and rectified linear unit (relu) functions are among the activation functions.

Refined Northern Goshawk Optimization (RNGO)

RNGO optimizes the river flow prediction process. The search mechanism of RNGO's three steps makes up the algorithm, such as population initialization, prey identification, and prey capture. This allows for effective prey capture and search.

Initialization

First, the matrix Z can be applied to show the population initialization of the northern goshawk following equation (6).

$$Z = \begin{bmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_M \end{bmatrix} = \begin{bmatrix} Z_{1,1} & Z_{1,2} & \cdots & Z_{1,N} \\ wZ_{2,1} & Z_{2,1} & \cdots & Z_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{M,1} & Z_{M,2} & \cdots & Z_{M,N} \end{bmatrix} \quad (6)$$

Where j-th separate in entire people is represented by $Z_j, 1 \leq j \leq M$. The measurement of the detached purpose (N) and the population size (M) are the corresponding values. The fundamentals of Z_j can be computed for a single-objective optimization problem then lower bound (LB) then upper bound (UB) using equation (7).

$$w_j = LB + rand.(UB - LB), 1 \leq j \leq M; 1 \leq i \leq N \quad (7)$$

Prey Identification

If the person's selected objective Z_j is $prey_j$, as represented in equation (8), before equation (9) put on the RNGO aggressive it is prey.

$$prey_j = Z_o = j = 1,2, \dots M; o = 1,2, \dots, j-1, j+1, \dots, M \quad (8)$$

$$\begin{cases} Z_j^{new} = Z_j + q(prey_j - JZ_j), & Fit(prey_j) < Fit(Z_j), \\ Z_j^{new} = Z_j + q(Z_j - prey_j), & Fit(prey_j) \geq Fit(Z_j), \end{cases} \quad (9)$$

Where J is a vector made up of 1 or 2, and q is a random vector with integers in the range [0, 1]. To make the algorithm more random and carry out a more exhaustive space search, q and J are employed. Equation (10) will then update each unique Z_j.

$$\begin{cases} Z_j = Z_j^{new}, Fit(Z_j^{new}) < Fit(Z_j) \\ Z_j = Z_j, Fit(Z_j^{new}) \geq Fit(Z_j) \end{cases} \quad (10)$$

Prey Capture

Equation (11) shows that the northern goshawk is capable of pursuing and capturing prey in any circumstance due to its great pursuit speed.

$$Z_j^{new} = Z_j + Q(2q-1)Z_j \quad (11)$$

Where $Q = 0.02(1 - s/S)$. The current iteration is S, while the maximum number of iterations is s. After that, Equation (12) updates each unique Z_j.

$$\begin{cases} Z_j = Z_j^{new}, Fit(Z_j^{new}) < Fit(Z_j) \\ Z_j = Z_j, Fit(Z_j^{new}) \geq Fit(Z_j) \end{cases} \quad (12)$$

There are still certain chances to advance the RNGO algorithm's exploitation and exploration capabilities, despite its benefits of simplicity, high precision, and ease of implementation in resolving test functions and certain engineering optimization issues. By presenting the polynomial interpolation plan and then the multi-plan opposing learning models, this study proposes the RNGO method. The combination of RNGO with DNN improves the river flow prediction. Algorithm 1 illustrates the RNGO-DNN method.

Algorithm 1: Refined Northern Goshawk Optimized Deep Neural Network (RNGO-DNN)

1. Initialize:
   - Set population size (M), max iterations (S), bounds (LB, UB)
   - Define DNN structure and initialize RNGO parameters (q, J, Q)
2. Population Initialization:
   - For each individual j in the population:
     $w_j = LB + rand.(UB - LB)$
     Evaluate the fitness of Z_j using DNN's prediction error (MAPE)
3. Iterate (for s = 1 to S):
   a. Prey Identification:
      - For each Z_j, find prey with better fitness
      - Update Z_j position based on prey and RNGO rules
   b. Prey Capture:
      - Update Z_j with pursuit speed Q:
        $Z_j^{new} = Z_j + Q(2q-1)Z_j$
      - Update Z_j if Z_j^{new} improves fitness
4. Dynamic Adjustment:
   - Update pursuit speed Q with iteration Q = 0.02(1 – s/S)
5. Final Prediction:
- Train DNN on optimized features (Z_j^{new}) and output predictions.

End
algorithm

Result

The objective is to forecast the river flow using the RNGO-DNN method. To estimate the effectiveness of the proposed, the following metrics are evaluated: Root Mean Squared error (RMSE), R-squared (R^2), Mean Absolute Error (MAE), and Training and Loss Accuracy. For estimating the effectiveness, the proposed DNN-NGO is compared with other existing approaches such as Exponential LGBM (light gradient boosting machine) [Kedam et.al., (2024)], and Random Forest [Kedam et.al., (2024)]. Table 1 shows the result of the comparison.

Table 1. Comparison of matrices

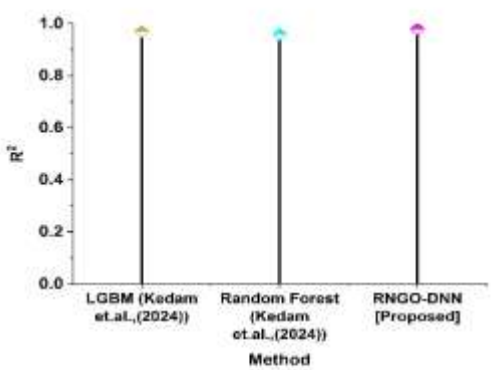
Method	MAE	RMSE	R2
LGBM [Kedam et.al., (2024)]	0.12	0.21	0.97
Random Forest [Kedam et.al., (2024)]	0.10	0.23	0.96
RNGO-DNN [Proposed]	0.08	0.20	0.98

R- Squared (R^2)

A statistical metric known as R-squared shows how much of the alteration in a dependent variable can be accounted for by an independent variable; as shown in Equation (13), it estimates the percentage of the volatility of the dependent variable that can be predicted. It is shown in Equation 13 and Fig 2.

$$R^2 = 1 - \frac{\sum_{l=1}^{m}(S_l - Q_l)^2}{\sum_{l=1}^{m}(S_l - \mu)^2} \tag{13}$$

Figure 2. Output of R^2



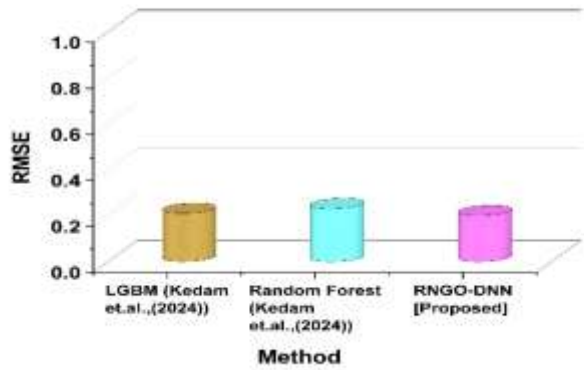
The R^2 values in this table show how well each model predicts river flow data; higher values denote better model performance. A value nearer 1 indicates a better match between the model and the observed data. R2 values vary from 0 to 1. In this case, the RNGO-DNN model obtains an R^2 of 0.98, meaning that the model correctly explains 98% of the variation in river flow data. While remaining strong, the R^2 values of 0.97 and 0.96 obtained by the Random Forest and LGBM models, respectively, are marginally lower, indicating that RNGO-DNN more accurately identifies patterns and correlations in the data. The RNGO-DNN's strong R^2 validates its efficacy and dependability in precisely forecasting river flow.

Root Mean Squared Error (RMSE)

It computes the standard difference among the values that a method forecasts then the definite values. It provides an approximation of the correctness of the model, or how well it can forecast the wanted value. The lower the RMSE value, the better the method. It comes from the mean-squared error (MSE), as shown in Equation (14) and Fig 3.

$$RMSE = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(g_j - g_j^{pred}\right)^2} \tag{14}$$

Figure 3. Results of RMSE



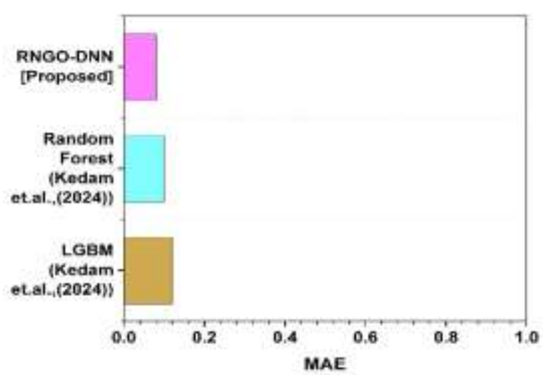
The average amount of inaccuracy in each method of river flow predictions is designated in this table by the RMSE, where reduced numbers denote higher prediction accuracy. The RNGO-DNN method in this case had the highest accuracy, with an RMSE of 0.20, the lowest of the three approaches. In contrast to the RNGO-DNN, the RMSE values of LGBM and Random Forest are 0.21 and 0.23, correspondingly, indicating higher forecast errors. This designates that the RNGO-DNN method is the most successful of the three in reducing forecast errors since it offers a more accurate fit to the observed river flow data.

Mean absolute error (MAE)

MAE is a statistic that measures the normal error in the collection of the forecasts. It expresses the mean total change among the prediction and real values. It shows the output of MAE in Equation (15) and in Fig 4.

$$MAE = \frac{1}{m}\sum_{j=1}^{m}\left|g_j - g_j^{pred}\right| \tag{15}$$

Figure 4. Outcomes of MAE

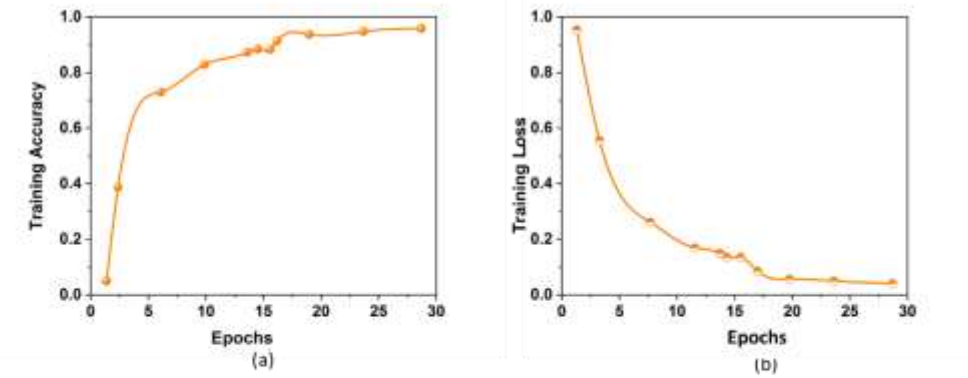


The table gives the MAE of each prediction of river flow method for the differences between the expected and the actual values. Each model's preciseness is expressed by their MAE values; less MAE value means better accuracy of prediction. The suggested RNGO-DNN model outperforms Random Forest with an MAE of 0.10 and LGBM with an MAE of 0.12, achieving the lowest MAE of 0.08. This implies that by reducing the average error in the predicted river flow values, RNGO-DNN's improvement optimization produces more accurate predictions.

Training loss and Training accuracy

Training loss refers to the error or difference between the forecast output of a method and the actual target during the prediction. Training accuracy measures how often the model correctly predicts the target values during the training process. Accuracy of training and loss graphs are used to show how well the suggested model performs. Here, the y-axis shows the accuracy and loss, respectively, and the x-axis shows the number of model training epochs. Fig. 5 illustrates the Outcomes of Training loss and training accuracy.

Figure 5. Result of Training loss and training Accuracy



As the method decreases errors, the accuracy loss in graph (a) dramatically drops during the first epochs, suggesting successful learning. Graph (b) designates that the method attains a high degree of forecast accuracy as training goes on, with the training accuracy increasing gradually and stabilizing. Collectively, these patterns show how the method can efficiently lower loss while quickly enhancing performance throughout training

Discussion

The objective of the research is to exactly predict river flow patterns to facilitate effective management of water resources then the avoidance of flooding. The existing approaches such as LGBM (Kedam et.al., (2024)) and Random Forest (Kedam et.al., (2024)). The Light Gradient Boosting Machine's (LGBM) vulnerability to overfitting is a drawback, especially when working with tiny datasets or when hyperparameters are not adjusted correctly. Furthermore, compared to simpler models, LGBM may be harder to interpret, making it difficult to comprehend the significance of features and the decision-making process LGBM (Kedam et.al., (2024)). Random Forest has the drawback of being computationally demanding and slower to anticipate because of the enormous number of trees it creates. The decision-making process can also be difficult to understand since its models may be harder to interpret than simpler ones Randomforest (Kedam et.al., (2024)). Optimization methods modeled along the lines of effective hunting tactics that the northern goshawk uses to provide very accurate predictions are used by RNGO-DNN. For complicated forecasting tasks like the estimation of river flows, it is ideal since the hybrid methodology used increases both speed and reliability of convergence.

Conclusion

The objective of the research is to exactly prediction river flow patterns to facilitate effective management of water resources then the avoidance of flooding. Communities can better prepare for environmental variations with the method's accurate predictions. Planning and addressing issues pertaining to water are made easier as an outcome. RMSE (0.20), R^2 (0.98), and MAE (0.08) were achieved by the RNGO-DNN technique for River flow forecast. Future scope includes improving the method by adding real-time information to prediction river flow even more exactly. The approach's worldwide applicability can be increased by extending it to various geographic locations and environmental circumstances. Furthermore, the methods integration with early warning systems can advance plans for catastrophe planning and response. This study reliance on the availability and quality of historical river flow data, which might differ between locations and time periods, is one of its limitations. Furthermore, unconsidered external influences like climate variability and changes in land use can have an impact on the model's performance.

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