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Research Article

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Prediction of Runoff Using Hybrid SVM-SSA in Baitarani River Basin, Odisha, India

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HIGHLIGHTS

- Developed a hybrid SVM-SSA model for monthly runoff prediction in the Baitarani River Basin.
- Inclusion of specific and relative humidity as input variables enhanced model performance.
- The SVM-SSA model achieved high predictive accuracy.

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ABSTRACT

Accurate prediction of surface runoff is essential for effective water resource management, particularly in regions susceptible to hydrological variability such as the Baitarani River Basin in Odisha, India. Traditional hydrological models often fail to capture the complex, nonlinear, and non-stationary behavior of rainfall-runoff processes, especially under the influence of climatic and anthropogenic changes. In this study, a hybrid model integrating Support Vector Machine (SVM) with Salp Swarm Algorithm (SSA) is proposed to enhance the accuracy of monthly runoff prediction. The performance of the SVM-SSA model is compared against conventional Artificial Neural Network (ANN) and standalone SVM models using datasets from Anandpur and Champua gauging stations. Inputs include rainfall, temperature, specific humidity, and relative humidity, offering a comprehensive representation of climatic influences. Model performance is evaluated using statistical metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Willmott's Index (WI). The results demonstrate that the hybrid SVM-SSA model significantly outperforms the conventional models, achieving R^2 values of 0.9847 and 0.9771 at Anandpur and 0.9844 and 0.9756 at Champua for training and testing phases, respectively. These findings suggest that coupling machine learning with metaheuristic optimization provides a promising approach for runoff prediction in complex river basins.

1. INTRODUCTION

Water is one of the most critical natural resources, essential for sustaining life, economic development, and environmental balance. Despite covering about 71% of the Earth's surface, only a small fraction of this water—approximately 3%—is freshwater, and even less is readily accessible for human use. Surface water, particularly river runoff, plays a key role in meeting the agricultural, industrial, and domestic water

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demands of growing populations, especially in developing countries like India.

Surface runoff is a major component of the hydrological cycle and represents the flow of excess water over land due to precipitation exceeding infiltration capacity. It is a key factor in flood generation, soil erosion, and water availability. Accurate estimation of runoff is critical for water resource planning, flood risk assessment, irrigation scheduling, and sustainable watershed management. However, runoff prediction remains challenging due to the complex, nonlinear interactions between climatic variables (e.g., rainfall, temperature, humidity), land surface conditions, and topography.

Conventional hydrological models rely on physical equations and empirical relationships to simulate runoff. While effective in some contexts, these models often require extensive data and suffer from structural uncertainties, particularly in regions with sparse observations or changing land use. In recent years, data-driven approaches—particularly machine learning (ML) techniques—have gained attention due to their flexibility, robustness, and ability to model nonlinear processes without requiring explicit physical formulations.

Artificial Neural Networks (ANNs) have been widely used for hydrological modeling but suffer from drawbacks such as slow convergence and vulnerability to local minima. Support Vector Machines (SVMs), with their strong generalization capabilities and robustness to overfitting, have shown promise in hydrological applications. However, the performance of SVM models largely depends on the optimal selection of hyperparameters, which is often a non-trivial task.

To address these limitations, this study proposes a hybrid machine learning model integrating SVM with the Salp Swarm Algorithm (SSA), a recent metaheuristic optimization technique inspired by the swarming behavior of salps in the ocean. SSA enhances the SVM model by efficiently optimizing its parameters, thereby improving predictive performance.Artificial Intelligence (AI) techniques have gained considerable attention in hydrology for modeling complex and nonlinear systems such as rainfall-runoff processes. Among these, Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) have been widely used due to their data-driven nature and ability to model systems without requiring explicit physical assumptions. ANNs have shown good predictive capabilities in flood forecasting and streamflow modeling. However, they often suffer from slow convergence, a tendency to get trapped in local minima, and a need for large datasets to ensure generalization (Dawson & Wilby, 1998; Ghumman et al., 2011). These limitations can reduce their practical effectiveness in certain hydrological applications.

SVMs have emerged as a strong alternative, especially in cases involving limited datasets. Based on the principles of statistical learning theory, SVMs are capable of identifying complex input-output relationships while maintaining good generalization and robustness against overfitting (Deka., 2014). They have been used effectively for runoff forecasting, sediment load estimation, and groundwater level modeling (Samantaray et al., 2024; Himanshu et al., 2017). Nevertheless, the performance of SVMs is highly dependent on the appropriate tuning of hyperparameters such as the penalty factor (C), kernel parameters (γ), and epsilon (ε) in the loss function. Improper selection of these parameters can significantly affect model accuracy and convergence behavior.

To address these limitations, researchers have explored hybrid models, combining machine learning techniques with metaheuristic optimization algorithms. For instance, SVMs have been coupled with Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Firefly Algorithm (FFA), and Whale Optimization Algorithm (WOA) to enhance hyperparameter tuning (Remesan et.al., 2009; Pisarenko et al., 2005). These hybrid approaches have generally demonstrated better predictive performance, particularly in dealing with nonlinearity and data uncertainty in hydrological models.

The Salp Swarm Algorithm (SSA) is a relatively recent addition to the family of nature-inspired optimization algorithms. SSA mimics the swarming behavior of salps in the ocean and is known for its simplicity, global search capabilities, and minimal parameter tuning requirements. It has been effectively used in several engineering and environmental applications, including energy demand forecasting and image processing (Pachpor et al., 2024; Islam et al., 2002). In hydrology, SSA has been integrated with models such as Extreme Learning Machines (ELM), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and ANN for streamflow and groundwater modeling (Samantaray et al., 2022; Cheghabaleki et al., 2024). These studies demonstrated that SSA can enhance model accuracy and convergence speed by avoiding premature local optima.

Despite the promising results of SSA-based models, there is a clear research gap in the application of hybrid SVM-SSA models for runoff prediction. To the best of our knowledge, no existing studies have applied this combination in the context of Indian river basins, particularly the Baitarani River Basin. Furthermore, most existing runoff prediction models overlook critical atmospheric variables such as specific humidity and relative humidity, despite their significant influence on evapotranspiration and surface runoff. The inclusion of these parameters has the potential to improve the model's ability to simulate hydrological processes more realistically.

While traditional AI models and their hybrids have contributed significantly to hydrological modeling, there remains scope for further enhancement. Integrating SSA with SVM offers a promising solution to optimize model performance, while the inclusion of underutilized climatic variables can improve input quality. Based on these observations, this study aims to: (i) develop a novel hybrid SVM-SSA model for monthly runoff prediction in the Baitarani River Basin; (ii) evaluate the impact of specific and relative humidity as inputs; and (iii) compare the model's performance with conventional ANN and SVM approaches.

2. STUDY AREA AND DATA COLLECTION

The study is conducted in the Baitarani River Basin, one of the significant river systems of eastern India, primarily located in the state of Odisha, with a small portion extending into Jharkhand. The river originates from the Guptaganga hills in Keonjhar district, Odisha, at an elevation of approximately 900 meters above mean sea level, and traverses around 360 kilometers before discharging into the Bay of Bengal near Chandabali. The total drainage area of the basin is about 14,218 km², with approximately 736 km² lying in Jharkhand and the rest within Odisha (Fig 1).

Topographically, the basin is divided into three distinct zones—Upper, Middle, and Lower Baitarani. The upper basin comprises highlands and rugged terrain, mostly covered with forest and iron ore formations from the Dharwar group. The middle region transitions into a mix of hills and plains, while the lower basin is predominantly alluvial and located in the coastal region, making it prone to flooding. The river has 65 tributaries, with major ones including the Salandi, Kusei, Khairi-Bhandan, and Deo rivers. The region receives the majority of its precipitation from the southwest monsoon (June to October), contributing to high seasonal variability in streamflow.

Climatically, the basin experiences tropical monsoon conditions with distinct wet and dry seasons. The average annual rainfall ranges between 745 mm and 1595 mm, with the upper basin recording relatively higher rainfall. Temperature varies from a minimum of 6.8°C in winter to a maximum of 45°C during summer, while relative humidity fluctuates between 39.63% and 83.08%, peaking during the monsoon months. These conditions significantly influence the runoff response and hydrological dynamics within the basin.

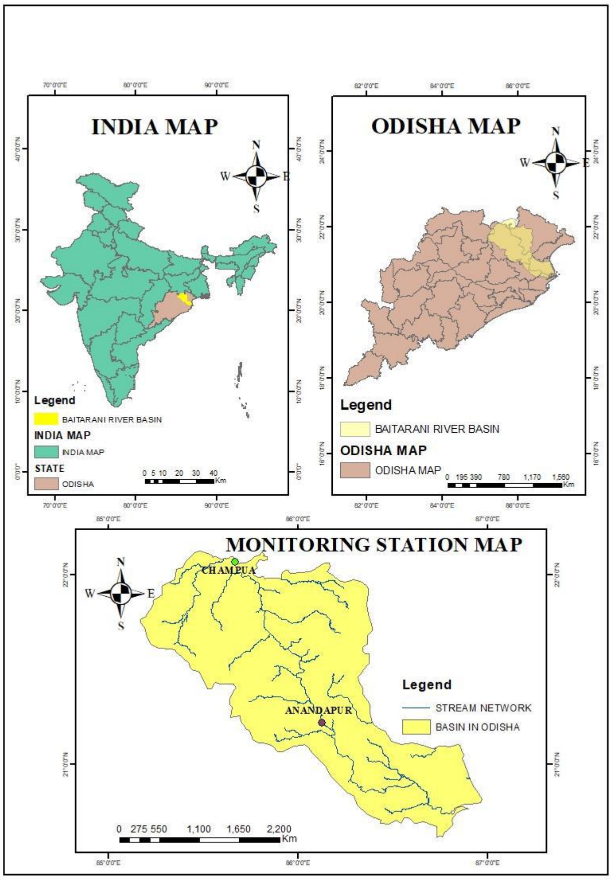
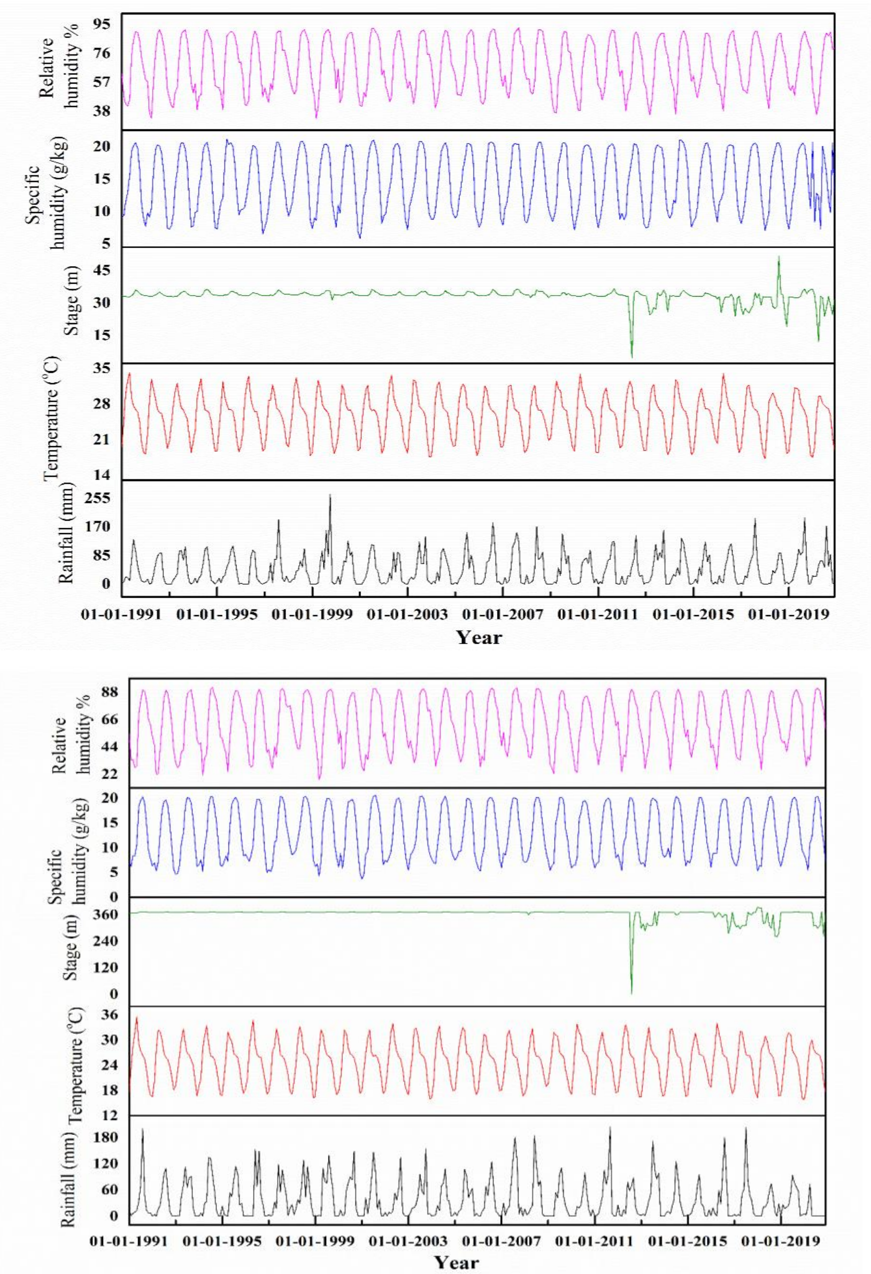


Figure 1. Study area Map

The hydrological modeling in this study relies on monthly historical data for a set of key meteorological and hydrological variables: rainfall, temperature, specific humidity, relative humidity, and runoff (Figure 2) . These datasets were obtained from various authentic sources, including the Central Water Commission (CWC) and India Meteorological Department (IMD).

Two key gauging stations were selected for model calibration and validation: Anandpur (latitude: 21.2148°N, longitude: 86.1249°E) and Champua (latitude: 22.0650°N, longitude: 85.6666°E). These stations were chosen due to their spatial representativeness within the basin and availability of long-term data. The dataset spans a significant time frame, ensuring sufficient variability to train and test machine learning models effectively.



a)

b)

Figure 2. Range of datasets used for a) Anandpur and b) Champua

Before model application, all datasets were subjected to preprocessing techniques, including missing value treatment, normalization, and time series alignment. Exploratory data analysis was performed to assess trends, seasonality, and statistical characteristics of the variables. Additionally, data were transformed to dimensionless forms where necessary to improve convergence and accuracy in the machine learning models.

This comprehensive dataset, incorporating both conventional meteorological variables and underutilized inputs such as specific and relative humidity, serves as the foundation for evaluating the performance of the proposed hybrid SVM-SSA model for monthly runoff prediction.

3. METHODOLOGY

3.1 Artificial Neural Network (ANN):

The ANN model employed consists of multiple layers of interconnected neurons, typically including an input layer, one or more hidden layers, and an output layer (Figure 3). Each neuron processes inputs through weighted connections and applies an activation function to capture nonlinear relationships within the data. Despite its flexibility and powerful modeling capacity, the ANN faces limitations such as slow convergence during training and challenges in accurately predicting peak or extreme values due to issues like overfitting or vanishing gradients.

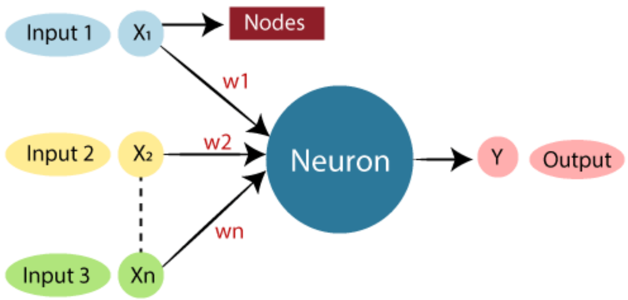


Figure 3. Illustration of a Neural Network

Starting from the previous layer, a neuron puts in the values of every neuron to its connected layer neuron. Within the below figure 4 the neuron is contained three inputs. Those 3 values are multiplied with the weights and supplemental along (w1, w2, w3). The strength between 2 neurons is set by weight values. Those square measure the values that may be biased in the learning procedure. Then a bias value is going to be supplemental with the previous summation. In spite of everything these summations the neuron utilizes an activation algorithm to the worth. This is often the operating methodology of a neuron.

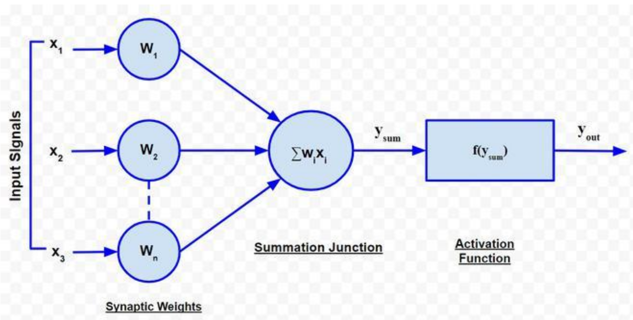


Figure 4. Operations performed in a neuron

3.2 Support Vector Machine (SVM):

Support Vector Regression (SVR), an extension of the SVM framework for regression tasks, is used for modeling continuous variables. SVR constructs a hyperplane in a high-dimensional feature space that best fits the data within a margin of tolerance. Kernel functions (e.g., linear, polynomial, radial basis function) are employed to transform the input data into this feature space, enabling the model to capture complex nonlinear relationships (Figure 5).

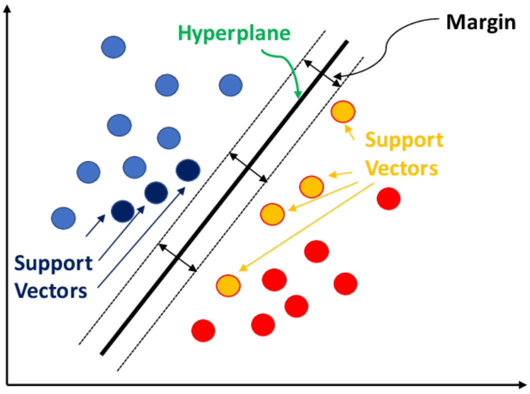


Figure 5. Classification using Hyper-plane

3.3 Salp Swarm Algorithm (SSA):

The Salp Swarm Algorithm is a nature-inspired metaheuristic optimization technique based on the swarming behavior of salps in the ocean. SSA is effective in global optimization problems due to its ability to balance exploration and exploitation. In this study, SSA is utilized to optimize the hyperparameters of the SVM model, enhancing its predictive accuracy by avoiding local minima and improving convergence speed (Figure 6).

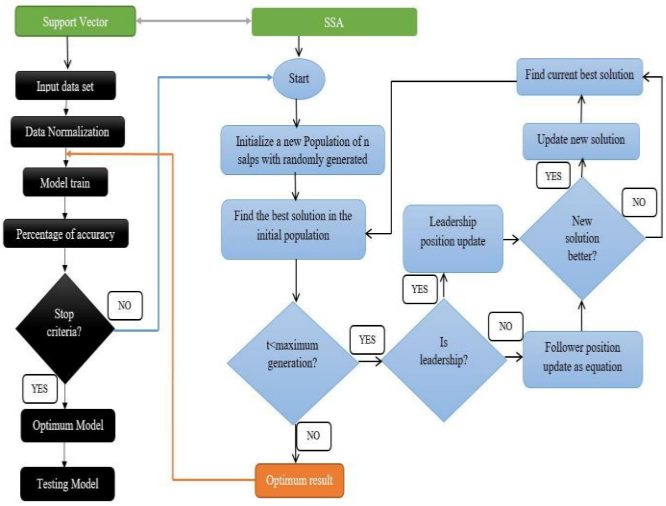


Figure 6. Flowchart of SSA algorithm

3.4 Hybrid SVM-SSA Model

The proposed hybrid model integrates SSA with SVM to optimize the SVM hyperparameters automatically. SSA iteratively searches the hyperparameter space (such as penalty parameter C and kernel parameters like gamma) to find the combination that minimizes prediction error . This integration enhances the robustness and accuracy of the SVM model compared to manual or grid-based tuning methods (Figure 7).

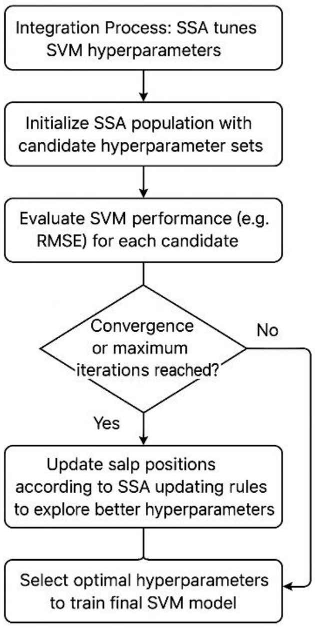


Figure 7. Flow chart of methodology for Hybrid SVM-SSA Model

3.5 Data Processing

Key meteorological and environmental variables such as rainfall, temperature, humidity, wind speed, and solar radiation are selected as input predictors based on their relevance to the target variable. To ensure uniform scaling, input variables are normalized (e.g., min-max scaling or z-score normalization), which helps accelerate model training and improve stability. A 5-fold cross-validation strategy is employed to validate the model performance robustly and prevent overfitting by dividing the dataset into training and testing folds.

3.6 Performance Evaluation

Model performance is assessed using multiple statistical metrics to ensure comprehensive evaluation:

Root Mean Square Error (RMSE): Measures the average magnitude of prediction errors, penalizing larger errors.

$$RMSE = \frac{\sum_{i=0}^{n}\left(x_{comp}^{i}-\overline{x}_{comp}\right)\left(x_{obs}^{i}-\overline{x}_{obs}\right)}{\sqrt{\sum_{i=0}^{n}\left(x_{comp}^{i}-\overline{x}_{comp}\right)^{2}\left(x_{obs}^{i}-\overline{x}_{obs}\right)^{2}}} \quad (1)$$

Mean square error (MSE): Represents is a commonly used metric to measure the average squared difference between predicted values and actual (true) values. It is often used in regression analysis and machine learning to evaluate the performance of a predictive model.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(x_{comp}^{i} - x_{obs}^{i}\right)^{2} \quad (2)$$

Coefficient of Determination (R^2): Indicates the proportion of variance in the observed data explained by the model.

$$R^{2} = \frac{\left[\sum_{i=0}^{n}\left(x_{comp}^{i}-\overline{x}_{comp}\right)\left(x_{obs}^{i}-\overline{x}_{obs}\right)\right]^{2}}{\sum_{i=0}^{n}\left(x_{comp}^{i}-\overline{x}_{comp}\right)^{2}\sum_{i=0}^{n}\left(x_{obs}^{i}-\overline{x}_{obs}\right)^{2}} \quad (3)$$

Willmott Index (WI): A dimensionless index reflecting the agreement between observed and predicted values, with values closer to 1 indicating better model performance.

$$WI = 1 - \left[\frac{\sum_{i=1}^{n}\left(x_{obs}^{i}-x_{comp}^{i}\right)^{2}}{\left[\sum_{i=1}^{n}\left(\left|x_{comp}^{i}-\overline{x}_{obs}\right|+\left|x_{obs}^{i}-\overline{x}_{obs}\right|\right)^{2}\right]}\right], \quad 0 \le \mathrm{WI} \le 1 \quad (4)$$

Where, x_{comp} = Simulated Value , $\overline{x_{comp}}$ = Average Simulated Value , x_{obs} = Observed Value, $\overline{x_{obs}}$ = Average Observed Value .

4. RESULTS AND DISCUSSION

4.1 Model Performance at Anandpur and Champua

The performance of the three predictive models—Artificial Neural Network (ANN), Support Vector Machine (SVM), and the proposed hybrid SVM-SSA—was evaluated for monthly runoff prediction at Anandpur and Champua gauging stations in the Baitarani River Basin. Each model was trained and tested using identical input variables: rainfall, temperature, specific humidity, and relative humidity. The dataset was split into training and testing sets to ensure robust model validation.

Table 1. Performance Evaluation results

Model Name	RMSE	R^2	MAE	WI	RMSE	R^2	MAE	WI
	Training				Testing			
SVM1:SSA	8.41	0.972	0.967	0.9777	10.901	0.9644	1.0071	0.9685
SVM2:SSA	7.09	0.9736	0.9386	0.9795	10.68	0.9665	0.991	0.9713
SVM3:SSA	6.446	0.9743	0.9073	0.9806	10.117	0.967	0.9674	0.972
SVM4:SSA	4.669	0.9757	0.8867	0.9819	10.008	0.9682	0.9106	0.9741
SVM5:SSA	3.668	0.9762	0.7275	0.9823	9.019	0.9704	0.8999	0.9768
SVM6:SSA	1.73	0.9781	0.6991	0.9848	8.119	0.9721	0.8563	0.9774
SVM7:SSA	0.705	0.9798	0.672	0.9854	8.013	0.9728	0.817	0.9786
SVM8:SSA	0.407	0.9806	0.6388	0.9871	7.414	0.9733	0.8005	0.979
SVM9:SSA	0.208	0.9819	0.609	0.988	6.018	0.9749	0.7962	0.9802
SVM10:SSA	0.0769	0.9844	0.5934	0.9902	5.117	0.9756	0.7698	0.9817

The SVM-SSA hybrid model significantly outperformed the ANN and standalone SVM models in terms of all statistical evaluation metrics. At Anandpur station, the hybrid model achieved an R^2 of 0.9847 for the training phase and 0.9771 for the testing phase (Table 1). Similarly, at Champua station, it recorded an R^2 of 0.9844 during training and 0.9756 during testing. In contrast, the standalone SVM model showed slightly lower R^2 values, while ANN exhibited the least accurate performance, indicating limitations in handling nonlinearity and variability in the dataset (Figure 8).

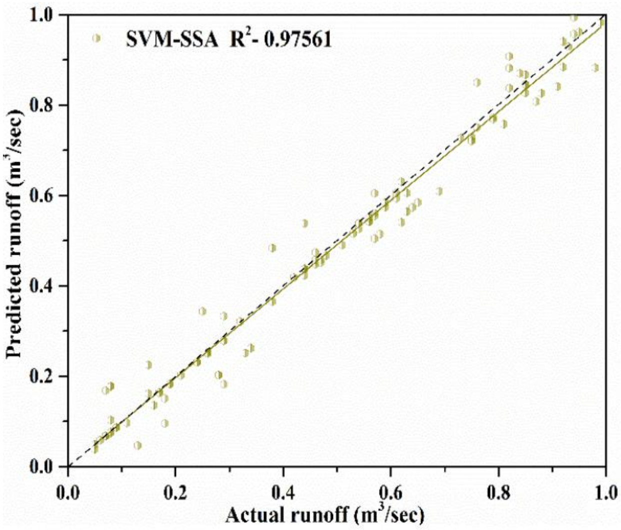


Figure 8. Scatter plots between observed and predicted runoff using SVM-SSA Model

Scatter plots between observed and predicted runoff values showed a tighter clustering along the 1:1 reference line for the SVM-SSA model, indicating minimal prediction bias (Fig 8). Time series plots further confirmed that SVM-SSA closely followed the observed runoff trends, capturing both peak and base flow conditions effectively. Box plots revealed that the SVM-SSA model had the least spread in prediction error distributions, suggesting better consistency and robustness. Histogram plots of residuals showed a more symmetric and narrow distribution for SVM-SSA compared to the other models, affirming its superior error minimization capability. The hybridization of SVM with SSA clearly improved the model's ability to generalize and predict runoff with higher accuracy and stability across varying hydrological conditions.

4.2 Analysis of Error and Uncertainty

To assess model reliability under different hydrological regimes, a detailed error and uncertainty analysis was performed. Particular attention was given to the model's ability to simulate extreme events, such as high runoff during monsoon peaks and low runoff in dry periods. The SVM-SSA model demonstrated strong generalization capabilities, maintaining low prediction errors even during abrupt runoff fluctuations.

The model was found to be especially effective in predicting peak flows, which are critical for flood forecasting and reservoir management. While ANN and SVM tended to underestimate peak runoff and overestimate base flows, the SVM-SSA model maintained closer alignment with observed values in both regimes. This was likely due to SSA's efficient global search mechanism, which optimized SVM parameters for better convergence across the entire solution space.

Prediction intervals were also narrower for SVM-SSA, indicating less uncertainty and higher confidence in its estimates. The model's robustness under diverse runoff conditions enhances its applicability for operational hydrological forecasting in the Baitarani River Basin. The SVM-SSA model not only outperformed conventional models in accuracy metrics but also demonstrated superior reliability in simulating both average and extreme runoff events, making it a promising tool for real-world water resource management.

5. CONCLUSION

This study introduces a novel hybrid machine learning approach, the Support Vector Machine optimized with Salp Swarm Algorithm (SVM-SSA), for monthly runoff prediction in the Baitarani River Basin, Odisha, India. Utilizing key hydro-climatic variables—rainfall, temperature, specific humidity, and relative humidity—the model was validated at two gauging stations (Anandpur and Champua) and benchmarked against conventional Artificial Neural Network (ANN) and standalone SVM models. The SVM-SSA model consistently outperformed the baseline methods, achieving R^2 values exceeding 0.98 in training and 0.97 in testing phases, along with superior RMSE, MAE, and Willmott Index scores. Notably, the hybrid model demonstrated enhanced capability in capturing both high and low flow events, with the inclusion of atmospheric moisture variables contributing to improved sensitivity and accuracy. These findings underscore the potential of the SVM-SSA framework as a robust and reliable tool for runoff modeling, with practical implications for flood forecasting, water resource management, and climate-resilient hydrological planning. Future work may focus on integrating real-time observations and remote sensing data to further enhance model responsiveness and applicability.

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