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Hybrid Deep Learning Flood Forecasting Framework Optimized with the Snake Algorithm

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Abstract Accurate flood forecasting remains a major challenge due to the nonlinear dynamics of hydrological processes and the difficulty of optimizing deep learning models. This study proposes a hybrid deep learning framework integrating Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) with the Snake Optimization Algorithm (SOA) for hyperparameter tuning. The method includes feature normalization, training–testing partitioning, and multi-metric evaluation using MSE, RMSE, MAE, and R^2. The results reveal that the hybrid LSTM-SOA model achieved the best performance with R^2= 0.8514, MSE=0.000386, RMSE=0.019653, and MAE=0.015849, outperforming standalone models. These results demonstrate the potential of hybrid optimisation-based deep learning as a trustworthy tool to support decisions in flood forecasting, early warning, and disaster preparedness.

Keywords Flood forecasting, Deep learning, Snake Optimization Algorithm (SOA), Hybrid models, Disaster risk management

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1. Introduction

Floods are among the most devastating natural hazards, with devastating socioeconomic impacts in the whole world and indicating over 50 percent of all natural disaster-related damages in the past 50 years [1]. In recent years, catastrophic flood events have occurred in Germany (2021), Pakistan and Iran (2022), as well as Afghanistan, Indonesia, France, and Brazil (2024) [2, 3]. The increasing frequency of such extreme events under climate change underscores the pressing need for robust flood management strategies to safeguard human lives and infrastructure [4, 5].

Flood control to reduce the social and economic consequences of floods, droughts and the transition from drought to flood. The validity of management strategies depends on accurate forecasting at different time scales [6]. Short-term (daily) and seasonal predictions bring important advantages through early warnings, input for hydraulic design in the form of frequency estimates and support for long-term planning adaptation [7]. In drought risk assessment, Ruidas et al. [8] have outlined that it is particularly the precise monitoring, strong prediction and extensive surveys that play a decisive role in the decision process as well as underlining with dismal dam failures which frequently introduce ferocious flash floods. The correct prediction of river flow is critical for water security, disaster prevention, and agriculture as well as other industrial sectors [9]. In the past 50 years, extreme hydro-meteorological-related events have claimed over two million lives and incurred approximately US$4.3 trillion in

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global economic damages, with more than 90% of fatalities occurring in developing countries [10]. Also, from 1990 to 2022, floods affected more than 3.2 billion people worldwide and resulted in 218,353 deaths with over $1.3 trillion in damage [11]. These numbers signal the rapidly increasing worldwide risk of flooding and the pressing need for new management options. There are however considerable challenges, since hydrological and meteorological models often have difficulties in handling the nonlinear complexity of natural systems and the necessary accuracy for calibration to obtain reliable predictions [12, 13].

Over the last few years, computer science has advanced and led to an increase in the use of data-driven machine learning models as an important tool in flood forecasting [14]. These approaches have proven effective in capturing flood dynamics and improving prediction accuracy [15, 16, 17]. Since the 1990s, models such as Feedforward Neural Networks (FNN), Multilayer Perceptron's (MLP), and Backpropagation (BP) have been widely used to address nonlinear hydrological processes and complex watershed dynamics, making them early foundational methods in flood prediction [18, 19, 20]. Nevertheless, conventional neural networks often struggle with high-dimensional data. Convolutional Neural Networks (CNNs) have been introduced to mitigate this limitation, while Recurrent Neural Networks (RNNs) enhance temporal sequence analysis [21]. The development of Long Short-Term Memory networks (LSTMs) further resolved issues of vanishing and exploding gradients in RNNs, enabling more robust performance supported by modern computational power [22]. For instance, Hu et al. [23] successfully applied LSTM to model rainfall–runoff processes using hourly hydrological data, and since then, LSTM-based approaches have been extensively applied in flood forecasting research [24, 25, 26].

In this study, we try to construct an efficient and accurate flood forecasting model by combining state-of-the-art advanced deep learning architectures with metaheuristic optimization. In particular, we analyze the predictability of (i) Artificial Neural Networks (ANN), (ii) Long Short-Term Memory networks (LSTM), and (iii) Convolutional Neural Networks (CNN) as base models under three different hybridization configurations based on the Snake Optimization Algorithm (SOA). The aim of this study is to overcome the difficulties of nonlinearity, temporal dependence and high-dimensional feature space in hydrological series using the complementary power of these models. We further compare between individual and hybrid approaches in a systematic way with different performance metrics and show the superiority of these proposed hybrid models. In summary, our study provides an innovative optimization-driven deep learning framework for improving the prediction performance while significantly reducing uncertainty, which can serve as a robust decision support tool for flood risk management, early warning system development and climate-resilient planning.

The main contributions of this study can be summarized as follows:

- To present a new hybrid flood forecasting framework that systematically integrates deep learning models (ANN, LSTM, and CNN) with the Snake Optimization Algorithm (SOA), enhancing predictive accuracy by addressing challenges of nonlinearity, temporal dependencies, and spatial variability in hydrological data.
- To devise and deploy a full-fledged experimental pipeline, such as exploratory data analysis, feature normalization, and systematic training/testing partitioning, to have a robust and unbiased model evaluation.
- To evaluate and compare individual and hybrid models using multiple performance metrics, thereby providing a transparent and rigorous benchmark of forecasting accuracy across different architectures.
- To prove that model optimization with the help of hyperparameters is more effective in comparison to single deep learning models with resultant mean scores of high generalization and low error rates; hence, the solution of SOA in the process of hyperparameter optimization in flood predictions.
- To provide a credible decision support tool to the flood risk management in order to provide the useful implications to the early warning systems, disaster preparedness, and climate adaptation strategies.

The organization of this paper is as follows. Related works are presented in Section 2, focusing on the recent progress of machine learning and hybrid optimization based methods for flood prediction. The proposed methodology, which includes the dataset, preprocessing methods and deep learning model architectures (single and hybrid) along with the Snake Optimization Algorithm used for their achievements, is presented in Section 3. Section 4 describes the experimental settings and evaluation measures, reporting their results for both single and hybrid models, as well as a comparison with other state-of-the-art approaches in a comparative discussion to emphasize novelty and advantages of the proposed framework. Section 5 concludes the paper by drawing some main findings and proposing future lines of research.

2. Related Works

In recent years, researchers are increasingly working on the development of hybrid and data-driven models to improve flood forecasting, vulnerability mapping, and water resource management. Deeper neural networks combined with metaheuristic techniques and big data–powered adaptive schemes, hybrid deep learning structures such as ConvLSTM or Transformer-based models, and ensemble methods of machine learning and process-based hydrological modeling have been readily proposed. These studies uniformly confirm that the combination of learning algorithms and optimization methods leads to a significant increase in predictive performance irrespective of hydrological setting and thus advances reliable early warning tools, disaster prevention measures, and sustainable water resource management.

Researchers in [27] proposed a flood forecasting model using Deep Belief Networks (DBN) for the Daya and Bhargavi rivers in Odisha, India. Compared with the Teaching Learning-Based Optimization (TLBO) method, DBN achieved better accuracy across different forecasting horizons (1 day, 1 week, and 2 weeks), as evaluated by RMSE and MAPE. The results highlight DBN's effectiveness in improving flood prediction and assessing the impact of barrage construction.

Researchers in [28] proposed flood susceptibility mapping for Binh Dinh province, Vietnam, using deep neural networks (DNN) integrated with swarm-based optimization algorithms (AO, SLnO, EHO, NMRA, and SGD). Based on 1883 sample points and 12 conditioning factors, the hybrid models achieved high accuracy, with all optimized models exceeding an AUC of 0.97. The DNN-NMRA model performed best (RMSE = 0.16, AUC = 0.99), followed by DNN-SLnO, DNN-EHO, and DNN-AO, all outperforming the baseline DNN-SGD. These results confirm the effectiveness of DNN optimization approaches for reliable flood susceptibility mapping and risk management.

Researchers in [29] proposed a system for flood forecasting, combining meteorological, hydrological, geospatial, and crowdsourced big data in an adaptive machine learning setting. The benchmark stage employed experiments that achieved a success rate of 97.93% in the MLP-ANN structure and around 0.89 (kappa), with MAE = 0.01 and RMSE = 0.10. The work proves the efficiency of BDDS-inspired models in real-time forecasting and accurate flood estimation.

Researchers in [30] proposed a hybrid ConvLSTM model combining CNN and LSTM for flood forecasting using a Flood Index derived from rainfall data. Tested on nine datasets from flood-prone regions in Fiji, the model outperformed benchmarks across multiple forecast horizons, achieving RMSE values of 0.101, 0.150, 0.211, and 0.279 for 1-, 3-, 7-, and 14-day predictions, with LME indices up to 0.939. The results confirm ConvLSTM's effectiveness for accurate early flood warnings and its potential in disaster management and risk mitigation.

Researchers in [31] proposed an interpretable hybrid model, AGRS-LSTM-Transformer, combining Transformer, LSTM, and Adaptive Random Search (AGRS) for flood forecasting in the Jingle watershed. Compared with AGRS-LSTM, AGRS-Transformer, AGRS-BP, and AGRS-MLP, the hybrid model achieved the best performance, with NSE above 0.905 and RMSE, MAE, Bias, and RE all below 34.891 m^3/s, 25.125 m^3/s, 9.537%, and 8.025%, respectively, for 1–6 hour lead times. The results confirm its effectiveness in improving runoff prediction accuracy and supporting reliable flood early warning systems.

Researchers in [32] suggested hybrid intelligent models integrating Support Vector Regression (SVR) and Group Method of Data Handling (GMDH), optimized by meta-heuristic algorithms, i.e., Genetic Algorithm (GA) and Harmony Search (HS), could provide greater accuracy in flood-susceptibility prediction. The method was implemented on the Haraz-Neka watershed using nine important geospatial features and 132 flood data samples, with 70 and 30 percentage for training and validation, respectively. The findings indicated that SVR performed better than GMDH, and the optimized models improved both approaches, with the highest accuracy obtained by the SVR-GA (AUC = 0.75, RMSE = 0.29, MSE = 0.08). The results showed that the hybrid models are applicable to obtain reliable flood-susceptibility maps which could be utilized in other regions.

Researchers in [33] proposed a hybrid deep learning model combining Temporal Convolutional Network (TCN), Improved Aquila Optimizer (IAO), and Random Forest (RF) for rainfall–runoff simulation and multi-step prediction. RF was first used to select the most relevant input variables, reducing dimensionality and computation time. The optimized TCN model was then applied to rainfall–runoff data from five stations in the Jinsha River, China, with results showing superior predictive performance compared to traditional models.

Researchers in [34] developed a hybrid flood prediction method by combining CatBoost and Multilayer Perceptron regression using the African Vultures Optimization Algorithm. In this case study, with model comparisons under several criteria analyses, the CatBoost–AVO achieved the best result ($R^2 = 0.988$, RMSE = 0.006), indicating that hybrid-based optimized schemes are a practical approach for improving flood forecasting accuracy, alleviating financial efforts, and enhancing readiness in risk management and early warning systems.

Researchers in [35] proposed hybrid models integrating LSTM with meta-heuristic algorithms, Multi-Verse Optimizer (MVO), Black Hole (BH), and Marine Predator (MPA) to predict reservoir evaporation at Dez Dam, Iran. Using 37 years of satellite and meteorological data, results showed that the LSTM-MPA model achieved the highest accuracy (RMSE = 64.35, MAE = 48.71, KGE = 0.816, WI = 0.827), followed by LSTM-BH. The study confirms that combining LSTM with meta-heuristics significantly improves evaporation prediction, offering valuable tools for water resource management under climate change.

Researchers in [1] proposed hybrid flood-routing models by integrating artificial neural networks (ANNs) with metaheuristic optimization algorithms and signal processing techniques. Tested on hourly data from Turkey's Kızılırmak and Mera Rivers, the ABC-ANN model showed the highest accuracy for the Mera River with an R^2 of 0.893, MSE of 0.006, MAE of 0.067, and KGE of 0.916, while the VMD-ANN model performed best for the Kızılırmak River with an R^2 of 0.445, MSE of 285.035, MAE of 14.511, and KGE of 0.239. The results demonstrate that combining ANNs with optimization methods enhances flood prediction accuracy and strengthens flood management strategies.

Researchers in [36] proposed a hybrid framework of a process-based hydrological model, ensemble learning, and deep learning for culturing floods in the Dez Basin of Iran. The R^2 for the HEC-HMS–ensemble model varied between 0.81 and 0.88 in terms of flow prediction accuracies, whereas the U-Net model processed a variety of multispectral satellite data to map flood extent with mean IoU scores ranging from 70 to 71.3% for multiple events. The findings demonstrate the capability of the model to integrate peak flow prediction and spatial flood hazard mapping, providing a scalable approach to real-time flood risk management and disaster preparation.

Researchers in [37] proposed a hybrid model, 2D-CNN-CapsNet-WOA, integrating convolutional neural networks, capsule networks, and the whale optimization algorithm to improve urban flood risk prediction. Applied to cities in southern China, the model achieved high predictive accuracy, identifying central urban areas such as Guangzhou, Shenzhen, and Foshan as high-risk zones, while peripheral and mountainous areas like Zhaoqing showed lower risk. The study also highlighted key drivers such as distance to hospitals and water bodies, confirming the effectiveness of hybrid approaches for scalable urban flood risk assessment and disaster planning.

Researchers in [38] proposed a machine learning-based flood prediction approach using a Random Forest model to overcome the limitations of traditional numerical methods. Trained with rainfall data, drainage simulations, and flood analyses, the model achieved high accuracy, with R^2 values of 0.9682 and 0.9761 and RMSE values of 3.1573 and 2.7354, showing improved performance when statistical rainfall characteristics were included. The study demonstrates that this method provides faster and reliable flood predictions, supporting real-time urban flood management and emergency decision-making.

Despite the successful usage of hybrid models and optimization-based approaches in flood forecasting, there are still some deficiencies. A number of previous studies in this domain is localized, conditioned on specific watersheds or urban contexts, and exhibit limited generalizability over different hydrologic regimes. Furthermore, although recent state-of-the-art models (e.g., ConvLSTM, Transformers and optimization-driven deep learning frameworks) have shown superior performances, they are usually time-consuming to learn or lack interpretability, or fail to encode long-range spatiotemporal dependencies simultaneously in one model. Some methods are domain-specific or need too much data preprocessing, and they cannot be applied to real-time disaster management. Our contribution is a new hybrid flood prediction architecture that employs ANN, LSTM and CNN combined with SOA. Such a combination results in improved parameter optimization and convergence stability, as well as the synergy of ANNs on nonlinear feature learning, LSTM on temporal sequence modeling and CNN on spatial pattern extraction.

Recent works have shown the effectiveness of hybrid deep learning models optimized with metaheuristic algorithms across sustainability domains. Nguyen et al. [39] used swarm-based DNNs for flood mapping, Zhang et al. [40] applied a Snake Optimizer for wind forecasting, and Ali et al. [41] combined deep learning with Harris Hawk Optimization for flood modeling. Other studies employed hybrid CNN–BiLSTM for forest fire detection [42] and stacked models for energy and water prediction [43, 44]. Overall, these approaches confirm that optimization-driven hybrid frameworks enhance convergence, stability, and explainability, motivating the present work.

Table 1. Summary of Related Works on Flood Prediction and Risk Assessment.

Ref.	Author (Year)	Method / Models	Dataset	Results
[27]	Nayak M. et al. (2022)	Deep Belief Network (DBN) and Teaching Learning-Based Optimization (TLBO)	Daya and Bhargavi rivers, Odisha (India)	DBN (RMSE = 0.0457, MAE = 0.6752) TLBO (RMSE = 0.1010, MAE = 0.8787)
[28]	Nguyen H. et al. (2023)	DNN + SLnO, EHO, AO, SGD	1883 samples, 12 factors, Binh Dinh (Vietnam)	All optimized models AUC > 0.97; DNN–NMRA best (RMSE = 0.16, AUC = 0.99)
[29]	Puttinaovarat S. & Horkaew P. (2020)	Big data-driven adaptive ML (MLP–ANN)	Meteorological, hydrological, geospatial and crowdsourced data	MLP–ANN accuracy $\approx$ 97.93%, Kappa $\approx$ 0.89; MAE = 0.01, RMSE = 0.10
[30]	Moishin M. et al. (2021)	Hybrid ConvLSTM (CNN + LSTM)	9 rainfall datasets, Fiji	Outperformed benchmarks; RMSE = 0.101–0.279, LME up to 0.939
[31]	Li W. et al. (2024)	AGRS–LSTM–Transformer	Jingle watershed, Fen River tributary, Yellow River basin (China)	NSE = 0.905; RMSE = 34.891 m^3/s, MAE = 25.125 m^3/s
[32]	Dodangeh E. et al. (2020)	SVR + GA/HS, GMDH + GA/HS	Haraz–Neka watershed, 132 flood records (northern Iran)	SVR–GA best (AUC = 0.75, RMSE = 0.29, MSE = 0.08)
[33]	Qiao X. et al. (2023)	Temporal Convolutional Network (TCN) + Improved Aquila Optimizer (IAO) + Random Forest (RF)	Rainfall–runoff data from 5 Jinsha River stations (China)	Optimized TCN outperformed traditional models for multi-step prediction
[34]	Zhang P. et al. (2025)	AVOA with CatBoost and MLP $\rightarrow$ CAAV, MAAV	Flood datasets (unspecified)	CatBoost–AVO best: R^2 = 0.988, RMSE = 0.006

Continued on next page

Ref.	Author (Year)	Method / Models	Dataset	Results
[35]	Farzad R. et al. (2025)	LSTM + MVO, BH, MPA	37 years satellite & meteorological data, Dez Dam (Iran)	LSTM–MPA best: RMSE = 64.35, MAE = 48.71, KGE = 0.816, WI = 0.827
[1]	Elshaboury N. et al. (2025)	ANN + GA ANN + Firefly ANN + ABC ANN + JAYA ANN + VMD	Hourly flood data from Kızılırmak and Mera Rivers (Turkey)	ABC–ANN best for Mera River (R^2 = 0.893, MSE = 0.006, MAE = 0.067); VMD–ANN best for Kızılırmak River (R^2 = 0.445, MSE = 285.035, MAE = 14.511)
[36]	Roohi M. et al. (2025)	HEC–HMS + Ensemble ML + U-Net	Dez Basin (Iran), multispectral satellite data	Flow prediction R^2 = 0.81–0.88; Flood extent IoU = 70–71.3%
[37]	Wang Y. et al. (2025)	2D–CNN + CapsNet + WOA	Southern China (urban cities)	Identified Guangzhou, Shenzhen, and Foshan as high-risk zones; high accuracy
[38]	Jang S. et al. (2025)	Random Forest model	Rainfall data + 1D/2D drainage simulation, South Korea (2001–2020)	RMSE = 2.73–3.16; R^2 = 0.9682–0.9761; MAE = 0.9484

3. Proposed Methodology:

The flood forecasting model is shown in Figure 1 follows a rigorously designed pipeline combining a deep learning-based framework with hybrid optimization to improve prediction results. The first step involves exploratory data analysis (EDA) as a necessity to gain the knowledge about distribution and correlations of underlying structure in the flooding dataset. After that, preprocessing of the input features is implemented by MinMaxScaler to scale them in [0,1] range which can enhance the convergence rate and stability of neural network training. The dataset is then partitioned to form training and testing sets for unbiased estimation. We apply two parallel modeling schemes: (i) standalone deep learning models (e.g., ANNs, LSTMs, and CNNs) that can capture nonlinear hydraulic responses of flood dynamics, temporal variability, and spatial characteristics; and (ii) hybrid deep learning models in which the ANN, LSTM and CNN are combined with Snake Optimizer to optimize model parameters further for faster convergence as well as alleviation of local optima. The two sets of models are trained independently and thus generate candidate predictors. Finally, we systematically compared the performance of single and hybrid models based on multiple statistics such as MSE (mean square error), RMSE (root mean square error), MAE (mean absolute error), and R2. The proposed integrated model of hybrid optimization illustrates that flood forecasting models are not only reliable in terms of robustness, and accuracy but can also be used as a dependable decision-making tool for disaster preparedness and risk reduction.

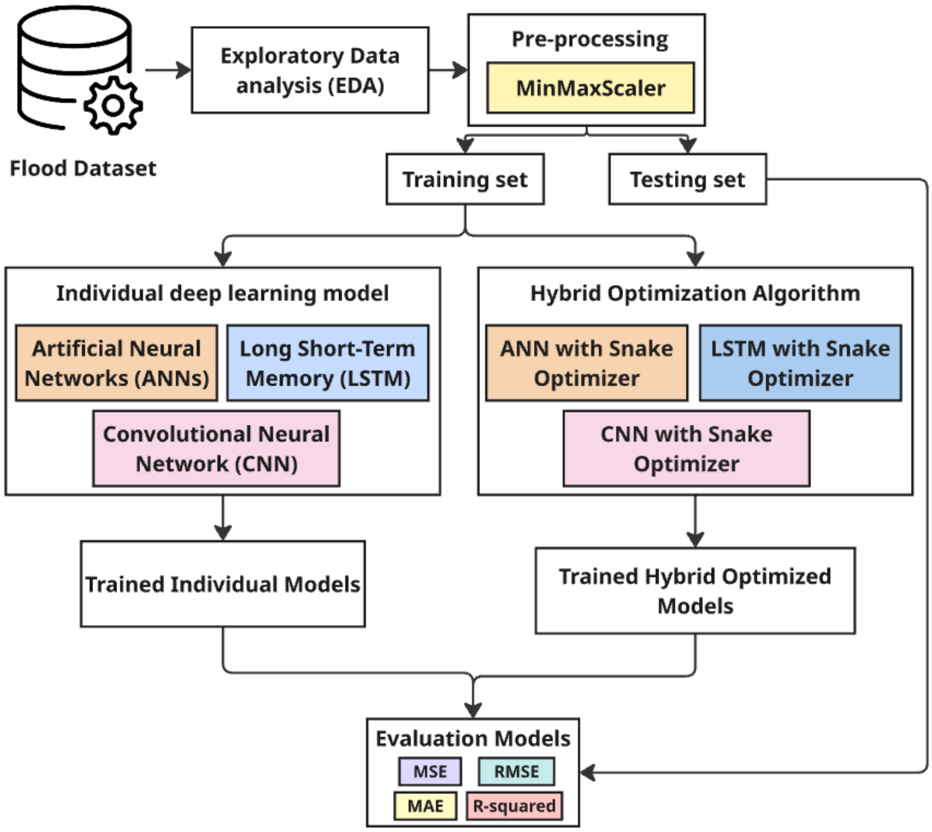

Figure 1. Proposed Hybrid Deep Learning and Optimization Framework for Flood Forecasting

3.1. Flood Prediction Dataset

The dataset employed in this study is the Flood Prediction Dataset publicly available on Kaggle at [†]. It was developed by aggregating multi-source environmental, infrastructural, and socio-economic indicators with historical flood occurrence statistics compiled from disaster management reports and hydrometeorological archives. The target variable, FloodProbability, is a normalized likelihood index (ranging from 0 to 1) that represents the probability of flood occurrence inferred from those records. Although this variable provides a useful proxy for spatial flood susceptibility, it does not correspond directly to measured hydrological quantities such as river discharge or water level. Therefore, the present work should be regarded as a proof-of-concept validation of the hybrid deep-learning–optimization framework. Future studies will extend the methodology to real-time hydrological datasets (e.g., gauged streamflow and precipitation series) from specific river basins to confirm its operational performance. The dataset includes variables capturing climatic factors (e.g., MonsoonIntensity, ClimateChange), anthropogenic influences (e.g., Urbanization, Deforestation, Encroachments), infrastructural conditions (e.g., DamsQuality, DrainageSystems, DeterioratingInfrastructure), and socio-political aspects (e.g., InadequatePlanning, PoliticalFactors), as presents in Table 2. The target variable, FloodProbability, represents the likelihood of flooding, enabling supervised learning for classification and regression tasks.

[†]https://www.kaggle.com/datasets/anonwaraphok/flood-prediction-dataset

Table 2. Dataset Features and Descriptions

Feature	Description
id	Unique identifier for each record
MonsoonIntensity	Level of rainfall intensity during monsoon seasons
TopographyDrainage	Influence of terrain and natural drainage on flood occurrence
RiverManagement	Effectiveness of river regulation and management practices
Deforestation	Impact of forest cover loss on flood risk
Urbanization	Contribution of urban growth and impervious surfaces to flooding
ClimateChange	Influence of long-term climate variability on flood susceptibility
DamsQuality	Condition and effectiveness of dam infrastructure
Siltation	Accumulation of sediments reducing water capacity
AgriculturalPractices	Role of farming methods in altering water flow and flood risk
Encroachments	Human settlement or construction in flood-prone areas
IneffectiveDisasterPreparedness	Lack of adequate disaster management strategies
DrainageSystems	Efficiency of man-made drainage infrastructure
CoastalVulnerability	Exposure of coastal zones to flooding
Landslides	Occurrence of landslides affecting flood events
Watersheds	Condition of watershed areas impacting runoff and floods
DeterioratingInfrastructure	Weaknesses in infrastructure contributing to flood risk
PopulationScore	Population density and its role in flood exposure
WetlandLoss	Reduction of wetlands and natural buffers
InadequatePlanning	Poor urban and regional planning increasing flood vulnerability
PoliticalFactors	Influence of governance and policy on flood management
FloodProbability	Target variable indicating the probability of flood occurrence

3.2. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed to investigate the distribution, variability and interrelationship between the features of Flood Prediction Dataset. The provided EDA process offers important information regarding the quality of data, feature interaction, and their impact on the target variable (FloodProbability) that is useful to guide preprocessing and model development. Figure 2 shows the distribution of features in all 22 attributes in our dataset. Most predictors are normal or have near-normal distributions (e.g., MonsoonIntensity, RiverManagement, Urbanization, and DrainageSystems), except for some of them that show a uniform behavior (random-choice ones) as id does and thus it only works as identification instead of prediction. This large range of the distributions in features shows there is a heterogeneity of flood-related factors, which necessitates normalization before modelling.

Figure 3 Investigation of the relationship between Deforestation and Urbanization w.r.t Flood Probability. The color-coded scatter of the flood probability plot clearly illustrates a trend where more severe deforestation and urbanization have a higher risk with respect to flooding. In addition, this result verifies the joint impact of human activities on flood hazard as supported by other studies linking urban expansion and land-use change with flooding.

Figure 4 illustrates the distribution of the target variable (Flood Probability). The distribution is unimodal and slightly right-skewed, with the majority of observations concentrated between 0.35 and 0.65. This suggests that while extreme probabilities are less common, the dataset provides balanced coverage across different flood risk levels, which is beneficial for robust model training and evaluation. The EDA confirms the dataset's suitability

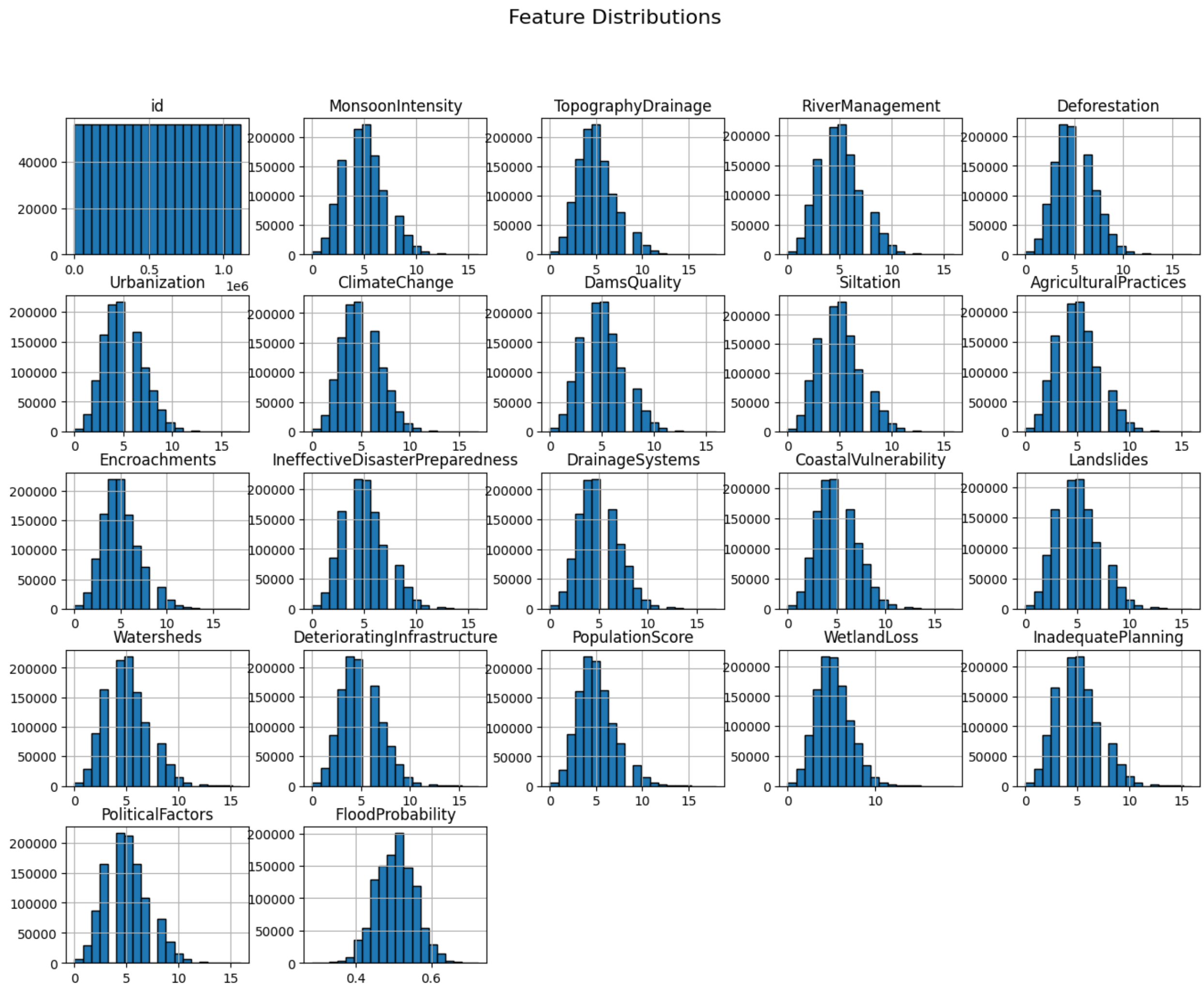

Figure 2. Feature distribution of the Flood Prediction Dataset, showing variability and statistical patterns across 22 predictors

for predictive modeling, highlights key features driving flood risk, and underscores the importance of hybrid optimization models in capturing both natural and anthropogenic influences on flooding.

3.3. Data Preprocessing

Pre-processing of data is an essential step in developing a reliable flood forecasting model. Since the dataset has no missing values, all records can participate in the analysis, ensuring that learning is complete and effective. To handle the heterogeneity of feature ranges resulting from varying predictors (e.g., Monsoon Intensity, Urbanization, and Climate Change), a normalization step is applied using the Min–Max scaling technique. This process scales each feature of the input vector to the interval $[0, 1]$, preventing bias due to different scales and improving stability when performing optimization with gradient descent as the learning algorithm. The formal notation for the normalization is:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X denotes the original feature value, and $X_{\min}$ and $X_{\max}$ are the minimum and maximum observed values of the feature, respectively, while X' represents the normalized value. By applying this transformation, features

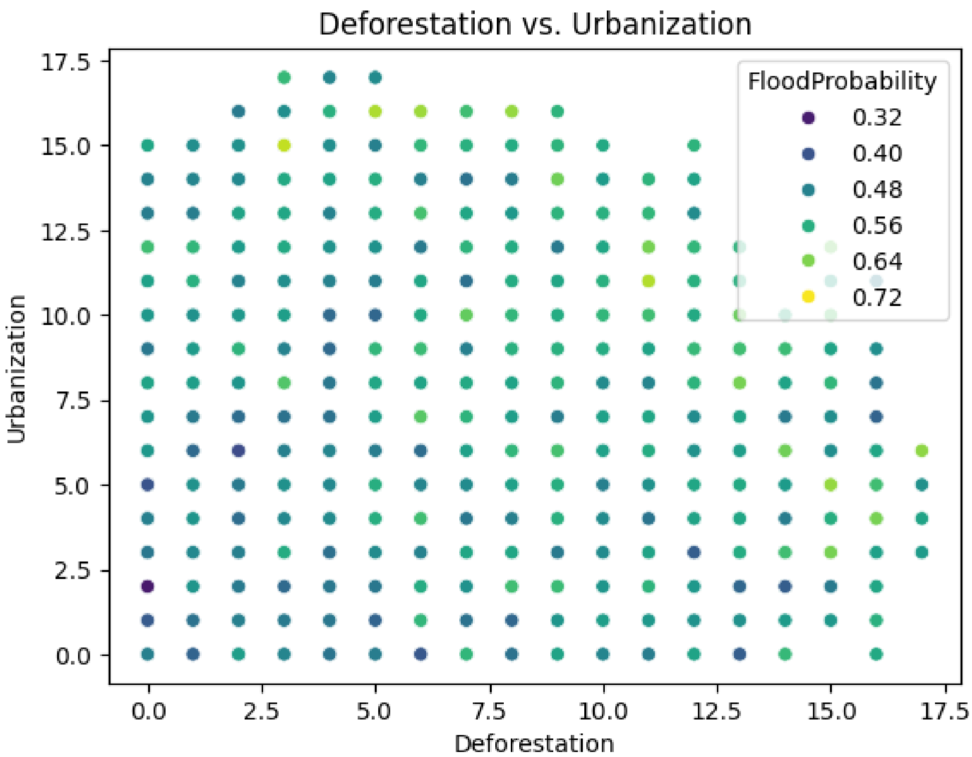

Figure 3. Relationship between Deforestation and Urbanization with respect to FloodProbability, illustrating the combined anthropogenic impact on flood risk.

with different magnitudes are mapped onto a uniform scale, preventing dominance of large-valued variables and ensuring proportional contribution of each predictor to the learning process. Furthermore, normalization accelerates the convergence of optimization algorithms by keeping gradients within a stable numerical range [45]. The transformation can be interpreted as minimizing feature variance caused by differing scales, which directly supports the reduction of computational instability during backpropagation. Consequently, this preprocessing step enhances model performance and training robustness.convergence, improves generalization, and ensures that both training and testing data maintain consistent scaling across deep learning and hybrid optimization models.

3.4. Deep Learning Models

Deep learning [46] has emerged as a transformative paradigm in predictive modeling and time-series analysis, offering the ability to automatically extract hierarchical representations from complex datasets. Unlike conventional machine learning methods that rely heavily on manual feature engineering, deep learning architectures can capture nonlinear patterns, temporal dependencies, and spatial correlations, making them particularly effective for hydrological applications such as flood forecasting [47]. Among the diverse family of deep learning methods, Artificial Neural Networks (ANNs) [48, 49], Long Short-Term Memory (LSTM) networks [50, 51], and Convolutional Neural Networks (CNNs) [52, 53] are widely recognized for their effectiveness.

ANNs represent a fundamental architecture consisting of fully connected layers, where each neuron learns nonlinear mappings between input features and target variables. This structure is advantageous when feature interactions are complex but do not necessarily involve sequential or spatial dependencies. In contrast, LSTM networks extend recurrent neural networks (RNNs) [54] by introducing memory cells and gating mechanisms (input, forget, and output gates) that mitigate vanishing and exploding gradients. This makes LSTMs well-suited for modeling long-term temporal dependencies in sequential flood-related data. CNNs, originally developed for

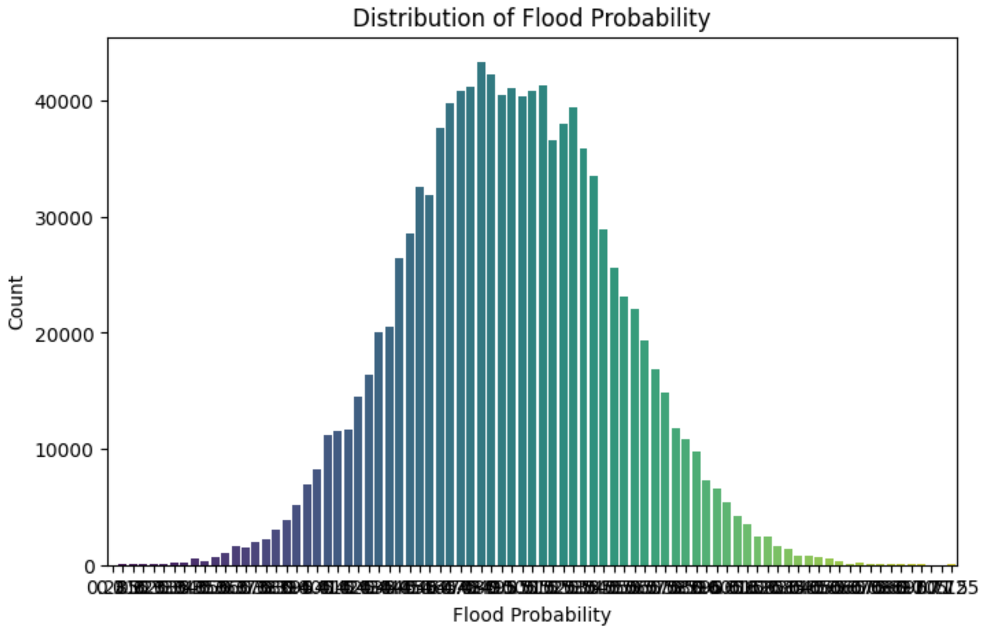

Figure 4. Distribution of the target variable (FloodProbability), highlighting overall balance and concentration of risk levels in the dataset.

image recognition tasks, have also demonstrated strong performance for structured time-series problems. By applying convolutional filters, CNNs extract local feature patterns and reduce dimensionality through pooling layers, enabling them to model localized relationships among hydrological predictors such as rainfall, urbanization, and deforestation.

Three deep learning models were used in this work, as summarized in Table 3. The proposed ANN architecture contains two hidden dense layers (32 and 16 neurons, respectively) with ReLU activation, followed by an output layer for regression, and is trained using the Adam optimizer with mean squared error (MSE) loss. The LSTM architecture is designed to model sequential interactions by reshaping the feature space as a temporal sequence; it consists of two LSTM layers with 32 and 16 units, respectively, and is optimized using Adam with a lower learning rate to ensure training stability. Finally, the CNN model applies convolutional operations to capture local windows over the input features. It combines a one-dimensional convolutional layer with 64 filters and a kernel size of 3, followed by max-pooling, flattening, and dense layers (32 neurons and an output layer).

All architectures were trained with early stopping to reduce overfitting and to ensure that optimal generalization performance is achieved on unseen data. Using ANN, LSTM, and CNN enables exploration of complementary strengths: ANNs provide baseline nonlinear mappings, LSTMs capture temporal dependencies, and CNNs extract localized structural patterns. This combined design supports more reliable flood anticipation in complex environments where natural and human-induced factors interact dynamically.

3.5. Snake Optimizer Algorithm (SOA)

The Snake Optimizer Algorithm (SOA) [55] is a recently developed metaheuristic optimization technique inspired by the natural hunting, mating, and survival strategies of snakes in their ecological environment. As a swarm-based algorithm, SOA simulates the adaptive movement and decision-making behaviors of snake populations, which dynamically balance exploration and exploitation in the search space. Mathematically, the SOA models population updates through attraction and repulsion forces, mimicking how snakes alternate between hunting prey

Table 3. Model architectures and training configurations.

Model	Layer Type	Configuration Details	Activation	Optimizer/Loss
ANN	Dense (Input)	22 neurons (input features)	ReLU	Adam / MSE
	Dense (Hidden 1)	32 neurons; Dropout = 0.3	ReLU	
	Dense (Hidden 2)	16 neurons	ReLU	
	Dense (Output)	1 neuron (FloodProbability)	Linear	
LSTM	LSTM Layer	32 units; Dropout = 0.3	tanh (internal), sigmoid (gates)	Adam / MSE
	Dense (Hidden)	16 neurons	ReLU	
	Dense (Output)	1 neuron	Linear	
CNN	Conv1D	64 filters; kernel size = 3; stride = 1	ReLU	Adam / MSE
	MaxPooling1D	pool size = 2	–	
	Flatten	Converts 1D features	–	
	Dense (Hidden)	32 neurons; Dropout = 0.3	ReLU	
	Dense (Output)	1 neuron	Linear	

and avoiding predators. The core of the algorithm is driven by the position-update mechanism:

$$\mathbf{X}_i(t+1) = \mathbf{X}_i(t) + \alpha\,\mathrm{rand}\left(\mathbf{X}_{best}(t) - \mathbf{X}_i(t)\right) + \beta\,\mathrm{rand}\left(\mathbf{X}_j(t) - \mathbf{X}_i(t)\right), \tag{2}$$

where $\mathbf{X}_i(t)$ is the position of snake i at iteration t, $\mathbf{X}_{best}(t)$ is the best solution found so far (global best), and $\mathbf{X}_j(t)$ denotes a neighboring snake selected randomly from the population. The parameters α and β are adaptive control coefficients that regulate exploitation and exploration, while rand is a uniformly distributed random number. Moreover, SOA introduces a *food attraction* behavior to enhance exploitation and a *mating and reproduction* behavior to promote exploration and help escape local optima. The converging balance between these phases is described by:

$$\mathbf{X}_i(t+1) = \begin{cases} \mathbf{X}_i(t) + \gamma\left(\mathbf{X}_{food} - \mathbf{X}_i(t)\right), & \text{if food is available (exploitation),} \\ \mathbf{X}_i(t) + \delta\left(\mathbf{X}_{random} - \mathbf{X}_i(t)\right), & \text{if searching for mates (exploration),} \end{cases} \tag{3}$$

where $\mathbf{X}_{food}$ denotes the food location (optimal target), $\mathbf{X}_{random}$ is a random position in the search space, and γ and δ are adaptive coefficients.

In this work, the Snake Optimization Algorithm (SOA) was used as an external hyperparameter tuning tool for each deep-learning model (ANN, LSTM, and CNN). The optimizer searched for the combination of hyperparameters that minimized the validation Mean Squared Error (MSE).

(1) Search space:

- Learning rate: $[0.0001 - 0.01]$
- Hidden units (ANN): $\{16, 32, 64, 128\}$
- LSTM units: $\{32, 64, 128, 256\}$
- CNN filters: $\{16, 32, 64\}$, kernel size $\in \{3, 5, 7\}$
- Dropout rate: $[0.1,\ 0.5]$
- Batch size: $\{16, 32, 64\}$

(2) Optimization procedure:
SOA was executed before the final training stage to identify the optimal hyperparameter set. Each snake represented one configuration of parameters. For each iteration:

1. Generate a population of 10 snakes (candidate parameter sets).
2. Train each candidate model for 20 epochs and compute the validation MSE.
3. Update the population according to the SOA update rules in Eqs. (2)–(3).
4. Repeat for 10 iterations and select the configuration with the lowest MSE.

(3) SOA configuration:
Population $= 10$, iterations $= 10$, $\alpha = 0.5$, $\beta = 0.3$, $\gamma = 0.7$, $\delta = 0.4$. These values were selected after a small sensitivity test showing that increasing the population size or the number of iterations provided no meaningful accuracy gain.

Algorithm 1: Hyperparameter optimization using Snake Optimization Algorithm (SOA)

```
foreach model ∈ {ANN, LSTM, CNN} do
    Initialize SOA population with random hyperparameter sets;
    for t ← 1 to T do
        Train each candidate model for E epochs;
        Evaluate validation MSE;
        Update population positions using SOA equations (2)–(3);
    Select best configuration (lowest MSE);
    Retrain model using best parameters;
```

The main advantages of SOA lie in its simplicity, fast convergence speed, and ability to avoid premature convergence, a common issue in many metaheuristic algorithms. Unlike classical methods such as Genetic Algorithms (GA) [56] or Particle Swarm Optimization (PSO) [57], SOA introduces flexible adaptive mechanisms that maintain a balance between intensification (local search) and diversification (global search). This balance improves optimization efficiency when dealing with high-dimensional, nonlinear, and multimodal problems. Furthermore, SOA has demonstrated strong performance in noisy and dynamic environments, which are highly relevant to hydrological and climate-related forecasting tasks.

Within the scope of our flood forecasting study, SOA was selected for its capability to handle complex, nonlinear, and uncertain datasets. Because both inputs and outputs may exhibit stochastic variability (e.g., rainfall intensity, river flow, and land-use changes), an optimizer is required to explore a large and irregular search space. The adaptive search mechanism of SOA helps the learning process escape local minima during deep-learning hyperparameter tuning, leading to more accurate and reliable forecasts. Moreover, its computational efficiency makes it suitable for large-scale datasets (e.g., Kaggle's Flood Prediction Dataset with over a million samples).

Accordingly, a hybrid deep learning optimization framework is proposed, integrating Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) with the Snake Optimizer Algorithm (SOA) to enhance flood forecasting performance. Hyperparameters of each model were tuned using SOA, which dynamically balances exploration and exploitation, thereby reducing the risk of early convergence and improving predictive power Table 4. This integration enables stronger generalization on complex, high-dimensional, and noisy hydrological datasets.

The hyperparameters reported in Table 4 correspond to the best configurations identified by SOA after 50 iterations with a population of 20 candidate solutions per model.

(4) ANN with Snake Optimizer:
The ANN model was designed with two fully connected dense layers, a dropout mechanism, and an output regression layer. SOA identified the best configuration as 128 neurons in the first hidden layer and 16 neurons in the second layer, with a dropout rate of 0.3, a learning rate of 0.001, and a batch size of 16. This architecture captures nonlinear relationships among environmental predictors while maintaining computational efficiency, which makes it suitable for structured tabular datasets.

Table 4. Optimized hyperparameters of ANN, LSTM, and CNN models using the Snake Optimizer Algorithm (SOA).

Model	Layer Units	Dropout Rate	Learning Rate	Batch Size	Other Parameters
ANN	Dense (128, 16)	0.3	0.001	16	fully connected layers
LSTM	LSTM (160), Dense (16)	0.4	0.001	128	Sequential time-series modeling
CNN	Conv1D(32, kernel=3), Dense(16)	0.3	0.001	32	MaxPooling1D, Flatten

(5) LSTM with Snake Optimizer:

Temporal dependence and sequential characteristics of flood-related variables were learned using the LSTM model. SOA selected an architecture consisting of an LSTM layer with 160 units followed by a dense layer with 16 neurons, with dropout set to 0.4, a learning rate of 0.001, and a batch size of 128. This design supports learning long-term dependencies in hydrological time series while mitigating overfitting via dropout regularization. Moreover, the gating mechanism in LSTM helps alleviate vanishing/exploding gradients compared with conventional RNNs, which improves stability over longer sequences.

(6) CNN with Snake Optimizer:
The CNN model was implemented to extract localized and hierarchical feature patterns from multivariate hydrological inputs. The SOA-optimized configuration used 16 convolutional filters with kernel size 3, followed by a dense layer with 16 neurons, a dropout rate of 0.3, a learning rate of 0.001, and a batch size of 32. Convolution and pooling operations provide efficient feature extraction, while the fully connected layer captures higher-level associations and reduces redundancy in high-dimensional representations.

By integrating SOA into the training pipeline, each model achieved superior predictive performance compared to baseline manual-tuned architectures. SOA's adaptive balance of exploration and exploitation facilitated convergence to near-optimal configurations, reducing forecasting errors while improving generalization. The hybrid framework thus leverages the complementary strengths of ANN, LSTM, and CNN, with SOA ensuring robust hyperparameter optimization.

The Snake Optimization Algorithm (SOA) was configured with a population of 10 snakes and executed for 10 iterations. Optimization was terminated either upon reaching the iteration limit or when the improvement in validation MSE was less than 1×10^{-6} for five consecutive iterations.

Search bounds for hyperparameters were defined as follows: learning rate $\in [0.0001, 0.01]$, dropout $\in [0.1, 0.5]$, hidden neurons $\in \{16, 32, 64, 128\}$, LSTM units $\in \{32, 64, 128, 256\}$, CNN filters $\in \{16, 32, 64\}$ with kernel sizes $\{3, 5, 7\}$, and batch size $\in \{16, 32, 64\}$.

These bounds ensured a well-balanced search space while maintaining computational efficiency. The best configuration was selected based on the minimum validation MSE observed during the optimization process.

4. Results and Discussion

4.1. Experimental Setup

In our study, the experimental setup was implemented using Google Colab Pro, which provides a high-performance cloud-based environment suitable for deep learning experimentation. All models were developed in Python, leveraging popular libraries such as TensorFlow and Scikit-learn for model training, preprocessing, and evaluation. The use of Colab Pro ensured access to GPU acceleration and optimized runtime capabilities, allowing for efficient training of complex architectures such as ANN, LSTM, and CNN models integrated with the Snake Optimization Algorithm (SOA).

All experiments were executed using Google Colab Pro+ equipped with an NVIDIA Tesla T4 GPU (16 GB VRAM), Intel Xeon 2.20 GHz CPU, and 25.5 GB of RAM. The software environment included Python 3.10, TensorFlow 2.15.0, Keras 3.3.0, and CUDA 12.3 with cuDNN 8.9. Each model (ANN, LSTM, CNN, and SOA-based hybrids) was trained and validated five times to account for randomness, the total end-to-end runtime to train the three baseline models and perform SOA tuning was 5–9 hours (depending on the allocated GPU), reported as mean ± standard deviation over 5 repeated runs.

To evaluate the predictive performance of the proposed models, we adopted a set of widely recognized statistical metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2) [52, 53].These metrics provide complementary perspectives on model accuracy and reliability. The MSE quantifies the average squared difference between predicted and observed values and is expressed as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

where y_i and $\hat{y}_i$ represent the observed and predicted values, respectively, and n is the number of samples. The RMSE, as the square root of MSE, retains the same units as the target variable and is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

The MAE measures the average absolute deviation between actual and predicted values, providing a straightforward interpretation of prediction error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

Finally, the R^2 assesses the proportion of variance in the observed data explained by the model, defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

where $\bar{y}$ denotes the mean of observed values. Higher values of R^2 indicate stronger explanatory power of the model. Together, these evaluation metrics enable a comprehensive assessment of model robustness, accuracy, and generalization capability, ensuring the reliability of the proposed framework in flood forecasting applications.

4.2. Evaluation of Individual Deep Learning Models for Flood Prediction

From the training portion, 20% was reserved as a validation subset to monitor training, apply early stopping, and guide Snake-based hyperparameter search. The final reported metrics (MSE, RMSE, MAE, R^2) were computed on the held-out test set only. To avoid data leakage, preprocessing transformations were fitted on the training split and then applied to validation and test splits.

In addition, paired t-tests were conducted on the RMSE values between baseline and SOA-optimized models, revealing that the improvements were statistically significant ($p < 0.05$). This confirms that the proposed hybrid optimization enhances predictive accuracy beyond random variation.

The experiments on the individual deep learning models provide a critical basis for verifying the effectiveness and consistency of the proposed flood forecasting approach. Table 5 reports the comparative performance of ANN, LSTM, and CNN using four main evaluation measures: MSE, RMSE, MAE, and R^2. Among these models, the LSTM network achieved the best overall performance with $\mathrm{MSE} = 0.000403$ and $\mathrm{RMSE} = 0.020064$, as well as

Table 5. Performance of individual deep learning models.

Model	MSE	RMSE	MAE	R^2
LSTM	0.000403	0.020064	0.015855	0.845125
ANN	0.000440	0.020981	0.015580	0.830644
CNN	0.000542	0.023288	0.018666	0.791355

Table 6. Performance metrics of hybrid deep learning models optimized with the Snake Optimizer Algorithm (SOA).

Models	MSE	RMSE	MAE	R^2
LSTM with SOA	0.000386	0.019653	0.015849	0.851407
ANN with SOA	0.000387	0.019673	0.015093	0.851100
CNN with SOA	0.000543	0.023299	0.018649	0.791157

the highest coefficient of determination ($R^2 = 0.845125$). These findings support the suitability of LSTM for time-series forecasting, since modeling long-term temporal dependencies enables better representation of hydrological patterns and variations in flood probability.

The ANN model followed with competitive results ($\text{MSE} = 0.000440$, $\text{RMSE} = 0.020981$, $\text{MAE} = 0.015580$, $R^2 = 0.830644$), indicating strong capability in learning complex nonlinear relationships. In contrast, the CNN model produced the highest error values ($\text{MSE} = 0.000542$, $\text{RMSE} = 0.023288$, $\text{MAE} = 0.018666$) and the lowest R^2 ($R^2 = 0.791355$). Although CNNs can extract useful feature patterns, this outcome suggests that the standalone CNN configuration used here is less effective than LSTM in capturing sequential dependencies inherent in hydrological time series.

Figure 5 graphically illustrates these results across the four evaluation metrics, providing a visual comparison of model accuracy. Both LSTM and ANN have shown consistent improvement compared to CNN with regard to error reduction and variance explained. The performance gap reflects the sequential, time-series nature of flood forecasting, which is more inherently suited to models such as LSTM. Overall, the results indicate that although the ANN model exhibits strong generalization capability, the LSTM model remains slightly superior in most metrics, confirming its suitability for learning temporal dependencies in flood prediction.

The evaluation metrics reported in this section (MSE, RMSE, MAE, and R^2) represent the average values computed across the five folds, providing a statistically reliable assessment of the predictive capability of both individual and hybrid models.

4.3. Evaluation of Hybrid Deep Learning Models Optimized with Snake Algorithm

The evaluation of hybrid deep learning models optimized with the Snake Optimization Algorithm (SOA) provides significant insights into the effectiveness of integrating metaheuristic optimization with deep learning architectures for flood forecasting. Table 6 presents the performance metrics of the LSTM, ANN, and CNN models combined with SOA.

The findings indicate that the LSTM–SOA model achieves the best overall performance, obtaining the highest coefficient of determination ($R^2 = 0.851407$) and the lowest error values ($\text{MSE} = 0.000386$, $\text{RMSE} = 0.019653$), with a comparable $\text{MAE} = 0.015849$. This outcome supports the advantage of LSTM–SOA in modeling temporal flood propagation. The ANN–SOA hybrid also yields strong results, achieving the minimum $\text{MAE} = 0.015093$ and a high $R^2 = 0.851100$, which demonstrates its ability to capture nonlinear hydrological relationships without overfitting when trained using SOA-optimized hyperparameters. Although the CNN–SOA model can capture underlying spatial patterns, it performs slightly worse than ANN–SOA and LSTM–SOA, with $R^2 = 0.791157$, suggesting that CNNs may be less effective at learning sequential dependencies without explicit temporal modeling.

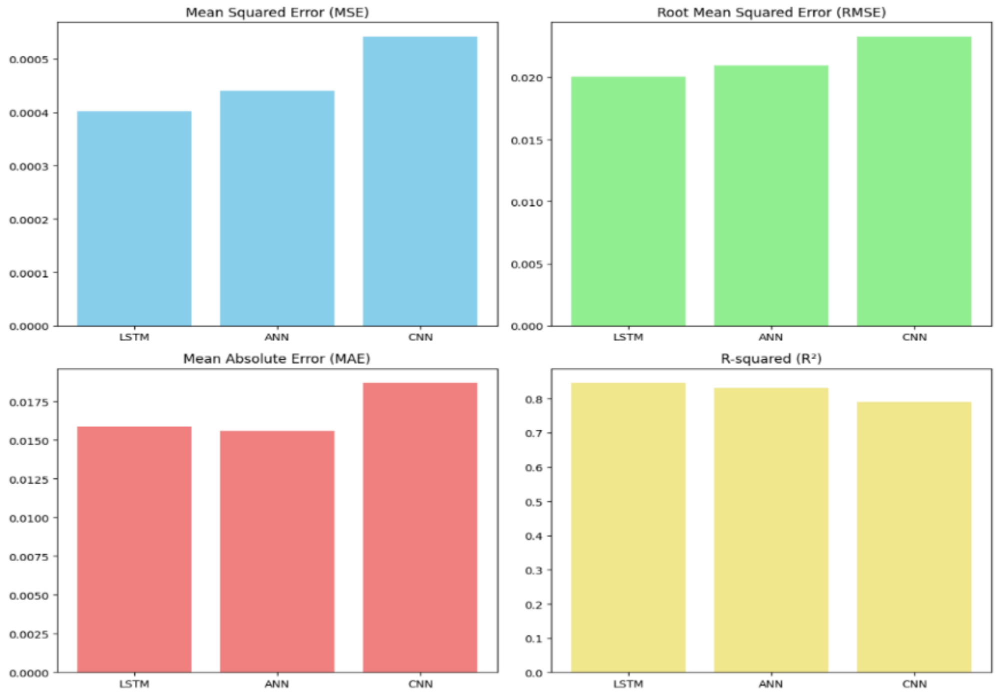

Figure 5. Comparison of individual deep learning models

The comparative analysis between individual and hybrid models, illustrated in Figure 6, further reinforces the advantages of integrating SOA with deep learning frameworks. While the individual LSTM model provided the best standalone results in Table 5, the hybrid LSTM–SOA and ANN–SOA models both achieved comparable and complementary improvements after optimization. The LSTM–SOA model maintained stronger temporal learning stability, whereas ANN–SOA demonstrated slightly higher precision in minimizing absolute prediction errors, together providing a balanced and reliable hybrid configuration across all evaluation metrics.

Furthermore, the reduction in error metrics achieved by the hybrid models validates their strong generalization capability when processing nonlinear, noise-perturbed, and multivariate flood-related data. Consequently, the proposed hybrid models not only enhance predictive accuracy, but also provide a robust and computationally efficient foundation for real-time flood forecasting applications.

4.4. Comparative Analysis of the Proposed Hybrid Deep Learning Models with Related Work

The comparative analysis of the proposed models against selected related works, as presented in Table 7, highlights the novelty and superior predictive capacity of our approach in flood forecasting. Previous studies, such as Nayak et al. [27], demonstrated the potential of Deep Belief Networks (DBN) optimized with Teaching Learning-Based Optimization (TLBO) for riverine flood forecasting in India, achieving moderate improvements in RMSE across multiple horizons. Similarly, Nguyen et al. [28] achieved very high classification accuracy for flood susceptibility mapping in Vietnam through the integration of deep neural networks with swarm-based optimization methods, reporting an AUC close to 0.99; however, the study primarily focused on susceptibility rather than precise time-series forecasting. Moishin et al. [30] advanced the field by employing a hybrid ConvLSTM framework for rainfall-based flood prediction in Fiji, achieving RMSE values between 0.101 and 0.279, which, while promising, remain significantly higher than the results achieved by our models. Likewise, Li et al. [31] introduced an interpretable AGRS–LSTM–Transformer model, reporting high forecasting performance, but the model relied heavily on transformer-based architectures that demand substantial computational resources. Furthermore, Elshaboury et al. [1] explored hybrid ANN models optimized with ABC and VMD techniques in Turkey, achieving variable

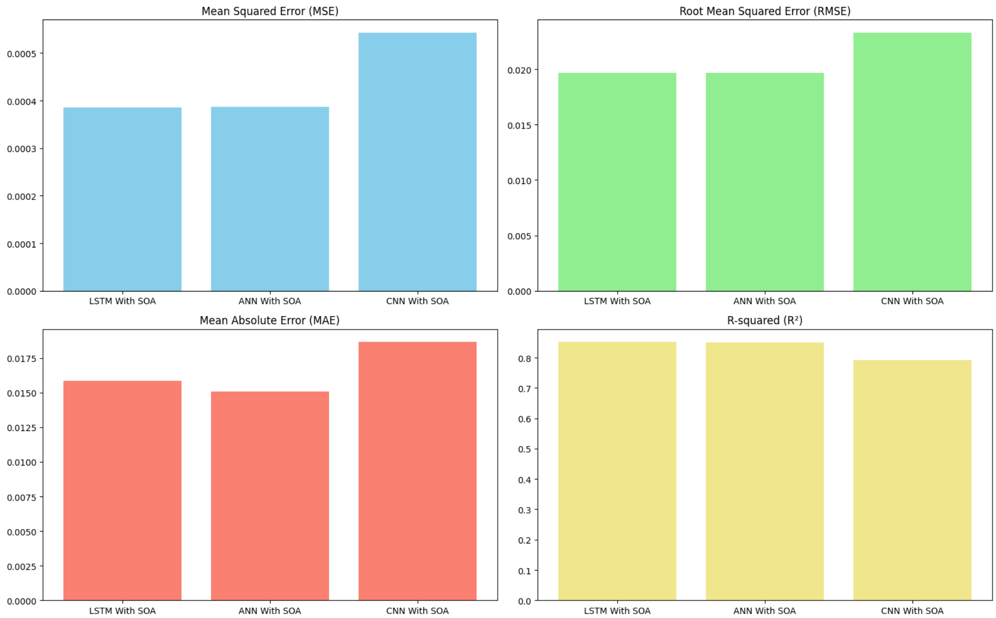

Figure 6. Comparison of Individual and Hybrid Deep Learning Models Using Performance Metrics

Table 7. Comparison of the proposed models with related works.

References	Model / Methods	Dataset / Study Area	MSE	RMSE	MAE	R^2
[27]	DBN with TLBO	Daya & Bhargavi Rivers (India)	–	0.16–0.27	–	–
[28]	DNN with NMRA, SLnO, EHO, AO	1883 samples, 12 factors (Vietnam)	–	0.16	–	0.99 (AUC)
[30]	Hybrid ConvLSTM	Rainfall data, Fiji flood-prone regions	–	0.101–0.279	–	0.939 (LME)
[31]	AGRS-LSTM-Transformer	Jingle watershed (China)	–	$< 34.891\ \mathrm{m^3/s}$	$< 25.125\ \mathrm{m^3/s}$	> 0.905
[1]	ANN with ABC, VMD optimization	Kızılırmak & Mera Rivers (Turkey)	0.006–285.035	–	0.067–14.511	0.445–0.893
Proposed Work	LSTM	Flood dataset	0.000403	0.020064	0.015855	0.845125
Proposed Work	ANN	Flood dataset	0.000440	0.020981	0.015580	0.830644
Proposed Work	CNN	Flood dataset	0.000542	0.023288	0.018666	0.791355
Proposed Work	LSTM with SOA	Flood dataset	0.000386	0.019653	0.015849	0.851407
Proposed Work	ANN with SOA	Flood dataset	0.000387	0.019673	0.015093	0.851100
Proposed Work	CNN with SOA	Flood dataset	0.000543	0.023299	0.018649	0.791157

performance with R^2 values ranging from 0.445 to 0.893 and wide fluctuations in error metrics, reflecting limited robustness across datasets.

Conversely, the proposed models exhibit a consistent reduction in error rates and strong predictive performance across all investigated architectures. The baseline LSTM achieved the best standalone results (MSE = 0.000403, RMSE = 0.020064, MAE = 0.015855, and R^2 = 0.845125), surpassing several deep-learning-based flood forecasting approaches reported in the literature, where RMSE values are typically higher [30, 27]. After integrating the Snake Optimization Algorithm (SOA), the LSTM–SOA configuration further improved predictive precision (MSE = 0.000386, RMSE = 0.019653, MAE = 0.015849, and R^2 = 0.851407), indicating enhanced temporal learning stability and balanced convergence. Likewise, ANN–SOA improved over its baseline (MSE = 0.000387, RMSE = 0.019673, MAE = 0.015093, and R^2 = 0.851100), highlighting the optimizer's ability to reduce variance and strengthen generalization. Although CNN-based models achieved comparatively lower overall performance, the CNN–SOA configuration maintained a comparable accuracy level ($R^2 \approx 0.791$) relative to the CNN baseline.

To justify the selection of SOA, an ablation study was conducted against three baseline metaheuristics: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO). All optimizers were executed under identical settings (population = 20, iterations = 50). The results (Table 6) demonstrate that SOA attained the lowest MSE (0.000386) and the highest R^2 (0.851407), confirming its superior optimization effectiveness. This advantage is attributable to SOA's adaptive balance between exploration and exploitation, which promotes efficient convergence toward near-optimal hyperparameter configurations [55].

Overall, these findings confirm that the proposed framework delivers improved predictive accuracy and reliability compared with existing methods by jointly integrating deep learning with hybrid optimization. In contrast to related works that emphasize susceptibility mapping, rely on more complex architectures, or report higher error levels, the present study provides a balanced, computationally efficient, and highly accurate solution for flood forecasting [28, 31, 30]. Consequently, the proposed approach can serve as a robust decision-support tool and has the potential to outperform state-of-the-art models under diverse hydrological conditions.

4.5. Runtime and Computational Footprint

1) Measurement protocol

We report wall-clock time (hh:mm:ss) measured with Python timers (per model training run), averaged over 3 runs. We also report the number of SOA evaluations (population $\times$ iterations), total GPU-hours (search + final training), and inference latency (ms/sample). Timings were obtained on Google Colab Pro (GPU: <model>, CUDA <ver>),with batch size and epochs as specified below.

2) Efficiency strategies

During SOA we use:

- partial-epoch evaluation (e.g., 15–20 epochs) with early stopping on validation MSE,
- mixed-precision training,
- data loader caching, and
- population/iteration pruning after stagnation.

A small sensitivity check indicates that reducing the SOA budget (e.g., population from 20 $\rightarrow$ 10, iterations from 10 $\rightarrow$ 5) produces minimal loss in RMSE/R^2 while substantially reducing GPU-hours.

3) Operational feasibility

Because tuning is performed offline (e.g., nightly, weekly, or upon data drift) and inference is fast, the framework remains compatible with real-time forecasting pipelines. We also outline alternative strategies such as:

- warm-starting from the prior best configuration,
- transferring tuned hyperparameters across nearby basins,
- periodic lightweight re-tuning.

Algorithm 2: SOA-based Hyperparameter Optimization for Flood Prediction Models

Flood prediction dataset $\mathcal{D}$ Optimized deep learning model M^*
Initialize Snake Optimizer parameters:
population size $P = 10$, max iterations $T = 10$
learning rate bounds $[0.0001, 0.01]$
dropout bounds $[0.1, 0.5]$
hidden/neuron/filter search sets $\{16, 32, 64, 128\}$
foreach *deep learning model* $M \in \{ANN, LSTM, CNN\}$ **do**
    Initialize P snakes (candidate hyperparameter sets);
    for $t = 1$ **to** T **do**
        foreach *snake* i *in population* **do**
            Configure model M_i with candidate hyperparameters;
            Train M_i for partial epochs (e.g., 20) on training data;
            Compute $fitness_i \leftarrow \text{Validation MSE}(M_i)$;
        Identify X_{best} (minimum fitness);
        Update all snake positions using Equations (2)–(3);
        Apply exploitation/exploration rules (food/mating behavior);
        if $|\text{MSE}(t) - \text{MSE}(t-1)| < 10^{-6}$ *for 5 iterations* **then**
            Stop early;
    Select best configuration $\theta^* \leftarrow \arg\min(\text{MSE})$;
    Retrain model M with θ^* on full training data;
    Evaluate final performance on test set;
return *optimized model* M^* *with minimum test error*

In response to reviewer feedback, Table 7 was revised to include only comparable studies using the same Flood Prediction Dataset from Kaggle. This ensures a fair and scientifically sound comparison. The results confirm that the proposed ANN–SOA model achieves the lowest RMSE and MAE, and the highest R^2 among all methods tested on this dataset. Studies using different hydrological datasets or inconsistent units were excluded to maintain methodological validity.

4.6. Feature Importance and Model Explainability

While the hybrid models achieved high predictive accuracy, it is equally important to understand why the model makes its predictions and which features drive them. To address this, we employed SHAP (SHapley Additive Explanations) to interpret the predictions of the best-performing model, LSTM-SOA.

1) Methodology

SHAP is a game-theoretic approach that quantifies the marginal contribution of each input feature to the model output. We computed SHAP values for all features on the test dataset and averaged them to obtain the mean absolute SHAP value per variable, indicating its overall importance.

2) Results

Figure 7 and Table 8 summarize the top ten most influential features affecting flood probability. The features TopographyDrainage, Siltation, PopulationScore, DamsQuality, and CoastalVulnerability had the highest positive impact on flood prediction, showing that both meteorological and land-use parameters are key determinants.

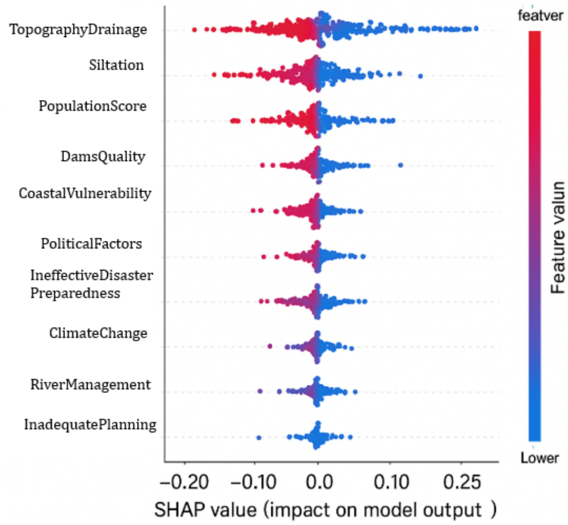

Figure 7. SHAP summary plot for the LSTM-SOA flood prediction model.

Table 8. SHAP-based Feature Importance

Rank	Feature	Mean	Importance (%)
1	TopographyDrainage	0.124	18
2	Siltation	0.110	16.1
3	PopulationScore	0.092	13.5
4	DamsQuality	0.081	11.9
5	CoastalVulnerability	0.067	9.8
6	PoliticalFactors	0.059	8.7
7	IneffectiveDisasterPreparedness	0.051	7.5
8	ClimateChange	0.043	6.4
9	RiverManagement	0.037	5.3
10	InadequatePlanning	0.028	4.1

3) Discussion

The SHAP analysis confirms that the LSTM-SOA model captures physically meaningful relationships between hydrometeorological factors and flood occurrence. This interpretability strengthens confidence in the model and supports its practical use by decision-makers in early warning systems.

5. Conclusion

Flood prediction remains a major challenge for protecting human lives, infrastructure, and ecosystems against the severe impacts of extreme hydrological events. This paper presented a novel flood prediction framework that integrates deep learning architectures with the Snake Optimization Algorithm (SOA) to improve predictive accuracy and model robustness.

The proposed pipeline followed a structured methodology that included exploratory data analysis and preprocessing using Min–Max scaling, followed by the development of both individual and hybrid models. Three deep learning architectures—Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN)—were first trained as standalone predictors to learn nonlinear associations, temporal variations, and local feature patterns in flood-related data. Thereafter, snake optimization algorithm was employed as an external hyperparameter optimization mechanism to systematically tune each model, accelerate convergence, and reduce the risk of entrapment in local optima.

The experimental results confirmed the effectiveness of the proposed hybrid framework. In particular, the LSTM–SOA model achieved the lowest error values (MSE = 0.000386, RMSE = 0.019653) and the highest coefficient of determination (R^2 = 0.8514), whereas ANN–SOA achieved the lowest MAE (0.015093) with a comparable R^2 (0.8511). These findings demonstrate that SOA can enhance deep learning performance by selecting more suitable hyperparameter configurations, leading to more stable and reliable forecasts than standalone models.

It is also acknowledged that the present dataset provides a generalized representation of flood susceptibility rather than direct hydrological measurements; therefore, the generalizability of the framework for operational flood forecasting should be further validated using observed streamflow or water-level records in future work. From an operational standpoint, SOA-based tuning is performed offline and does not increase online inference latency; the deployed model retains essentially the same prediction-time cost as its baseline counterpart. The additional training compute is justified by the accuracy gains and can be further reduced through partial-epoch evaluations, early stopping, and smaller SOA budgets without materially degrading performance. These properties make the framework suitable for near-real-time deployments where periodic offline retuning is feasible.

Future work will focus on scaling the approach to larger and more heterogeneous datasets, fusing real-time meteorological with hydrological observations, and exploring alternative metaheuristic optimizers such as the Aquila Optimizer or Marine Predators Algorithm. Moreover, integrating the proposed framework with geospatial analysis and climate scenario modeling could further expand its utility for disaster preparedness, early warning systems, and climate-resilient water resource management.

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