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Enhancing Flood Management and Early Warning Systems in Mountain Rivers: An ANN-Based Approach

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Abstract The study focuses on developing an HEC-RAS 1D model to simulate flood hydrographs at desired locations, considering the inflows from two different rivers Rishiganga and Dhauliganga. The objective is to analyze the impact of inflow hydrographs from the aforementioned rivers, utilizing three sets of flood data: high flow (2400 m3/sec), low flow (15 m3/sec), and 1.5 times the high flow (3600 m3/sec) peaks. An Artificial Neural Network (ANN) model, employing the Feed-forward Backpropagation method, is utilized to train the neurons using the maximum flow hydrograph. The trained ANN model is subsequently tested with two unseen inflow hydrographs of low and 1.5 x high flow to evaluate its robustness. The findings reveal that the ANN model performs very well in flood estimation, providing efficient predictions based on the testing with the maximum flow and validating with the minimum and 1.5 times higher inflow hydrographs. Its primary advantage lies in saving time, enabling timely actions when flood warnings are issued. This research significantly contributes to flood management and shall enhance the lead time in disseminating early warning to local authorities and communities. Work shall help in providing timely and accurate flood predictions for proactive measures during any flood event. The study's significance is rooted in its potential to enhance flood preparedness and response in areas affected by the Rishiganga and Dhauliganga rivers, ultimately ensuring the safety and well-being of local communities and infrastructures.

Keywords: flood management, ANN model, hydraulic model, flood hydrograph, HEC-RAS, barrage

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1. INTRODUCTION

Floods stand as one of the most prevalent and devastating natural calamities worldwide. Particularly in arid mountainous regions where flash floods pose significant risks and destructiveness, characterized by high rainfall intensity and soil prone to rapid runoff conversion (Pant et al., 2018). In addition to accurate flood forecasting, flood lead time plays a crucial role in facilitating early adoption of flood warning systems, flood control measures, and other mitigation strategies, thereby reducing flood-related losses (Emerton et al., 2016). Despite advancements in disaster forecasting and prevention, floods in mountainous areas remain a persistent challenge globally (Kundzewicz et al., 2014; Şen et al., 2013). The accuracy of flood forecasting in these regions is hindered by limitations in hydrological station networks and meteorological data availability. Addressing these challenges necessitates the development of new models or methods capable of providing fairly accurate predictions with enhanced lead times. Moreover, it holds great significance for regional planning, irrigation management, sediment transport, and various hydrological applications.

Flood simulation and forecasting modeling systems are typically categorized into physically-based hydrological models and data based empirical models. Physically-based hydrological models offer clear physical interpretations and are instrumental in understanding hydrological processes (Yuan et al., 2020). However, their calibration can be resource-intensive and challenging in data-scarce regions. Conversely, empirical models, such as artificial neural ANN, rely on data correlations without explicit physical significance. ANNs have emerged as widely used tools for hydrological forecasting, offering potential solutions to the challenges faced by physically-based models (Dtissibe et al., 2020; Tabbussum & Dar, 2020). While traditional physical process-based and numerical analysis-based models hold their own significance, alternative approaches such as ANNs offer potential advantages in extending lead times, particularly in regions susceptible to flash floods, where flash floods can occur within minutes.

For a flash flood prone area, sensor-based flood estimation and forecasting are becoming very useful and popular (Khan et al., 2018). However, sensor-based systems initiate predictions after floodwaters reach sensor locations and can begin forecasting after the data is recorded, which does not provide sufficient lead time. In such cases, model computation time matters the most and here ANN brings an additional advantage of extending lead time by simulating flood hydrograph in few milli-seconds, substantially extending lead times and potentially minimizing damage. Moreover, ANNs demonstrate efficiency by requiring observed data from only one or two locations for training and operation, making them suitable for remote basins with limited data availability.

In the context of flood forecasting and warning systems, three key components—Flood Detection, Forecasting and Warning, and Response—play pivotal roles in monitoring, predicting, and mitigating flooding impacts. While significant progress has been made in India's ensemble prediction system for extreme precipitation events with lead times ranging from 1 to 3 days and even up to 15 to 20 days; however, challenges persist, particularly in predicting rare and complex events such as glacial bursts (Wang et al., 2024). Recent events like the Tapovan barrage flood disaster in February 2021 with lag time 16 minutes only (Sain et al., 2021), underscore the sudden and unpredictable nature of such occurrences, emphasizing the critical importance of sufficient lead time for effective response. An integrated approach at various levels, particularly in vulnerable mountainous regions, is essential for bolstering operational flood forecasting.

This study endeavors to explore ANN as an alternative modeling solution, aiming to produce fairly accurate outcomes within a short duration to provide extended lead times. Additionally, the study aims to assess the performance of the ANN model for hydrodynamic outcomes at the river scale and hydrological outcomes at the basin scale.

2. METHODOLOGY

2.1 Study Area

The research study is conducted in the aftermath of the devastating flood event that struck on February 7th, 2021, impacting a significant stretch of rivers in Uttarakhand, a state nestled in the north-western region of the Himalayas. The selected study area encompasses key river stretches and structure, including the Dhauliganga river (46 km), Rishiganga (0.5 km), Alakhnanda river (12 km), and the Tapovan barrage situated approximately 6 km downstream of the Dhauliganga-Rishiganga confluence near Raini village, as illustrated in Figure 1.

The climate of the region exhibits characteristics of both humid-temperate and dry-cold climates, with distinct seasonal variations. During the summer months, typically from May to June, the climate tends towards humid-temperate conditions, marked by average maximum temperatures ranging between 31 to 32°C. Conversely, in the winter months, particularly in January, the climate becomes dry and cold, with average minimum temperatures dropping to 4.8°C. The valley experiences an annual mean precipitation ranging between 500 to 1300 mm. Precipitation occurs in various forms throughout the year, with snowfall typically observed between November and February, while rainfall is more prevalent during the months of May and September (Rana et al., 2021).

2.2 Modelling Approach

The research was conducted in two distinct phases. Firstly, a hydrodynamic model of the designated study area was developed utilizing HEC-RAS. Key points of interest (POI), including the Tapovan barrage, Joshimath, and the Power House, were identified to assess the hydrograph as the flow originates from Dhauliganga near Kosa and from Rishiganga near Raini.

In the subsequent phase, the data generated from the hydrodynamic model simulation was employed to train, test, and validate a Neural Network model across varying flow conditions, encompassing both low and high flow ranges. The schematic flow chart outlining the methodology is presented in Figure 2.

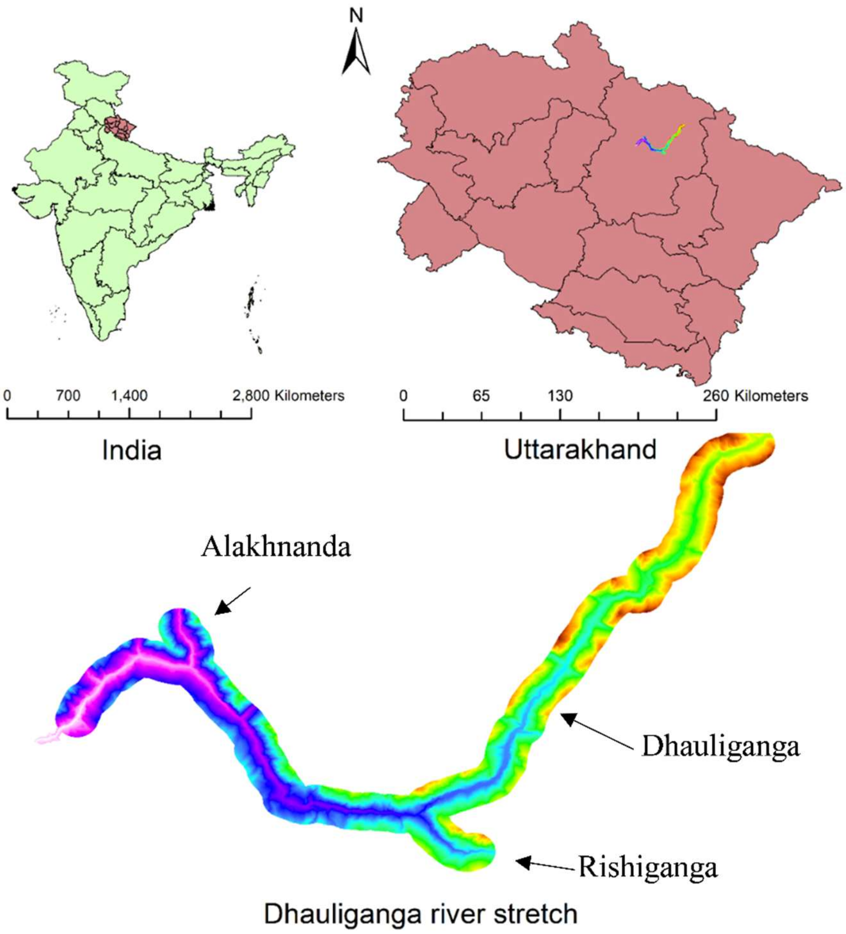

Figure 1. Study area: 54 km stretch of Dhauliganga river and location of the TVHP in Uttarakhand (India)

2.2.1 Data and Sources

Terrain: Remote sensing data emerges as a pivotal asset in the investigation, analysis, and understanding of natural disasters, particularly within challenging environments such as high mountainous terrain. In our research, we utilized high-resolution LiDAR (Light Detection and Ranging) data obtained from the Indian Institute of Technology Kanpur, with a grid cell size of approximately 3.6 meters. The application of digital elevation data (DEM) from LiDAR is used to generate the terrain and slope of the focused region in RAS-Mapper which helped in generating the accurate inundation maps. The geometry input features for the hydrodynamic model such as cross-section and river centre line were generated using this terrain.

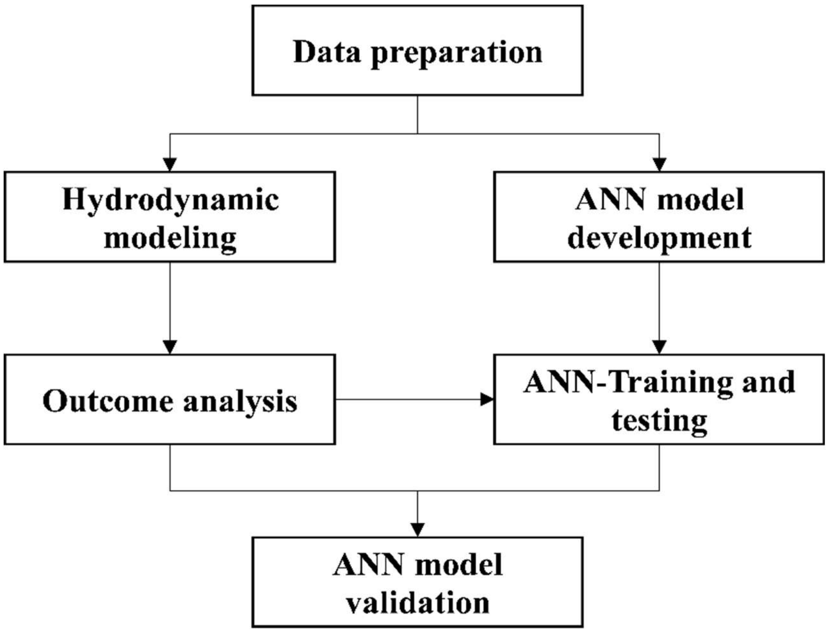

Figure 2. Flow chart of the adopted methodology

Land use land cover (LULC): The land use data of 2022-2023 were taken from the ESA Sentinal-2 imagery at 10 m resolution land use/land cover time series of the world attributed by Impact Observatory, Microsoft, and ESRI generated with Impact Observatory's deep learning AI land classification model, trained using billions of human-labelled image pixels from the National Geographic Society (Karra et al., 2021). The HECRAS manual suggests that mountainous natural streams, characterized by channels without vegetation and steep banks, should have a Manning coefficient ranging from 0.025 to 0.12. Thus, the chosen coefficients fall within this recommended range (Brunner, 1995).

Flow data: An advanced console was designed to seamlessly collect the live depth and velocity data from the sensors installed at Kosa, Raini and Thaiya and accurately convert it into discharge through a reliable depth-area relationship derived by the LiDAR data. This calculated flow data is then utilized in HEC-RAS as inflow hydrograph.

2.2.2 Hydrodynamic Modelling

This study endeavours to dynamically simulate floods originating from the Himalayan region, focusing on the Kosa and Raini rivers, employing a one-dimensional unsteady flow approach. In the of unsteady flow analysis, the HEC-RAS harnesses the 1D Saint-Venant equations, grounded in the fundamental principles of mass and momentum conservation for open-channel flow, complemented by Manning's equation to compute frictional slope (Shaikh et al., 2023). This computational framework facilitates the modeling of dynamic events, enabling the accurate simulation of flood events and the monitoring of discharge and water level fluctuations over time.

The study began by generating river cross-sections for the Dhauliganga, Rishiganga, and Alakhnanda reaches from inflow measurement sensors to establish the model. The spacing of cross-section lines was meticulously adjusted based on slope and model stability, ranging between 40 to 130 meters. Subsequently, other geometric parameters such as river center lines, bank lines, and additional hydrodynamic data were derived from terrain data using the RAS-mapper. The resulting geometry was then imported into the HEC-RAS geometry file to simulate hydrographs at Points of Interest (POIs). Figure 3 illustrates the channel profile and cross sections at POIs used for model setup in HEC-RAS. The finite-volume method implemented in HEC-RAS is heralded for its advantageous characteristics, encompassing conceptual simplicity, unwavering consistency, and geometric adaptability (Shaikh et al., 2023). This approach facilitates a more versatile treatment of unstructured mesh configurations while effectively approximating the average integral within a defined reference volume.

Boundary conditions for the 1D model were established at Kosa, Raini, and Thaliya, incorporating flow data necessary for analysis. Water surface elevation, flood hydrographs, and inundation maps were scrutinized at three key locations of interest: (a) Tapovan barrage, (b) Joshimath, and (c) Power plant. Three distinct scenarios were devised based on varying inflow conditions from Kosa and Raini, a constant flow is assumed from the Alakhnanda because the confluence of Alakhnanda with Dhauliganga river is downstream of Joshimath and Tapovan barrage:

- Scenario A: Hypothetical low inflow (peak 15 cumec) served as boundary conditions to assess model outcomes under low-flow conditions, extending the model's applicability range.

- Scenario B: Hypothetical high inflow (peak 2400 cumec) was utilized to examine model behavior and flood hydrographs during high-flow situations.

- Scenario C: Hypothetical 1.5 x high inflow (peak 3600 cumec) was employed to assess model behavior and flood hydrographs under conditions of 1.5 times higher flow than Scenario B.

Downstream boundary conditions were maintained as normal depth utilizing the average slope of the channel at the downstream end.

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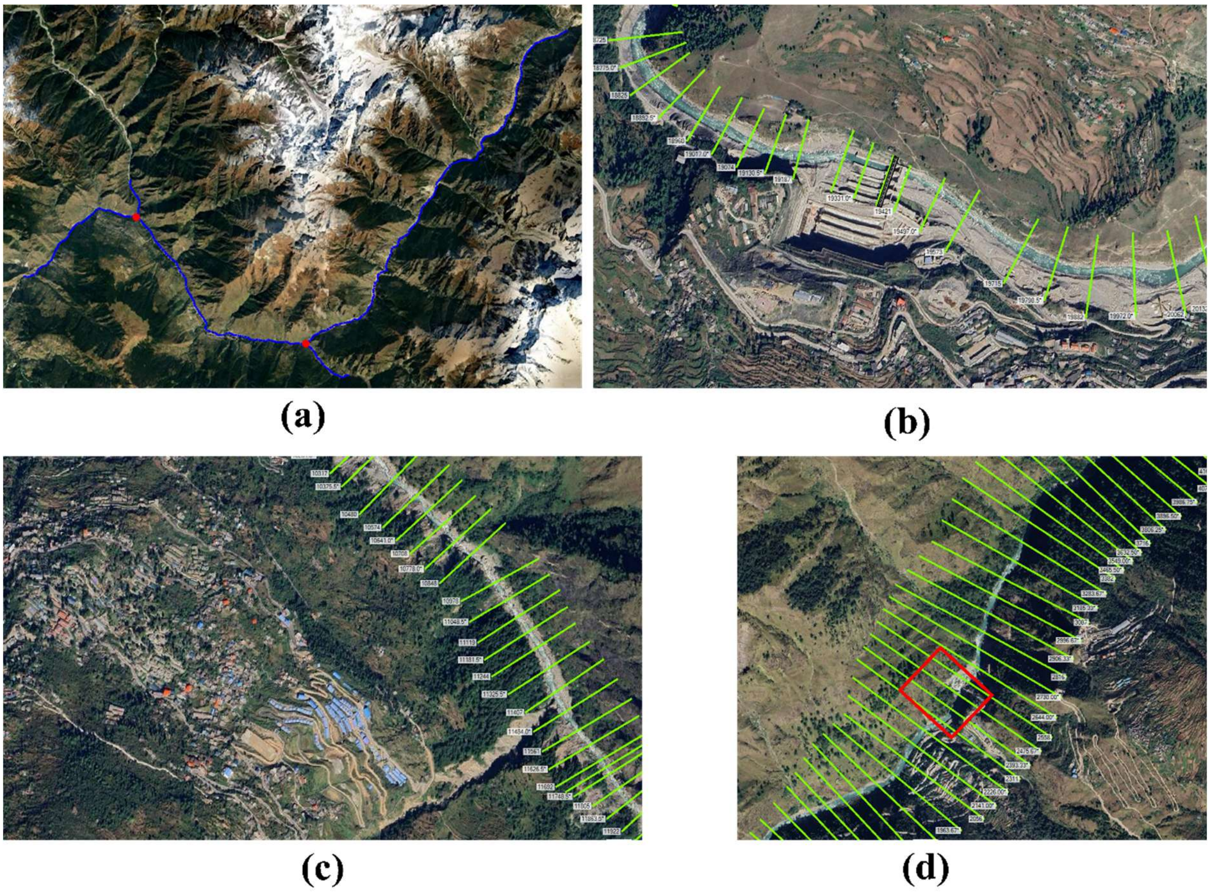

Figure 3. Geometry in hydrodynamic model at various POIs: (a) Centre line of all river stretches, cross-sections (b) at Tapovan barrage (Dhauliganga), (c) near Joshimath (Dhauliganga), and (d) near power house (Alakhnanda)

2.2.3 ANN Modelling at River Scale

In the present study, the modeling framework utilized a two-layer feedforward back-propagation neural network implemented in MATLAB. In the network architecture, a linear function was employed in the output layer, while a sigmoidal function, recognized for its efficacy in capturing nonlinear relationships within data, was employed in the hidden layer. The weights assigned to the hidden layer nodes were instrumental in capturing the intricate associations between input and output data. To optimize the network's performance, the Levenberg–Marquardt algorithm was selected for training, iteratively adjusting the weights and biases from their initially random values (Hanspal et al., 2013; Jain & Chakma, 2022).

To determine the optimal number of neurons in the hidden layer, a program was developed to optimie the network by minimizing the mean squared error (MSE) between the target and output layers. The program systematically assessed networks ranging from zero to 100 neurons, saving the configuration that yielded the most favorable results. The flowchart outlining the program's methodology is depicted in Figure 4.

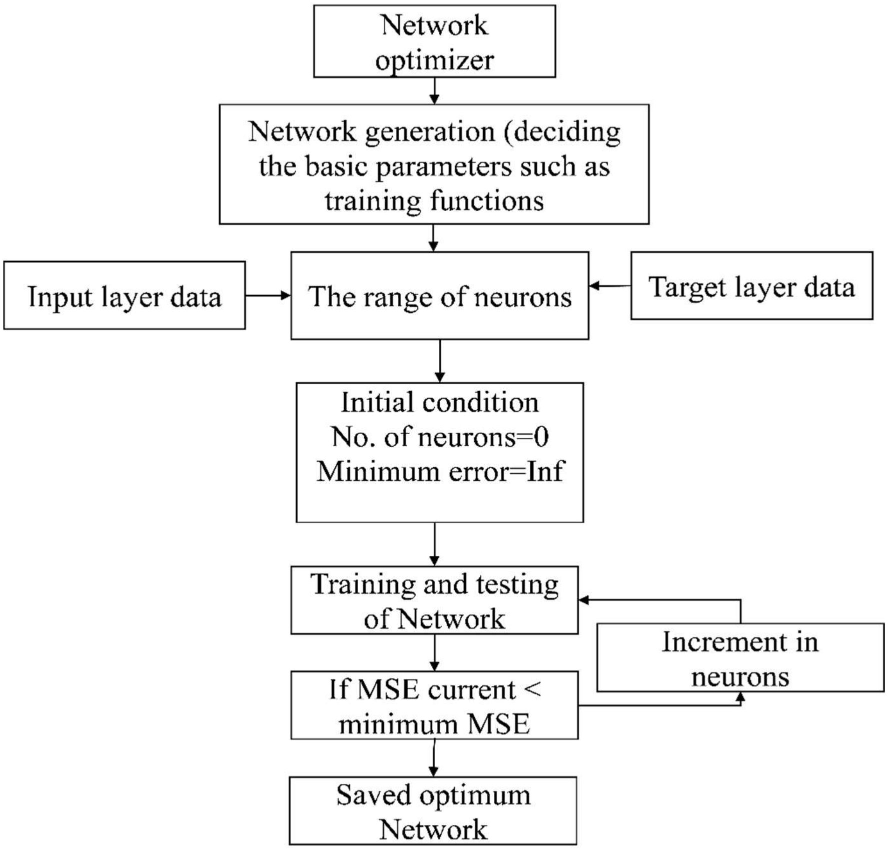

Figure 4. Flow chart of network optimizer program for the ANN optimizer program

Subsequently, the ANN model underwent training and testing using simulated hydrographs from scenario B of hydrodynamic modelling by dividing the data as 15% for testing, 15% for validation and 70% for training. To examine the model's performance across different scenarios (unseen by the network), hydrographs from scenarios A and C were employed. The input layer of the ANN model comprised inflow hydrograph ordinates from Kosa and Raini rivers (2 layers), while the output layer depicted hydrographs at Tapovan barrage, Joshimath, and the Power House (3 layers). thus, the network can be defined as 3-N-3 ANN model. The optimum number of neurons in hidden layer was estimated 3, The activation function for output layer and hidden layer were decided as linear and sigmoidal function. The schematic diagram of the network is presented in Figure 5.

2.2.4 ANN Modelling at Basin Scale

The utilization of Artificial Neural Networks (ANNs) at the basin scale was employed for runoff estimation, utilizing influential and generative parameters. Given that the inflow for the hydrodynamic model is sourced from the Kosa (Dhauliganga river), the Upper Dhauliganga basin was selected to showcase the performance of the ANN in rainfall-runoff modeling, as depicted in Figure 6.

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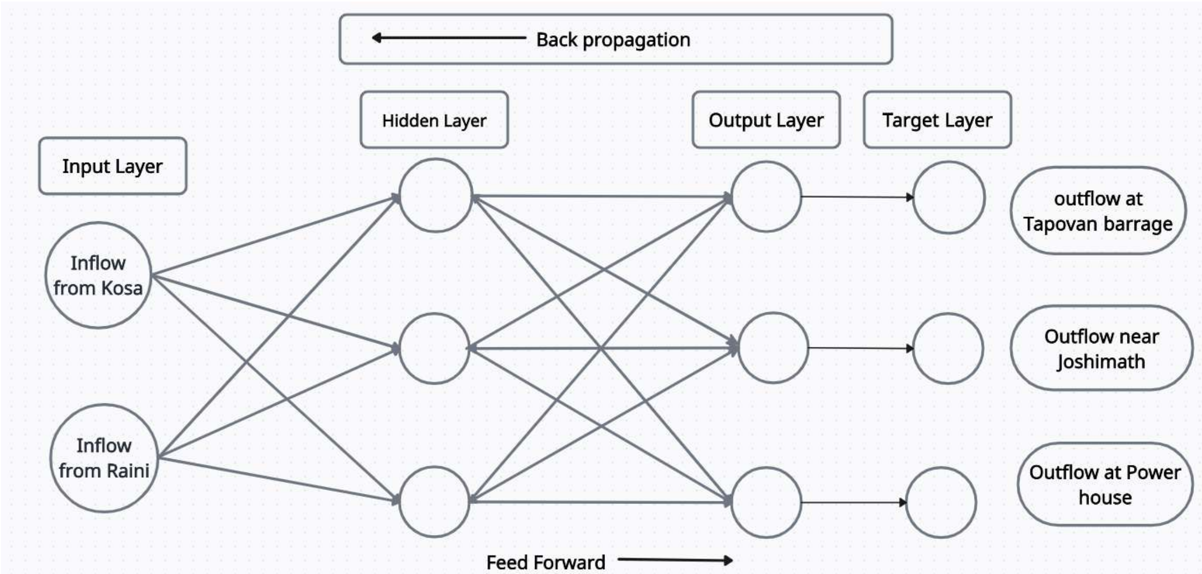

Figure 5. Structure of Feed Forward back propagation Neural Network used for the study

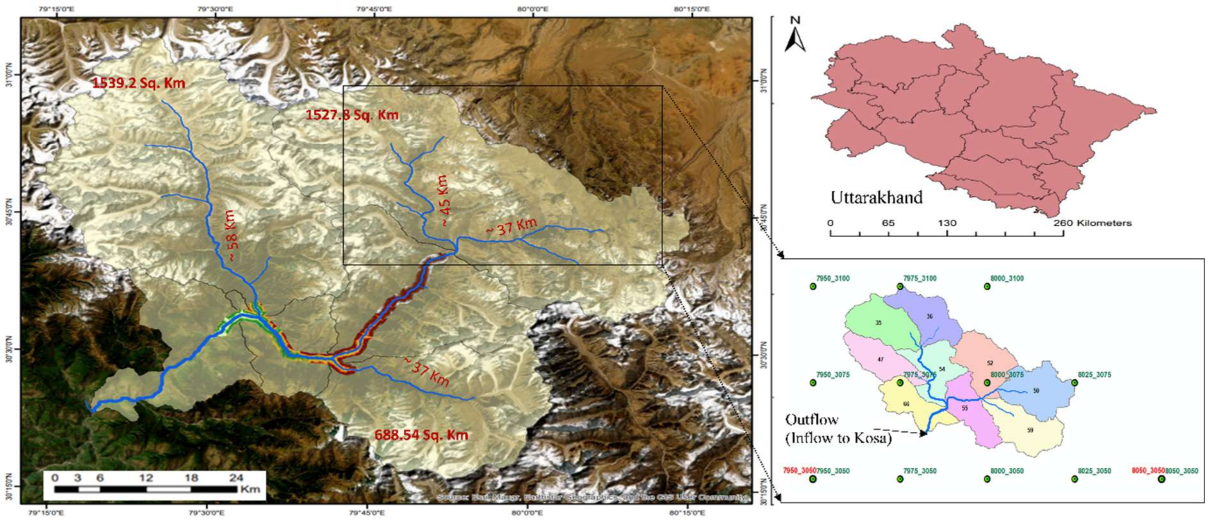

Figure 6. Upper Dhauliganga basin opted for the ANN modelling at basin scale

As detailed in the preceding section, a two-layer feed-forward and backpropagation ANN model was utilized, with the optimal number of neurons determined using the Network Optimizer program. Daily data of precipitation, maximum temperature, and minimum temperature from January 1st, 2004, to December 31st, 2016 (totalling 1096 data sets), constituted the input layer. Of this dataset, 70% was allocated for network training, 20% for testing, and 10% for validation. The outflow data at the outlet of the basin, estimated by the Soil and Water Assessment Tool (SWAT), formed the output layer, resulting in a 3-N-1 ANN model. The optimal number of neurons in the hidden layer was determined to be 4. Activation functions for the output and hidden layers were chosen as linear and sigmoidal functions, respectively. Temperature range governs a significant role in the Himalayan River, thus, considered as an input parameter along with precipitation (Chandel & Ghosh, 2021).

One notable advantage of employing ANNs lies in their capability to exploit the basin's inherent characteristics to respond effectively to rainfall events. The ANN model encapsulates the dynamics of river flow without necessitating the explicit consideration of physical processes, thereby streamlining the prediction of runoff. This predictive prowess translates into a substantial enhancement of lead time, enabling precise estimations of the runoff volume expected in response to varying rainfall events.

To assess and contrast the outcomes generated by the Artificial Neural Network (ANN) with those simulated by HEC-RAS across all scenarios, the statistical performance parameters were employed as recommended by Moriasi et al. (2007). These techniques included the Nash Sutcliffe Efficiency (NSE), R-square coefficient (R^2), Percent Bias (PBIAS), and Root Mean Square Error to Residual Standard Deviation Ratio (RSR).

3. RESULTS

The hydrodynamic model was employed to simulate three distinct inflow hydrographs: a low-flow peak (15 cumec), a high-flow peak (2400 cumec), and a peak 1.5 times higher than the high peak (3600 cumec). Each hydrograph was individually sourced from Kosa and Raini, with the remaining inflow set at a low constant value (4 cumec) to isolate the impact of each source. The resultant hydrographs were observed at Tapovan, near Joshimath, and near the Powerhouse.

For scenario B, which represents high flow, the inflow and resultant hydrographs for all three points of interest (POIs) were utilized as input and target layers, respectively, to train and test an artificial neural network (ANN) model at the basin scale. The optimal number of neurons in the hidden layer was determined to be 3 by the network optimizer program. To assess the efficiency of the trained network, it was tested with unseen inflow hydrographs representing low flow and 1.5 times the high inflow, covering a wide range. Subsequently, the ANN generated output hydrographs at all three POIs were compared with those produced by the hydrodynamic model, as discussed in the following section.

3.1 Assessment of ANN Model for Low Inflow

The research utilized an Artificial Neural Network (ANN) configuration of 3-N-3 to model various flow scenarios. In the case of low flow from Kosa, with a peak of 15 cumec, and constant low flow from Alakhnanda and Raini at 4 cumec, the ANN-generated hydrograph was compared with the output from HECRAS. Figure 7 illustrates this comparison, revealing that at Tapovan barrage, the peak was estimated to be 2.5% higher than HECRAS, with the arrived volume being 4.6% higher, as depicted in Figure 7 (a). Similarly, near Joshimath and the Powerhouse, the resultant peak discharge and arrival volume were estimated to be 4.31% and 6.92% higher, respectively, as shown in Figures 7 (b) and 7 (c).

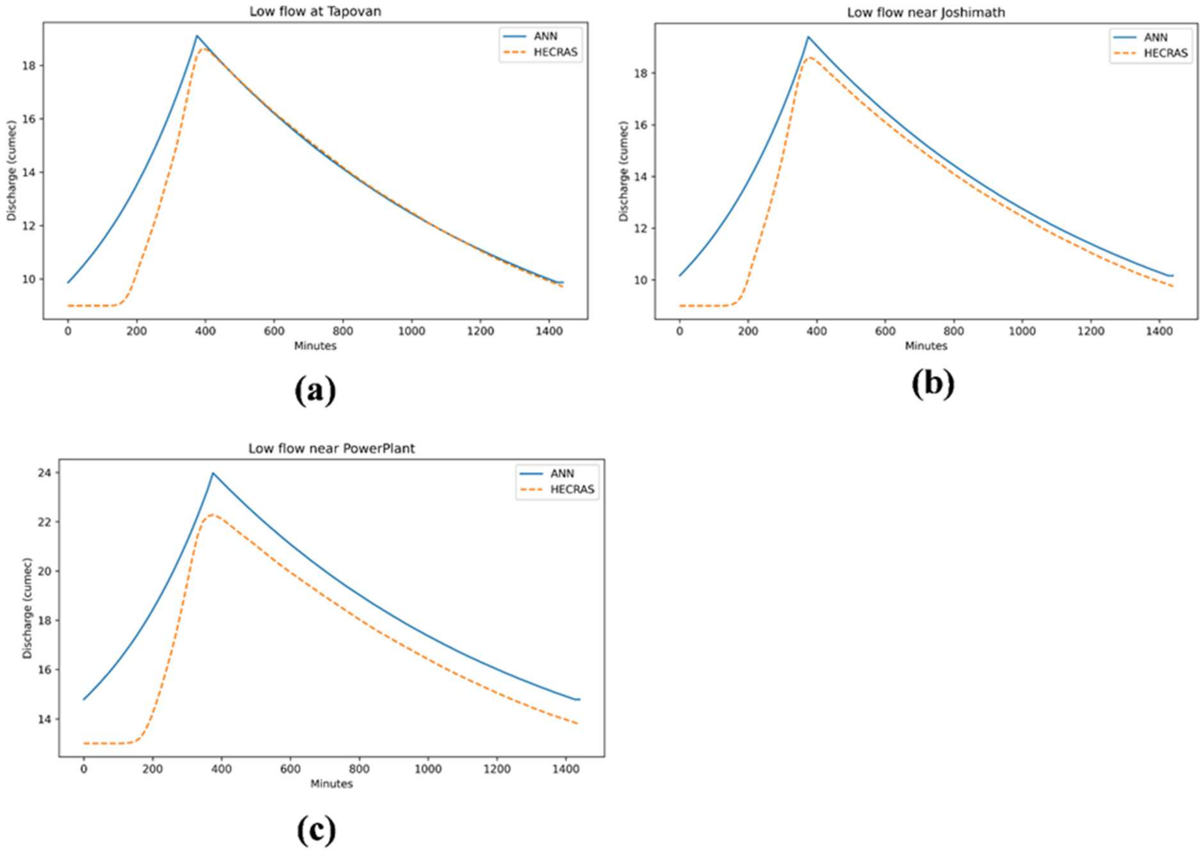

Figure 7. Comparison of ANN vs. HEC-RAS generated hydrographs for low inflow from Kosa at (a) Tapovan barrage, (b) Joshimath, and (c) Powerhouse.

For the scenario involving low flow from Raini, with a peak of 15 cumec, and constant low flow from Alakhnanda and Kosa at 4 cumec, the ANN (3-N-3) model was again employed. Figure 8 showcases the comparison between the ANN-generated hydrograph and HECRAS-generated outflow. At Tapovan barrage, the peak was estimated to be 15.68% lower than HECRAS, with the arrived volume being 9.8% lower, as illustrated in Figure 8 (a). Similarly, near Joshimath and the Powerhouse, the resultant peak discharge and arrival volume were estimated to be 15.6% and 10.1% lower, respectively, as shown in Figures 8 (b) and 8 (c).

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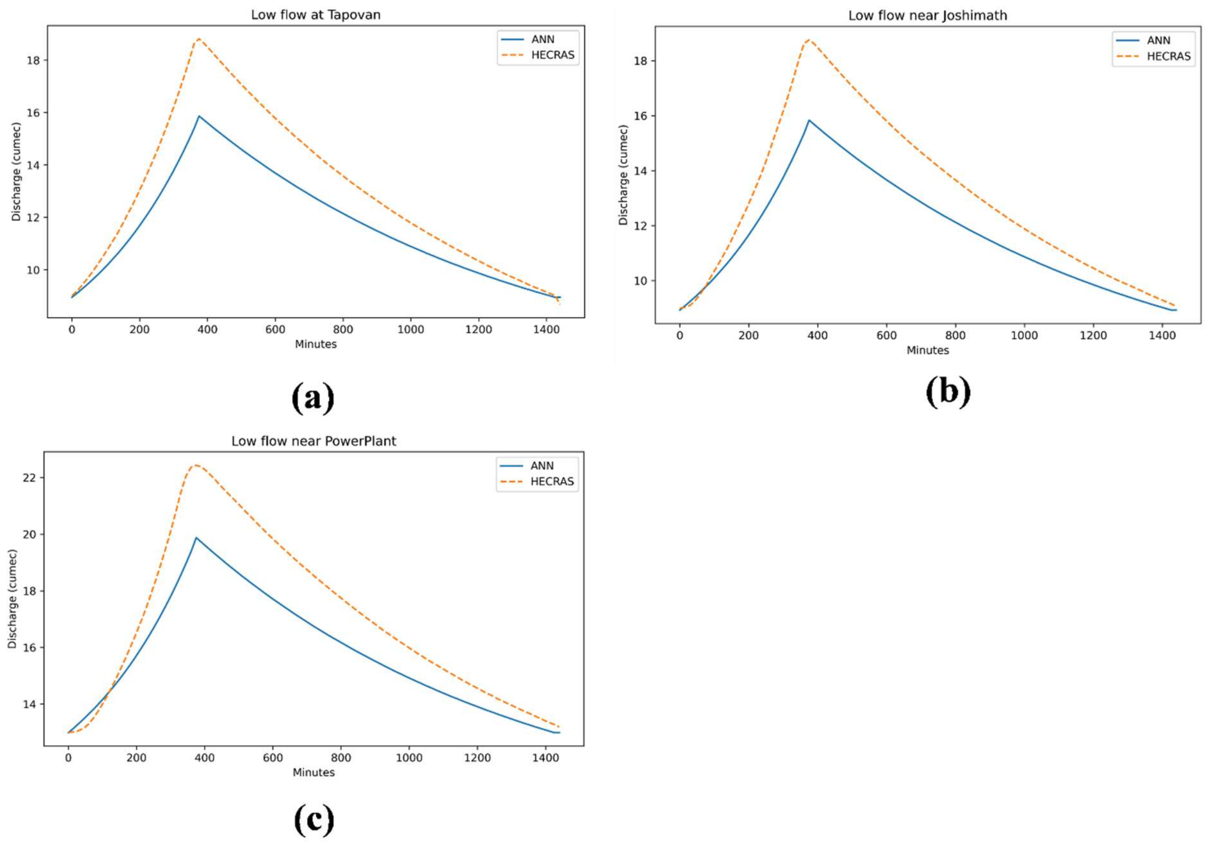

Figure 8. Comparison of ANN vs. HEC-RAS generated hydrographs for low inflow from Raini at (a) Tapovan barrage, (b) Joshimath, and (c) Powerhouse.

3.2 Assessment of ANN Model for High Inflow

In another scenario involving high flow from Kosa, with a peak of 3600 cumec, and constant low flow from Alakhnanda and Raini at 4 cumec and the ANN (3-N-3) model was utilized for this condition. Figure 9 displays the comparison between the ANN-generated hydrograph and HECRAS-generated outflow. The peak arrival time from Kosa to Tapovan barrage, Joshimath and, Power house were estimated as 75 mins. 90 mins and 105 mins, respectively. At Tapovan barrage, the peak was estimated to be 1.89% lower than HECRAS, while near Joshimath and the Powerhouse, the resultant peak discharge was estimated to be 1.2% lower, as shown in Figures 9 (a), 9 (b), and 9 (c) respectively. The arrival volume at all three locations showed insignificant differences compared to HECRAS estimates, with less than 1% variation only.

Finally, in the scenario involving high flow from Raini, with a peak of 3600 cumec, and constant low flow from Alakhnanda and Kosa at 4 cumec, the ANN (3-N-3) model was employed. Figure 10 presents the comparison between the ANN-generated hydrograph and HECRAS-generated outflow. The peak arrival time from Raini to Tapovan barrage, Joshimath and, Power house were estimated as 15 mins. 30 mins and 45 mins, respectively At Tapovan barrage, the peak was estimated to be 0.14% higher than HECRAS, while near

Joshimath and the Powerhouse, the resultant peak discharge was estimated to be 0.2% lower and 0.3% lower respectively, as depicted in Figures 10 (a), 10 (b), and 10 (c). Once again, the arrival volume at all three locations showed insignificant differences compared to HECRAS estimates, with less than 1% variation only.

Overall, the ANN (3-N-3) model demonstrated satisfactorily for the low flow conditions and promising performance in simulating hydrological process for high flow conditions, showcasing its potential as an alternative or complementary tool to conventional hydrological models like HECRAS.

The performance of the ANN model was assessed using well-established statistical evaluation techniques, as detailed in Table 1 across all analyzed scenarios. The results of this evaluation indicate that the ANN demonstrates notably superior performance under high-flow conditions, with key performance indicators such as R2, NSE, PBIAS, and RSR averaging at 0.99, 0.99, 0.35%, and 0.07, respectively. Conversely, under low-flow conditions, the model's performance, while acceptable, shows room for improvement, as evidenced by R2, NSE, PBIAS, and RSR values of 0.93, 0.72, 7.95%, and 0.53. Further refinement is thus warranted for optimizing outcomes in these scenarios. Detailed evaluations for each specific situation are provided in Table 1.

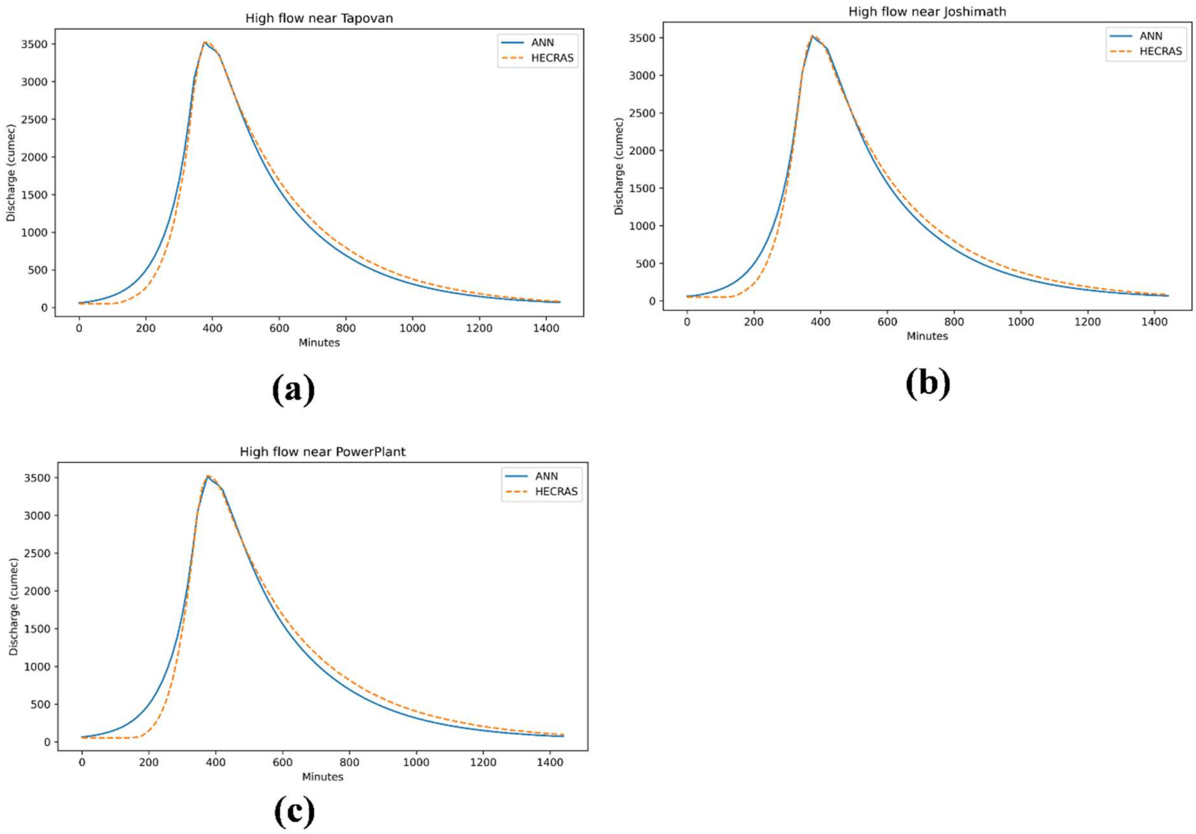

Figure 9. Comparison of ANN vs. HEC-RAS generated hydrographs for 1.5 x high inflow from Kosa at (a) Tapovan barrage, (b) Joshimath, and (c) Powerhouse.

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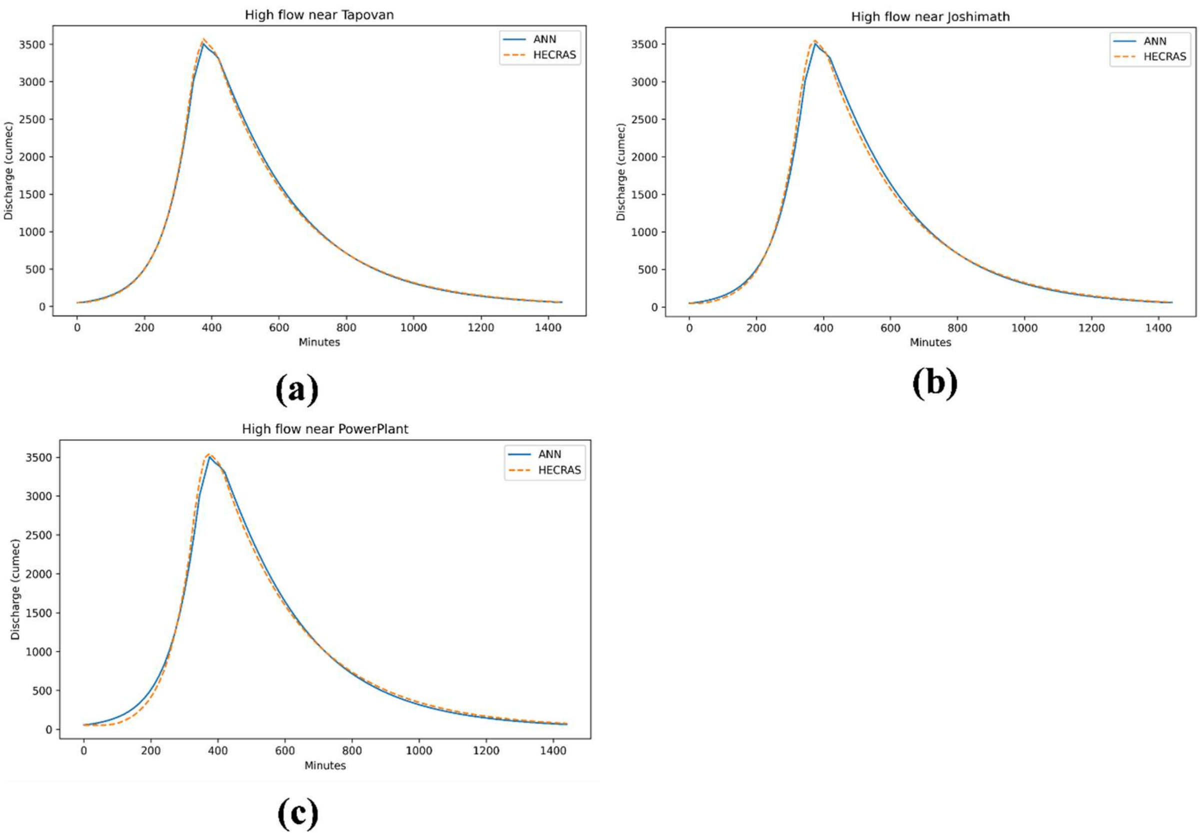

Figure 10. Comparison of ANN vs. HEC-RAS generated hydrographs for 1.5 x high inflow from Raini at (a) Tapovan barrage, (b) Joshimath, and (c) Powerhouse.

3.3 Assessment of ANN Model at Basin Scale

To achieve the maximum lead time, additional efforts were made to estimate the flow at the outlet of the basin utilizing precipitation and temperature data provided by the Indian Meteorological Department. As discussed in section 2.3.4, the ANN model (3-N-1) was utilized to process unseen daily input data from January 1st, 2017, to January 31st, 2017, after being trained using data from the previous 12 years to monitor its performance. Figure 11 displays the comparison of the basin outflow hydrograph generated by the ANN model, which was then compared with the hydrograph generated by the SWAT model, revealing an excellent agreement with the SWAT model's outcomes. The performance of the ANN model at the basin scale was evaluated using statistical evaluation tools, as presented in Table 2, demonstrating its excellent performance.

Further enhancement of the lead time from hours to days can be achieved if the model is employed using three days' prediction data of precipitation and temperature provided by the governing agency. These findings offer significant contributions to the field of hydrodynamic and hydrological modelling, enhancing the ability to predict and manage river flow dynamics faster and increasing the precious lead time in case of flood disaster.

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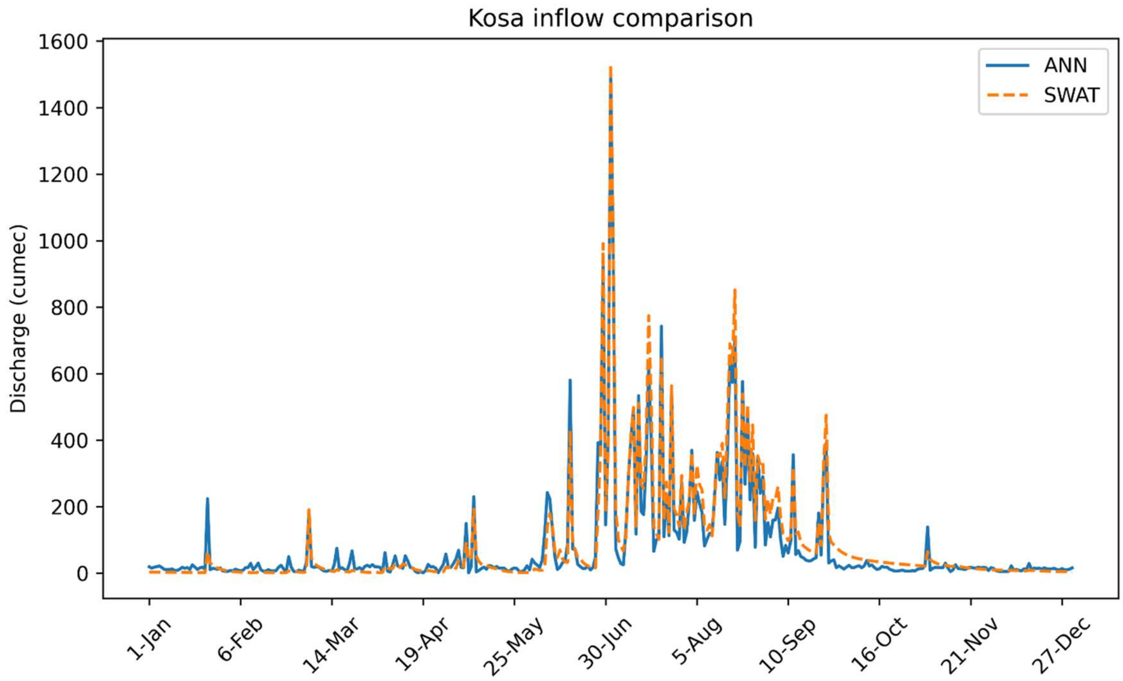

Figure 11. Comparison of flow simulated by SWAT vs. generated by ANN model

Table 1. Statistical performance analysis of ANN model at river scale for low and 1.5 x high flow at all three POIs

Scenario	Location	R^2	NSE	PBIAS	RSR
Low flow (from Raini)	Tapovan	0.990	0.710	9.830	0.540
	Joshimath	0.990	0.700	10.100	0.550
	Power house	0.990	0.710	7.370	0.540
Low flow (from Kosa)	Tapovan	0.860	0.820	-4.586	0.430
	Joshimath	0.874	0.780	-6.910	0.470
	Power house	0.885	0.610	-8.890	0.630
1.5 x high flow (from Raini)	Tapovan	0.990	0.990	-0.190	0.030
	Joshimath	0.998	0.990	-0.424	0.050
	Power house	0.997	0.990	-0.378	0.050
1.5 x high flow (from Kosa)	Tapovan	0.991	0.990	0.149	0.090
	Joshimath	0.992	0.990	0.292	0.090
	Power House	0.986	0.990	0.660	0.120

Table 2. Statistical performance evaluation of ANN model at basin scale

R^2	**NSE**	**PBIAS**	**RSR**
0.96	0.96	11.8%	0.21

4. DISCUSSION

The hydrodynamic simulation time is a crucial factor in flood forecasting and mitigation efforts. The duration of the simulation is dependent on several factors, including the dimension of computation and the geometry of the terrain. Typically, the simulation time ranges from 30 seconds for 1D to 40 minutes for 1D/2D models (Ghimire et al., 2022). However, 1D models are more sensitive to the terrain's geometry, which can vary significantly in complex regions such as mountainous areas. In the present study, a heterogeneous and complex geometry with uneven cross-section intervals and drastic slope variations was employed, resulting in a simulation time of 5 to 7 minutes. This time frame provides only 8 to 10 minutes of lead time for flood disaster mitigation actions. To address this issue, an artificial neural network (ANN) model was employed as a parallel modelling approach. The ANN model generated similar results in a matter of milliseconds, providing a 54% increase in lead time, which can vary based on peak flow values and regions. Moreover, incorporating IMD forecasts into the prediction model extended the forecast horizon, providing predictions for an additional day. It is important to note that the focus of this study was on a one-day rainfall forecast, as precipitation forecast accuracy tends to decrease with longer lead times. The integration of meteorological forecasts significantly enhanced the model's ability to offer extended lead times and longer-term predictions for rainfall runoff. These predictions hold immense value for applications such as flood forecasting, efficient water resource management, and comprehensive disaster preparedness.

The ANN model used in this study selected the input parameters that govern the outflow hydrograph. For basin outlet flood forecasting, precipitation and temperature were chosen, while the inflow hydrograph was included in the input layer for flood routing. Temperature is typically not considered an important parameter for runoff forecasting using ANN models (Kingston et al., 2005), but it is a significant parameter for runoff generation in Himalayan regions where snowmelt plays a crucial role (Chandel & Ghosh, 2021). Therefore, it is essential to determine input parameters based on data availability and strong correlation with the target layer (Yuan et al., 2020). The effectiveness of the ANN model heavily relies on the quality and quantity of available data (Chu et al., 2020). Inaccurate or insufficient data can result in unreliable forecasts, and for real-time systems, data continuity is crucial. For Artificial Intelligence (AI) based black box tools, data imbalance is common in flood forecasting, with a limited number of flood events compared to non-flood periods, which can be overcome using techniques like resampling or specialized loss functions. Lastly, flood patterns can change over time due to various factors, making the data non-stationary. ANN models may have difficulty adapting to such changes, necessitating regular data updates and model retraining.

The ANN model's flood routing performance was found to be satisfactory for high flow, which aligns with the study's focus on flood mitigation. The study's results demonstrate that ANN models can perform both flood forecasting and routing satisfactorily and can be useful in remote areas or arid mountainous regions where data are scarce. The main significance of this article lies in providing a network-based flood forecasting-flood routing framework. The ANN model's method is not limited to the approach used in this study, and superior methods can be selected based on regional characteristics to increase the model's prediction accuracy.

5. CONCLUSION

Sensor-based flood prediction faces a critical limitation as it hinges on detecting floods only once they have reached the sensor location, thereby initiating predictions after the flood event has already commenced. In contrast, artificial neural networks (ANNs) offer a distinct advantage by enabling prediction initiation immediately upon recording rainfall or measuring flow, thereby circumventing the delay inherent in conventional models, particularly in rugged terrains such as mountainous regions. In the depicted scenarios, the ANN model has exhibited remarkable performance across varying flow conditions, with average R2 and NSE values of 0.96 and 0.86, respectively. Notably, its performance excelled particularly in high-flow scenarios, showcasing exceptional average R2 and NSE values of 0.99. Moreover, when integrated with forecasts from the Indian Meteorological Department (IMD), ANNs can significantly enhance lead times. The application of ANNs for estimating flood potential at outlet points can save approximately 24 hours based on one-day precipitation forecasts. One notable strength of ANNs lies in their ability to function effectively with minimal observed data, often requiring data from just one or two locations for model training. This characteristic is particularly beneficial for remote basins where data availability is limited or absent altogether.

This methodology presents a promising solution, especially for smaller basins situated in remote regions where data scarcity poses a significant challenge and the lag time is relatively smaller. In essence, ANNs offer rapid results compared to alternative methods, thereby aiding in the mitigation of flash flood damage. These models can be trained to provide swift predictions and can be continuously updated in real-time as new data becomes available, thereby extending the lead time for flood forecasting. The use of ensemble learning and hybrid models can improve the accuracy and robustness of flood forecasting. When integrated with decision support systems, ANN-based models can provide actionable information for emergency response and management. However, regulatory frameworks and guidelines must be developed to ensure the reliability and accountability of these systems, especially when accounting for the effects of climate change.

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