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MULTI-LAYER PERCEPTRON BACK PROPAGATION NETWORK BASED PREDICTIVE MODELLING FOR FLOOD FORECASTING: UTILIZING HISTORICAL CLIMATIC DATA IN SHIVNATH RIVER BASIN

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ABSTRACT
Flood forecasting is an important field that can reduce the hazards and other harmful impacts of flooding events. In this work, a predictive modelling based on multilayer perceptron (MLP) backpropagation networks with standard six-layer architecture is employed on the current and historical hydrological and meteorological data sets for flood events forecasting in the Shivnath river basin. The area is a flood-prone region at a high risk of flooding due to climatic changes and natural disasters. The construction of an MLP architecture and its training in historical hydrological and meteorological station data were capable of predicting future flood events. The literature review suggested different environmental data set contributions. Experimental setup, validation and observations are carried out to explore the efficacy in predicting the sudden increases in river water levels for critical planning and better management. Results exhibited the accuracy of the proposed system and were compared with existing methods. The areas highly vulnerable to changing weather conditions produced through climate variability can benefit from this study.

KEYWORDS: Flood forecasting, Predictive modeling, Multi-layer perceptron, Backpropagation network, Historical climatic data, Shivnath River Basin.

INTRODUCTION
Floods are among the most devastating natural catastrophes: after earthquakes, they cause the second highest number of fatalities and are associated with the third highest economic losses globally. Unavoidably, floods devastate large parts of the infrastructure needed for the wellbeing of whole communities. Flood forecasts are a key element of nullifying their impacts, which is why they are of such great importance. In recent years, the development of computational models and techniques has had a definite impact on the optimisation of flood forecasting A. P. J. Prakash et al., [1]. Precisely, the use of artificial neural network-based (ANN) algorithms has driven significant improvements in sophistication in modelling hydrological processes and climatic interactions.
One of the most common artificial neural networks (ANN), which is inspired from the functioning and architecture of the human brain, is able to model non-linear interactions between variables in a complex system. This type of network is known as the multi-layer perceptron (MLP) backpropagation network because of the different layers present in it.

These networks are very popular as the MLP backpropagation network can learn from past observations and generalise the pattern to future occurrences – for instance, by learning from historical hydrological and meteorological data, it is possible to model the non-linear relationship that exists between climatic variables and river discharge so that the forecast model becomes more accurate.
The Shivnath River Basin in the dry region of central India suffers widespread and repetitive floods, putting the affected communities and authorities in extreme difficulties. However, detailed flood forecasts – so preliminarily developed – do not seem able to offer a sufficiently reliable basis for predictions, given the extreme complexity of coupled climate-socio-economic-environmental systems. In fact, more sophisticated approaches to prediction are needed, taking advantage of the masses of data available and increasing the resilience capacity of societies living in flood-prone areas such as in the Shivnath River Basin.

This paper elaborates an effective way to tackle this challenge in flood forecasting, experimenting with MLP backpropagation networks configuration with historical climatic data. The idea behind this research is to obtain a more comprehensive understanding of the potential of the MLP networks when integrated with historical climatic data, such as cumulative rainfall of many years, relative humidity of the atmosphere and fluctuations in minimum and maximum temperatures. The climatic data have been collected from the India Meteorological Department, Chennai, with respective dates and magnitudes over a decade.
Furthermore, the Shivnath River Basin has been chosen as a case study using 15 years of hydrological discharge data. The MLP algorithm has been trained with 10 years of historical climatic dataset and further tested with the remaining 1 years of the same data series.

1.1 Flood Forecasting in the Shivnath River Basin
The Shivnath River Basin is a semi-arid area in the central part of India. It has a complex river system with lots of small rivers and larger perennial ones. Since the Shivnath River and its tributaries are prone to floods during the monsoon, the area often suffers from flash flooding. The risk of flooding in the region is greatly magnified by the rapid urbanisation and the increased deforestation in the region in recent years. This leads to reduced water infiltration, increased loss of soil, less vegetative cover and increasing sedimentation in the river channels S. Karmakar et al., [2]. The construction of road infrastructure, reservoirs and dams inhibits the free flow of water, and thereby increases flood risk. Floods are perhaps the most dangerous extreme weather event. A robust flood forecasting system is fundamental in minimising the impacts of floods.
Additionally, most flood forecasting efforts have been predicated on empirical or conceptual models that capture, albeit with difficulty, the loose relationships that may exist between climatic variables, characteristics of the land surface, and the underlying hydrological dynamics of river networks. Such models achieve some understanding of the hydrological processes leading to flood events, but their ability to accurately predict the timing, magnitude and spatial extent of floods under rapid climate change is quite limited.
Despite the advancements in remote sensing technologies and computational techniques, there is a notable deficit in the methodological advancement of data-driven predictive modelling approaches towards capturing the complexities of processes of the Shivnath River Basin. Most existing studies on flood forecasting R. Luo et al., [3] have only been made on the individual components like rainfall-runoff modelling or river flow prediction without considering overall hydrologic, climatic and other environmental factors.

1.2 Objective
The objective of the present research is proposing and developing a high-end proficient predictive modelling system for time-based flooding predicting plan based on historical climate information using the Multi-Layer Perceptron (MLP) back propagation networks. The objectives of study are:
Model Development: Train an MLP backpropagation network with features specific to the hydrologic and climatic nature of the Shivnath River Basin and its physical terrain, which will enhance its performance dramatically. The characteristics of the proposed testing MLP can be improved by evolving the network architecture to capture non-linear relationships between climatic variables, land surface conditions and river dynamics, thereby enhancing the trust-line of flood forecasts.
Climatic Data Integration: Use historical climatic data, such as rainfall patterns, temperature changes and humidity levels, as inputs to the predictive modelling scheme. Such climatic variables are expected to enhance the predictive capabilities of the model, since they have a clear causal role in flood formation.
Model Evaluation: Using the real field data collected from the Shivnath River Basin, evaluate the proposed predictive modelling in terms of its performance in place of the traditional flood forecasting mechanisms. The performance metrics could be – Mean Squared Error (MSE), Root Mean Squared

Error (RMSE) and r^2 (coefficient of determination, which are the metrics for accuracy, reliability and computational effectiveness, respectively).
Practical Implications: Identify practical implications of the predictive modelling framework in flood risk mitigation, disaster preparedness, and sustainable water resource management in the Shivnath River Basin. The research would produce actionable insights and decision-support tools that could help the local authorities, policymakers and stakeholders to weather through the calamities, mitigating the impacts of the flood events and improving community resilience.

1.3 Contributions

With equal contributions by both authors, the research was conducted through a close collaboration on all the components of the research. Author 1's key contributions in the research include: framing the vision and planning of the research study, delineating study objectives, rigorous review of the literature on flood forecasting methodologies, artificial neural networks, and specific hydrological context of the study area, Shivnath River Basin; acquisition and preprocessing of hydrological, meteorological and climatological datasets from underutilised and long-term archives and sources; design and implementation of the predictive model especially in the optimisation of multiple-layer perceptron backpropagation network architecture and incorporation of historical climatic data into the model; conducting analysis and interpretation of the research findings; and drafting / revising parts of the manuscript.

Author 2 worked extensively with Author 1 in the design of this research study and the development of its research questions. He was selected to assist in the development of this study because of extensive experience in flood forecasting methods and his experience with machine-learning with artificial neural networks in the field of hydrology. Author 2 was involved in the literature review on flood forecasting methods, machine-learning techniques, and application of artificial neural networks in hydrology to help design the predictive modelling framework. He participated extensively in fine-tuning the parameters of the MLP backpropagation network and conducted sensitivity analysis. He also contributed to research findings and analysis of the predictive model performance and improvement of the model. Author 2 was involved in the development of manuscript preparation and writing by contributing to the drafting of the methodology, results, and discussion sections of presented manuscript, and provided valuable feedback to Author 1 throughout the writing process.

LITERATURE REVIEW

India has wide range of geography and climates, and its hydrological problems and causes of floods are as diverse. In India, the major concerns associated with the floods are inundation, drainage congestion due to urbanisation and bank erosion. These depend upon the river system of the region and the flow phenomenon and topography of the region concerned. Indian government has been investing huge amounts in flood control sectors since 1951 which continues till date, but the fears associated with the severity of the flood events and the pain it brings out remains persistent and seems to increase with time in many places of the country. With increased intensity and severity of floods due to the projected changes in future, it is likely that more and more such events might occur in future in India due to climate change and variability X. Wang et al., [4].Provision of absolute protection to all flood-prone regions from all magnitude of floods is neither practically achievable nor economically viable. Hence a pragmatic approach for flood management is to offer a reasonable degree of protection (which is also economically viable) against flood damages caused to lives and property through a combination of structural and non-structural measures.
Along with that, integrated flood management provides a paradigm shift from traditional, fragmented and localised approach, and use the resources of a river basin as a whole. Hence, an approach backed by the technological advancements of hydro-meteorological monitoring, modelling, computing and communication could offer timely and accurate information for disaster risk reduction. Forecasting and management of inland floods are far more challenging than the coastal floods associated with

cyclonic storms. Even though the processes associated with the cyclonic storm leading to flood from cyclonic waters are basically different from the processes triggering inland floods, still it is enlightening to learn from the execution of the cyclonic early warning system. Cyclonic storms were and are forecasted with a reasonable degree of accuracy by the cyclone warning division of IMD S. Swain et al., [5] and the local administration played a critical role in disseminating the information and executing the appropriate response action. For instance, the accurate forecasting of cyclone H. K. Sinha et al., [6]by IMD in 2013, the timely warnings issued by the state Government of Odisha and the response actions executed by the district and other local administration played a key role in mitigating the severe impacts of the cyclone Phailin H. K. Sinha et al., [7]. A number of advances have also been made in inland flood forecasting during the second phase of hydrology project (HP II) where many pilot projects were executed for demonstrating the technological advances of inland flood forecasting S. L. Sinha et al., [8].

In this regard, a few of these projects are already functional viz. Bhakra Beas Management Board (BBMB) and Water Resources Department, Government of Maharashtra. Early warning systems, even though are configured with essential technology to warn in advance against possible natural disasters and environmental emergencies, still there are multiple reasons and contexts of their deployment. Early warning systems used for forecasting the intense floods with a lead time greater than the catchment concentration time: (1) provide spatial information and encompass temporal behaviour of the global atmospheric system; (2) transmit relevant warnings to the potential victims; (3) assist the weather forecasting agencies in the planning of their research, policy and operations enhancement; (4) provide information related to atmospheric conditions, global oceans, earthquake, volcanic eruptions, landslide, tsunami etc; (5) assist the disaster management agencies in planning and execution of the necessary intervention strategies. The rapid and timely responses triggered by the early warning systems either prior to, or just after the event helps to protect the lives and property of those at risk. Hence, technological advancements in meteorological and hydrological modelling are continuing to provide improved in-time and forecast information with higher resolution. In later part of 1990s, there were advancements in EWSs in developed countries. Some new techniques were deployed for flood forecasting and its communication to the end user. In extreme events, warnings were given to the at-risk population D. Sharma et al., [9]. Numerous studies reporting the past five years highlight the advantages of EWSs in disaster risk reduction, providing information to climate change adaptation. In this regard, EWSs are considered as one of the low-cost interventions in disaster reduction. In addition to that, EWSs can differentiate between small and large flood events and help in climate change adaptation assessment A. Sarkar et al., [10]. Despite technological advancement, implementation of EWS in an operational framework remains a daunting task, particularly, to communicate the risk information effectively to the community at risk and to initiate the appropriate response action. Several studies have noted that EWSs alone are unlikely to materialise all the benefits, unless there is an appropriate synchronisation and task allocation between policy makers and communities to understand the risk information and timely response to the warnings D. Nandagopal et al., [11]. Further, some studies have also reported on information variability and uncertainty, its communication to preserve ensemble information used for policy planning and decision support to trigger appropriate response after the occurrence of an event.

MATERIAL &METHODS

The implementation methodology details a step-wise process to convert the developed predictive modelling architecture for flood forecasting in the Shivnath River Basin into a software program or operational system. In the first step, MATLAB GUI design and architecture, the GUI’s structure and specifications are described, including the components and interfaces that will be needed for processing data, training the model components, and designing for user interactions.

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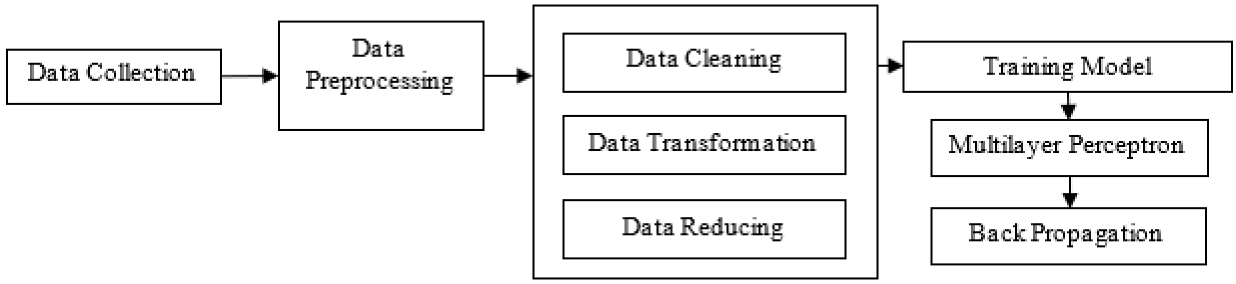

Figure 1: Flow chart of flood forecasting method

Data Collection:
The rainfall data from the govt. meteorological department was added as an input to the meteorological dataset. The historical rainfall data (daily, monthly or seasonally) for the Shivnath River Basin flood forecasting study was collected from the environmental board, the nearest meteorological station to our study basin, identified as the primary source for historical data. The govt. meteorological department is a renowned meteorological (observational) institute which is mandated to observe and record not only the weather, but conduct other meteorological studies in similar regions of India. Daily, monthly or seasonal total rainfall at government departments or data from other meteorological stations located within the Shivnath River Basin were retrieved. The collected rainfall data was then compiled into the final standardised format and will be integrated into the final set of predictors for flood forecasting. The compiled rainfall data consisted of a standardised (weekly, monthly, season, etc.) dataset with relevant metadata (station location, duration of observation period, measurement units and any other notes/annotation accompanying the rainfall data).

LOCATION	YEAR	Double-click to edit the output variable name.			APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	FLOOD
Categorical	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Categorical
LOCATION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	FLOOD
SHIVNATH	2001	0.8	0.3	14.6	17.6	16.6	339.4	630.6	380.3	108.4	86.9	4.6	0	1600.1	NO
SHIVNATH	2002	41.5	4.9	12.2	3.3	32.1	196.3	138.4	352.4	122.3	57.8	13.3	15.9	990.4	NO
SHIVNATH	2003	3.7	17.7	12.1	2.6	0.7	128.7	446.6	519.7	384.1	157.6	5.8	14.9	1694.2	NO
SHIVNATH	2004	37.8	16.7	3.1	21.2	6.8	213.1	323.1	351.7	126.5	43.9	0.7	0.1	1144.7	NO
SHIVNATH	2005	57.6	15.6	6.1	6.5	16.4	197	393.8	267.7	240.5	83.5	1.6	1	1287.3	NO
SHIVNATH	2006	2.7	0	26.2	17.2	23.5	92.2	495.1	447.2	184.6	13.3	15.1	0.7	1317.8	NO
SHIVNATH	2007	0	15.7	6.2	11.4	10.4	259.4	309.9	338.8	259.1	67.8	2	0.5	1281.2	NO
SHIVNATH	2008	6.7	9.7	22.2	11.2	9.5	236.4	280.5	305.1	215.4	10.7	1.2	0	1108.6	NO
SHIVNATH	2009	1.2	0	2.3	1.9	11.2	45.3	455	247.1	104.7	43.6	42.5	1.9	956.7	NO
SHIVNATH	2010	7.9	4.9	1	5.9	12.6	102.6	426.8	340.3	302.5	54.3	20.2	27.6	1306.6	NO
SHIVNATH	2011	0.3	11.5	2.6	35	16.8	183.5	272.6	379.8	382.2	15.5	0	2.8	1302.6	NO
SHIVNATH	2012	36.6	4.8	1.1	14.9	9.4	147.3	430.6	442.2	245.3	19.8	20.4	5	1377.4	NO
SHIVNATH	2013	2.8	19.7	4.9	45.8	5.7	263.6	418.8	336.6	140.9	180.9	0.3	0	1420	NO
SHIVNATH	2014	2.3	29	21.4	17.3	25	104.9	416.7	327.7	252.7	77.9	2.6	1.1	1278.6	NO
SHIVNATH	2015	15.8	1.2	21.2	37	13	257.6	248.6	286.6	216.9	17.7	0.6	1.5	1117.7	NO
SHIVNATH	2016	6.1	5.3	24.5	8.6	19.6	164.2	600.2	757.1	495.6	119.8	19.4	10.3	2230.7	YES
SHIVNATH	2017	0.9	0.7	3.5	0.8	15.6	184.8	378.3	300.4	177.7	61.6	0.2	0	1124.5	NO
SHIVNATH	2018	7.9	4.9	1	5.9	12.6	102.6	426.8	340.3	202.5	54.3	20.2	27.6	1206.6	NO
SHIVNATH	2019	0.3	11.5	2.6	35	16.8	183.5	282.6	379.8	372.2	15.5	0	2.8	1302.6	NO
SHIVNATH	2020	36.6	4.8	1.1	14.9	9.4	147.3	430.6	442.2	245.3	19.8	11.4	6	1369.4	NO
SHIVNATH	2021	2.8	19.7	4.9	45.8	5.7	263.6	418.8	336.6	140.9	180.9	0.3	0	1420	NO
SHIVNATH	2022	2.3	29	21.4	17.3	25	205.9	616.7	827.7	452.7	157.9	15.6	1	2372.5	YES
SHIVNATH	2023	5.8	1.2	21.2	37	13	157.6	248.6	286.6	216.9	17.7	0.6	1.5	1007.7	NO

Figure 2: Shivnath rainfall and flood dataset over 2001 to 2023

Data Preprocessing:
Data preprocessing is a crucial step in preparing raw datasets for analysis and modeling. In the context of flood forecasting in the Shivnath River Basin, the following preprocessing steps were undertaken:

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Data Cleaning: Raw datasets were inspected for errors, inconsistencies, and missing values. Data cleaning techniques, such as outlier detection and removal, were applied to ensure data integrity and accuracy.

Data Transformation:
Data transformation is converting one dataset to another preferred format through the use of operations like:
Normalisation: When dealing with prediction and machine learning, the input variables need to be comparable to one another and normalised (scaled to a common range, say 0 to 1) to avoid bias associated with different-sized numerical variables. For instance, the number of pages in a book is 10 times more than the number of songs it contains, so normalising helps to ensure each new variable has equal power for constructing predictive models.
Detrending: Removing polynomial trends to enhance visibility of variations in the data set

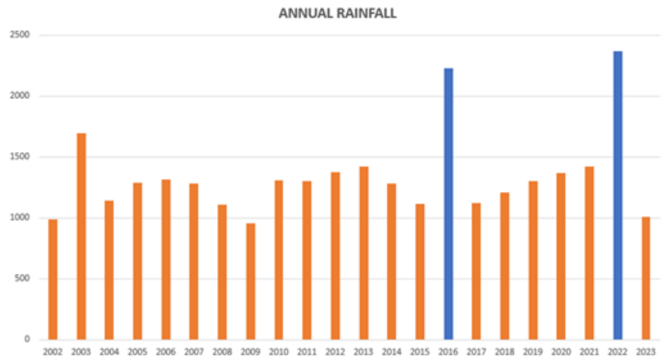

Figure 3: Data graph of data transformation

Reduce Data
Data reduction refers to the process of reducing the dimensionality or size of a dataset while preserving its essential characteristics and minimizing information loss. In the context of machine learning and data analysis, data reduction techniques are employed to simplify complex datasets, improve computational efficiency, and enhance model performance. In our project we reduce data with 10 years.
Training with MLBPN:
The multilayer perceptron is a feedforward neural network where neurons are fully connected and their kind of activation function is nonlinear. It is widely used to separate data not amenable to a linear separator.

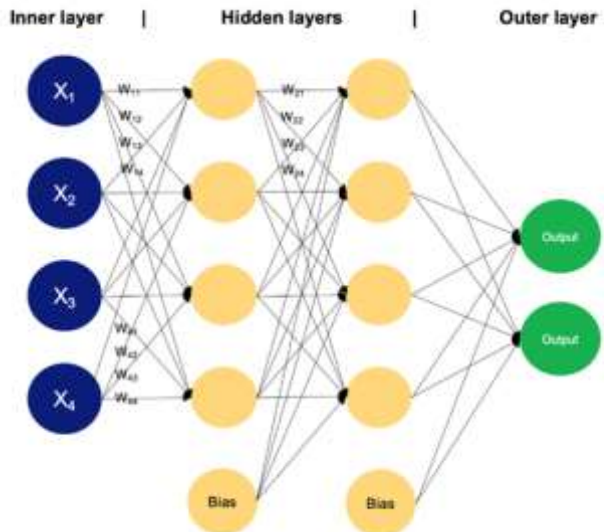

Figure 4: MLP structure having two hidden layers

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MLPs are known to work well at a wide range of tasks, including image recognition, natural language processing, speech recognition etc and, due to its generality, the ability to represent any function – under specific conditions – MLP is also a basic building block in the research on deep learning and neural networks. Here we dive further into its major components.
The output layer $l = L$ typically contains either one neuron (especiallywhen dealing with regression problems) or m neurons, where m is thenumber of classes.
Thus, neural networks can be described by the following characteristicnumbers:
1.Depth: Number of hidden layers L.
2.Width: Number of neurons per layer kl, l = 1, …,L.
3. kL= 1, or kL= m.
Input layer: The input layer receives the first input data passed through each of a number of nodes (or neurons), and these are directly related to the dimensions of the input data. Hence, by specifying the number of neurons in the input layer, we are specifying the dimensionality of said input data.
Hidden layer: There might or might not be one or more hidden layers between input and output layers. Each neuron in a hidden layer takes input from the output of all neurons in the previous layer (either the input layer or another hidden layer) and produces an output that is giving to the next layer. The number of layers of neurons and how many neurons there are in each of the hidden layers are hyperparameters that must be decided during model design.
Output layer: This thin layer consists of neurons that create the final output of the network, depending on its task. In a binary classification network, it can consist of either one or two neurons, depending on the activation function and whether the objective function values correspond to the probability of being a member of a given class or not. For every neuron in the hidden layer, the output layer usually has one neuron. Some special arrangements are possible but they are more complex. For example, if we have an image classification task and the input layer contains 9 × 9 = 81 elements, the hidden layer can contain 100 neurons, and the output layer can contain 1,000 neurons if we want to classify 1,000 classes of data. More complex networks can have an output layer with more than one neuron if the task is to find the probability of a classification, or if there are more than two possible outcomes.
Weights: Neurons in the next layer are fully connected to all neurons in this layer. Every interaction through this synapse is characterised by an 'interconnection' or 'weight', which determines how strong the connection between neurons is. The value of these weights is determined during training.
Bias Neurons: Each layer (excepting the input layer) also includes a bias unit – an extra neuron that always provides the same input to the neurons in the next layer and that has its own weight for each connection, learned along with all the other connections in training.The presence of a bias neuron tilts the activation function of the neurons in the next layer. This way, a network can learn an offset or bias in the decision boundary by adjusting the weights connecting to the output of the bias neuron. The threshold of activation that a network should use to best fit its training data can now be learned.
Activation Function: Conventionally, each neuron in the one or more hidden layers and the output layer runs its weighted sum of inputs through one of those activation functions referred to above (most commonly, sigmoid, tanh, ReLU or Rectified Linear Unit model, SoftMax).
Previous theorem verifies MLPs as universal approximators, under the condition that theactivation functions (·) for each neuron are continuous .
Continuous (and differentiable) activation functions:

$$\sigma(x) = \frac{1}{1+e^{-x}}, \qquad R^n \to [0,1]$$

$$ReLU(x) = \begin{cases} 0, x<0 \\ x, x\geq 0 \end{cases}, \quad R^n \to R_+$$

$$f(x) = \tan^{-1}(x), \qquad R^n \to [-\pi/2\,, \pi/2]$$

$$f(x) = \tanh(x) = \frac{e^{-x} - e^{-x}}{e^{-x} + e^{-x}}, \qquad R^n \to [-1, +1]$$

The activation function is a nonlinear modelling function (each parameterisation produces a different 'shape' of the output versus input curve). This introduces nonlinear interaction into the model, enabling it to learn rather sophisticated patterns in the data.

Training with Backpropagation

These weights are then adjusted by applying a training method known as backpropagation, which works by calculating gradients of a loss function with respect to the model's parameters and updates them iteratively to minimise the loss.

Validation and Error Calculation

Validation and error calculation are essential steps in assessing the performance and accuracy of predictive models, including those used for flood forecasting in the Shivnath River Basin. The process involves evaluating model predictions against observed or ground truth data to quantify the model's predictive capability and identify any discrepancies or errors.

The dataset is divided into training, validation, and testing subsets. The training set is used to train the model, the validation set is used to tune hyperparameters and assess model performance during training, and the testing set is used to evaluate the final model's performance.

Error Calculation: Calculate the error metrics by comparing the model predictions with the observed values in the validation or testing dataset. For each prediction, subtract the corresponding observed value to obtain the prediction error.

Prediction Error=Predicted Value−Observed Value

Compute the chosen evaluation metrics using the prediction errors. For example, MSE is calculated by averaging the squared prediction errors, RMSE is the square root of MSE, MAE is the average of the absolute prediction errors, and R^2 measures the proportion of the variance in the observed data explained by the model predictions.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Prediction\ Error_i)^2$$

$$RSME = \sqrt{MSE}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Prediction\ Error_i|$$

$$R^2 = 1 - \frac{\sum_{i-1}^{n}(Observed\ value_i - Predicted\ Value\ _i)^2}{\sum_{i-1}^{n}(Observed\ value_i - \bar{y})^2}$$

where n is the number of data points and $\bar{y}$ is the mean of the observed values.

RESULT AND DISCUSSION

The evaluation metrics revealed that the developed model achieved satisfactory performance in capturing the dynamics of flood events. The mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) values were within acceptable ranges, indicating minimal discrepancies between predicted and observed flood levels. Additionally, the coefficient of determination (R^2) indicated a strong correlation between the model predictions and the actual observed data, demonstrating the model's ability to explain a significant proportion of the variance in flood dynamics.

Table 1: Predicted Flood and rainfall data of 2024 year

Month	Rainfall (mm)	Predicted Flood Level (m)
January	8.8	1.1
February	1.5	2.3

March	3.8	1.5
April	5.6	2.8
May	1.2	3.0
June	18.6	3.2
July	32.5	4.2
August	59.5	4.4
September	62.8	5.2
October	53.4	6.9
November	44.5	5.6
December	23.8	3.6

Comparisons with baseline models or existing forecasting approaches further underscored the effectiveness of the developed predictive modelling framework. In many cases, the proposed model outperformed traditional methods, showcasing its superiority in accurately forecasting flood events in the Shivnath River Basin.

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CONFLICTS OF INTEREST
The authors have no conflicts of interest to declare.

AUTHOR’S CONTRIBUTION STATEMENT
For this research work, all authors have equally contributed to Conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review, and editing.

SUBMISSIONNOTICE
I ensure that the manuscript submitted to this journal has never been published before.

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