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FLOOD FORECASTING BY USING MACHINE LEARNING

[1]Mrs. V. Mounika(Assistant professor),
[2]JASWANTH TEJA P, [3]BHUVAN CHANDER N, [4]DEVI VARA PRASAD MUDAM, [5]GOPICHAND GOLLA,

Department: CSE(IOT),
MALLA REDDY INSTITUTE OF TECHNOLOGY AND SCIENCE, Telangana, Hyderabad.

Abstract—

An overflow of a substantial volume of water onto land is known as a flood. In response to changes in water level or discharges from hydraulic infrastructure, a flood prediction (FF) system will sound an alarm. The use of artificial neural networks (ANNs) in flood forecasting has greatly improved hydrology's capacity to foresee and prepare for potential disasters. In order to adapt to changing weather patterns, flood prediction systems are increasingly turning to machine learning algorithms (MLAs). The Upper Wardha project, which spans the whole Wardha river basin, is the focus of this study on flood prediction. In order to determine when to open and close the gate in real time using artificial neural networks (ANN), flood forecasting (FF) uses real-time estimate to provide the flood value.

Introduction

Reduced risks to human and environmental life may be achieved by flood forecasting, which is the practice of estimating the timing and length of floods based on the topographical features of river basins. Forecasting the incidence and size of flash floods at certain times is a challenging task for flood forecasting techniques. Flooding occurred as a result of persistent precipitation over a period of time. Regular rains may potentially build up to devastating floods if left unchecked. To reduce the risks to non-structural buildings via efficient and cost-effective management, flood forecasting methods are crucial. The government is notified of impending floods via a network of flood forecasting stations that cover areas prone to flooding. Hydraulic structures, like dams, rely on inflow forecasts to control the opening and shutting of spillway gates. There are many various kinds of flood structures that are necessary, including flood warning systems and methods for flood forecasting. Dams, weirs, and dykes may lessen the severity of floods but cannot eradicate them entirely. Methods for flood prediction that may provide early warning and reduce risks to people and the environment in real time [1].

One method for predicting floods is the rainfall-runoff and flood-routing model. The watershed or catchment area determines the inflow predicted by the flood prediction at specific sites along rivers throughout time. The downstream side then provides an evaluation of uncertainty, together with a restricted flood prediction based on transit time, to adequately support the decision-makers' operations [9]. Adapting flood risk assessments to changing climatic conditions via the use of artificial intelligence (AI) requires a deep understanding of how machine learning algorithms (MLAs) work. The process of flood forecasting involves collecting historical and current flood records, as well as real-time data collected from rain gauges at various return times, to train a machine learning system. Sources of the dataset include infiltration rate, water levels measured by automated rain gauges connected to satellite technology, and rainfall-runoff. This research focused on the area around the Wardha River. In the Vidharbha area of Maharashtra state, there is a significant irrigation project called the Upper Wardha project. Near the hamlet of Simbhora in the Taluka Morshi of the Amravati district, this project is located across the Wardha River. A gated spillway in the middle and a canal on each side make up the Upper Wardha project's physical features. In the Godavari River Basin, where the catchment receives an average rainfall of 840 mm, the Upper Wardha dam has a total grass irrigation (GI) area of 11690 ha and a gross capacity of 786 MCM.

2. Literature Review

For flood forecasting in the Tar River basin, the Muskingham equation is used in a mix of single and multi inflow model forms [11]. The Godavari River basin makes use of real-time flood forecasting, which improves model accuracy by calculating flood plain inundations and saves 12 hours compared to the usual technique [12]. AI-powered flood prediction tool [13]. A method for estimating stream flows that uses multiple linear regression to provide rainfall runoff data [14].

Critical review of current and future flood prediction and early warning systems in the United Kingdom and Scotland [15]. When comparing statistical and ANN approaches for river Mahanadi flood forecasting, the results show that ANN methods are more efficient and perform better after calibration [16].

The following are the many kinds of floods and how they are classified.

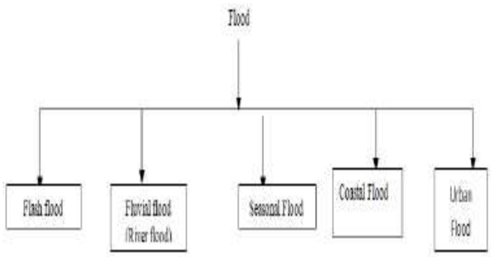


Fig.1:- Types and classification of flood

3. Methodology

A. Flood Forecasting Models: The length of time between rainfall and runoff, the intensity of the rainfall and runoff, the form of the catchment and its features, and the geographical extent are all factors that influence flood forecasting models. The use of time series analysis to stochastic models in hydrology [17]. Hydrological models have a hard time with flood prediction. Here are several different kinds of hydrological modeling structures:

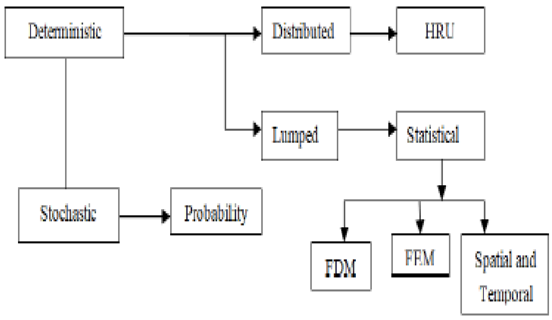
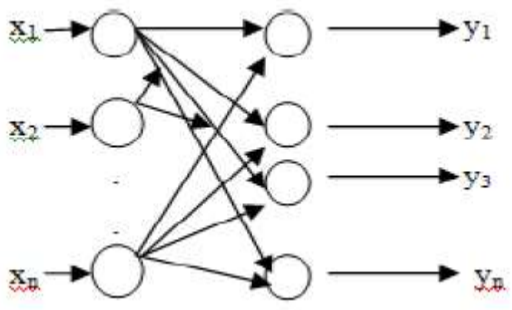


Figure 2: Structures for hydrological modeling

Flood Forecasting Using Artificial Neural Networks and Machine Learning (B.):- Neural Networks, which are reduced representations of the Neuronal System in a living organism. An example of a basic data set that ANN can handle is big data [18]. ANNs may be categorized into three main types: back propagation networks, multilayer feed forward networks, and single layer networks.



The Neural Network Model (Fig.3)

Method for Machine Learning (C)

The data on rainfall and runoff that is accessible in real-time form the basis of the real-time model. To further understand real-time flood forecasts, consider the following flow diagram. The method of estimating reservoir levels, storage volumes, and outflow rates at certain inflow hydrographs at different instants is known as flood forecasting. Variables like as rainfall intensity, runoff, evaporation, evapotranspiration, temperature, and the geometry of the catchment area are major determinants of the frequency and severity of floods. With the help of the Muskingum Equation, which provides the values of the input and outflow rates, the data required for flood routing may be understood. Machine learning is trained and trained on data collected from reservoir routing in order to make predictions and learn from real-time data. Due to its simplicity, the Muskingum technique of stream flow routing is most often employed. It works with known input hydrograph and certain fitted parameters without seeking more information.

You should not use this approach in situations where the reach is often impacted by back water or unstable flow conditions; instead, it is best suited for gradually varying flows if you want a high degree of precision.

Inflow, outflow, and storage change are governed by the connection

Storage=inflow-outflow

$$\vec{I} - \vec{O} = \Delta S$$

In this case, the average outflow throughout the specified time period is Volume of water held in the reservoir is denoted by Δ S.

$$\int_{S_j}^{S_{j+1}} S = \int_{j\Delta t}^{(j+1)} I(t)dt - \int_{j\Delta t}^{(j+1)\Delta t} Q\ (t)dt$$

At the beginning and conclusion of the jth time period, the values that flow in are Ij and Ij+1, respectively, whereas the values that flow out are Qj and Qj+1. Using explicit training, machine learning is possible to learn and enhance systems. Computer programs may now learn how to approach, gather, or retrieve data using machine learning.

Machine learning is capable of processing massive datasets.

Improve your flood forecasting and early warning systems with the use of artificial intelligence (AIS) training data.

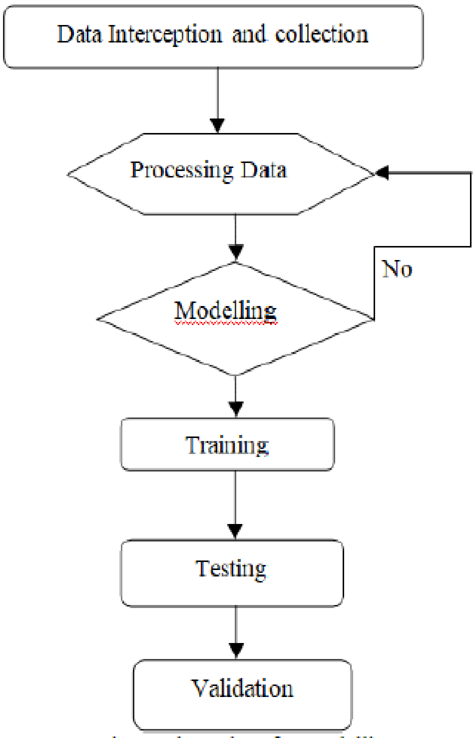


Fig. 4: Flow Chart for Modelling

4. Results and Conclusion

Using ANN in conjunction with ML and the stochastic method yields the following outcomes.

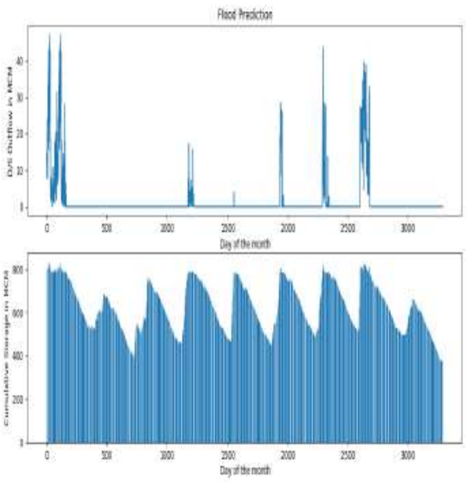


Fig.5: Cumulative Storage and days

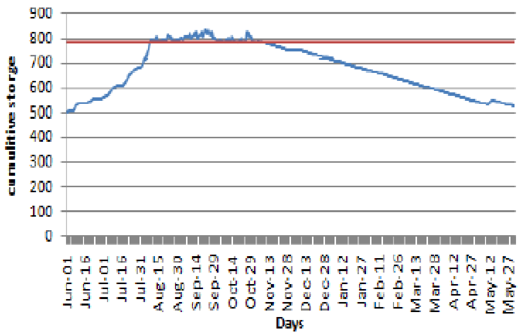


Fig.5: Cumulative Storage and days

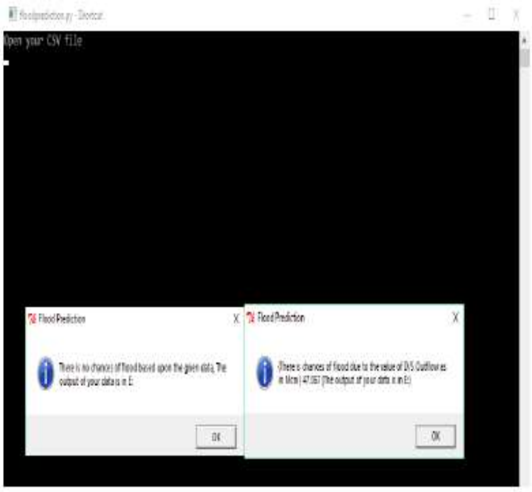


Figure 7: Flood Forecasted Outflow Value for Gate Opening

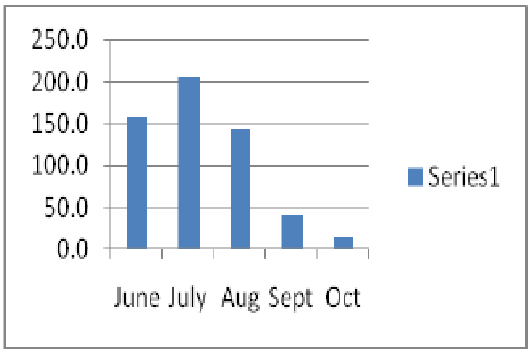


Fig.8:- Hyetograph

The best flood prediction methods are well-structured and rely on evaluations of rating criteria and existing data. There is a probability of flood value in the GUI when flood forecasting is done using real-time estimate. Machine learning-based real-time flood estimation can immediately compute massive amounts of data. The results of a comparison between machine learning-based flood modeling and the stochastic technique (i.e., the Muskinghum method) show that machine learning is more practical, easier, and more accurate. The predicted inflow rate in the reservoir determines when the gate is opened and closed.

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