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SMART FLOOD PREDICTION SYSTEM WITH FEDERATED LEARNING ARCHITECTURE

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ABSTRACT

Floods are among the most destructive natural disasters, causing significant damage to life, property, and infrastructure, thereby highlighting the need for accurate and timely forecasting systems. This study proposes a Flood Forecasting Model (FFM) using Federated Learning combined with deep learning techniques to enhance prediction accuracy while preserving data privacy. The model leverages distributed data from multiple sources such as weather stations, river sensors, and satellite data without transferring raw data to a central server. Instead, local models are trained on decentralized datasets using deep learning architectures such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks to capture temporal patterns in hydrological data. The trained models are then aggregated through a federated learning framework to produce a global model with improved generalization. This approach ensures data security, reduces communication overhead, and enables collaboration among different organizations without compromising sensitive information. Experimental results demonstrate that the proposed model achieves higher prediction accuracy and robustness compared to traditional centralized approaches, making it suitable for real-time flood prediction and disaster management systems.

Keywords

Flood Forecasting, Federated Learning, Deep Learning, LSTM, RNN, Hydrological Data, Time Series Prediction, Disaster Management, Distributed Learning

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I. INTRODUCTION

Floods are one of the most frequent and devastating natural disasters, causing extensive damage to human life, agriculture, infrastructure, and the environment. Accurate and timely flood forecasting is essential for effective disaster preparedness, early warning systems, and risk mitigation. Traditional flood prediction methods rely on hydrological models and centralized data processing, which often face challenges such as limited data availability, delayed information sharing, and reduced accuracy in dynamic environmental conditions.

With the advancement of artificial intelligence, deep learning techniques have shown significant potential in improving flood forecasting by analyzing large volumes of time-series data such as rainfall, river flow, and weather conditions. Models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are particularly effective in capturing temporal dependencies and patterns in hydrological data, leading to more accurate predictions. However, these approaches typically require centralized data collection, raising concerns about data privacy, security, and ownership, especially when data is distributed across multiple agencies and regions.

II. LITERATURE REVIEW

Recent research in flood forecasting highlights the growing use of deep learning techniques to improve prediction accuracy and reliability. Traditional hydrological models, while effective, often struggle with nonlinear patterns and dynamic environmental changes, leading researchers to adopt machine learning and deep learning approaches for better performance [1][2].

Deep learning models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been widely used for flood prediction due to their ability to capture temporal dependencies in time-series data like rainfall, river discharge, and weather conditions [3]. These models have shown significant improvements over conventional methods, particularly in handling complex and large-scale datasets [4].

With increasing concerns about data privacy and data sharing limitations, federated learning has emerged as a promising approach for distributed model training. It enables multiple organizations to collaboratively train models without sharing raw data, thereby preserving data confidentiality while improving model generalization [5].

Recent studies have explored the integration of federated learning with deep learning models for environmental and disaster prediction

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applications. These approaches demonstrate improved scalability, reduced communication overhead, and enhanced privacy protection compared to centralized systems [6][7].

Despite these advancements, existing systems still face challenges such as communication efficiency, model convergence, and handling heterogeneous data sources. Therefore, there is a need for a robust framework that effectively combines federated learning and deep learning for accurate and privacy-preserving flood forecasting [8].

III. EXISTING SYSTEM

The existing systems for flood forecasting primarily rely on traditional hydrological models and centralized machine learning approaches. Conventional methods use physical and statistical models to analyze rainfall, river discharge, and environmental factors to predict flood events. While these models provide useful insights, they often struggle to handle complex, nonlinear relationships in large-scale and dynamic datasets, leading to limited prediction accuracy.

With the advancement of artificial intelligence, centralized deep learning models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been introduced to improve forecasting performance. These models are capable of capturing temporal patterns in time-series data and have shown better accuracy compared to traditional approaches. However, they require large amounts of data to be collected and stored in a central server, which raises concerns related to data privacy, security, and ownership.

IV. PROPOSED SYSTEM

The proposed system presents a **Flood Forecasting Model (FFM)** using **Federated Learning integrated with deep learning techniques** to provide accurate, scalable, and privacy-preserving flood prediction. Unlike traditional centralized systems, this approach enables multiple data sources to collaboratively train a global model without sharing raw data, ensuring data security and ownership.

The system architecture consists of multiple components, starting with **data sources** such as weather stations, river sensors, satellite data, and historical hydrological records. Each data source acts as a local client where data is stored and processed independently. The collected data includes parameters like rainfall, temperature, humidity, river water levels, and flow rates.

At each local node, **deep learning models** such as Long Short-Term Memory (LSTM) or Recurrent Neural Networks (RNNs) are trained using the local time-series data. These

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models are capable of capturing temporal patterns and predicting future flood conditions. Instead of sending raw data to a central server, only the trained model parameters (weights) are shared.

V. METHODOLOGY

The proposed Flood Forecasting Model (FFM) using Federated Learning and deep learning follows a structured methodology to ensure accurate and privacy-preserving predictions. The process begins with **data collection**, where hydrological and meteorological data such as rainfall, river water levels, temperature, humidity, and flow rates are gathered from multiple distributed sources including weather stations, river sensors, and satellite systems. These datasets are stored locally at each participating node to maintain data ownership and privacy.

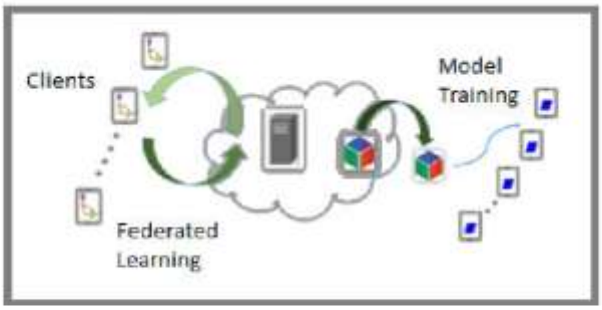
The next step involves **data preprocessing**, where the collected data is cleaned, normalized, and transformed into a suitable format for model training. Missing values are handled, noise is reduced, and time-series sequences are generated to capture temporal dependencies. This step ensures consistency and improves the quality of input data for deep learning models.

Following preprocessing, **local model training** is performed at each node using deep learning algorithms such as Long Short-Term Memory (LSTM) or Recurrent Neural Networks (RNNs). These models are trained on local datasets to learn patterns and trends in flood-related parameters. Once training is complete, only the model parameters (weights) are shared with the central server instead of raw data.

In the **federated learning process**, the central server aggregates the model updates received from all local nodes using techniques such as weighted averaging. This aggregated global model captures knowledge from multiple data sources while preserving privacy. The updated global model is then sent back to local nodes for further training, and this iterative process continues until the model converges.

VI. SYSTEM MODEL

System Architecture



VII. RESULTS AND DISCUSSIONS

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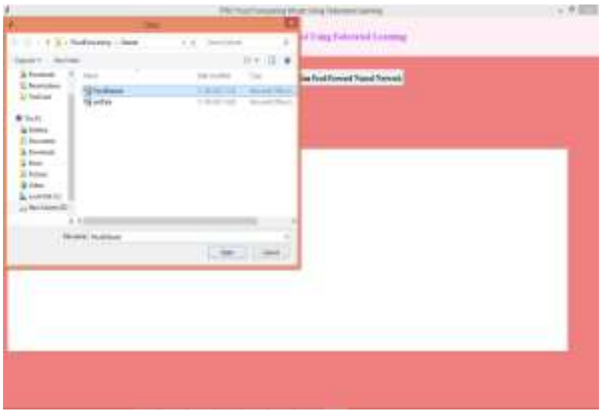
In above screen click on 'Upload Flood Dataset' button to load dataset and get below screen



In above screen selecting and uploading 'Flood Dataset' and then click on 'Open' button to load dataset

In above screen dataset loaded and now click on 'Pre-process Dataset' button to process dataset and get below output

In above screen dataset pre-processing such as normalization and shuffling completed and now click on 'Train & Test Split' button to split dataset and get below output

In above screen displaying dataset size and then displaying train and test size and now click on 'Run Feed Forward Neural Network' button to train propose FFNN algorithm and get below output

In above screen FFNN training completed and in above graph x-axis represents Number of Days and y-axis represents Water level where

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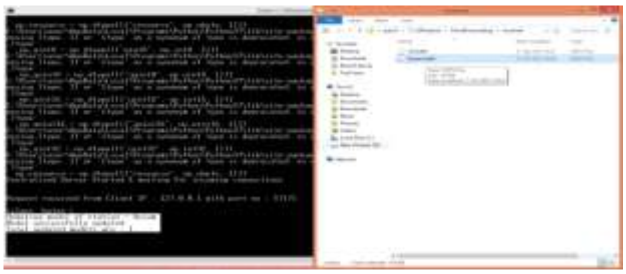
red line represents True water level and green line represents Predicted water level and we can see both lines are fully overlapping with little gap so we can say predicted and true values are very close and FFNN giving best prediction and now close above graph to get below output

In above screen in first 3 lines we can see FFNN algorithm MSE, RMSE and accuracy values and then we can see true and predicted water levels for future days and now click on 'Run Extension CNN2D Algorithm' button to train extension algorithm

In above screen with extension we can see both predicted and true which means reads and green lines are fully overlapping so we can say extension model is better than propose and we can see MSE and RMSE also lower compare to propose and accuracy is high for extension algorithm and now close above graph and then click on 'Upload Federated Model to Server' button to upload trained model to server and get below output

In above screen just enter some station name and then click OK button to upload model to server and get below output

In above screen we got response from server as 'model uploaded' and in below server screen we can see received model details



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In above screen in white colour text we can see server output about model saving and in server 'received' folder we can see 'Assam' model is saved and similarly for all given station server will saved model.

In above comparison graph x-axis represents algorithm names and y-axis represents accuracy and MSE values and we can see for extension algorithm accuracy is high and MSE, RMSE error is lower compare to propose FFNN algorithm and now close above graph and then click on 'Flood Forecasting using Test Data' button to upload test and then predict water level

In above screen uploading test data and then click on 'Open' button to get below output

In above screen before arrow symbol we can see test data and after arrow symbol =➔ we can see predicted water level

VIII. CONCLUSION

The proposed Flood Forecasting Model (FFM) using Federated Learning and deep learning techniques provides an efficient and privacy-preserving solution for accurate flood prediction. By combining the strengths of deep learning models such as LSTM and RNN with federated learning, the system is able to capture complex temporal patterns in hydrological data while ensuring that sensitive data remains decentralized and secure.

The approach overcomes the limitations of traditional and centralized systems by reducing data sharing risks, improving scalability, and enabling collaboration among multiple data sources. The use of distributed learning not only enhances prediction accuracy but also supports real-time forecasting and early warning systems, which are crucial for disaster management.

IX. FUTURE WORK:

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The proposed Flood Forecasting Model (FFM) using Federated Learning can be further enhanced in several ways to improve its accuracy, efficiency, and real-world applicability. Future work may focus on integrating more advanced deep learning architectures such as Transformer-based models and hybrid frameworks to better capture complex spatial-temporal patterns in flood-related data. Incorporating additional data sources such as real-time satellite imagery, radar data, and geographic information systems (GIS) can further improve prediction reliability.

Another important direction is optimizing the federated learning process by reducing communication overhead, improving model convergence, and handling heterogeneous data distributions across different nodes. Techniques such as adaptive aggregation, compression methods, and asynchronous updates can be explored to enhance system performance.

The system can also be extended by integrating edge computing for real-time local predictions and faster response during critical situations. Additionally, implementing explainable AI (XAI) techniques will help in making the model's predictions more transparent and understandable for decision-makers.

XI. REFERENCES

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, 2015.

[2] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.

[3] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, 1997.

[4] K. Cho et al., "Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation," *EMNLP*, 2014.

[5] H. B. McMahan et al., "Communication-Efficient Learning of Deep Networks from Decentralized Data," *AISTATS*, 2017.

[6] J.V.ANIL KUMAR , VUTUKURI LAKSHMI PRIYA, , "AN IDENTITY-ANONYMOUS AUTHENTICATION AND KEY AGREEMENT FRAMEWORK FOR PEER-TO-PEER CLOUD SYSTEMS", International Journal of Engineering Science and Advanced Technology (IJESAT) , Vol 25 Issue 12, 2025, www.ijesat.com, https://doi.org/10.64771/ijesat.2025.039, Page 306 to 316, ISSN:2250-3676, 2025.

[7] J.V.Anil Kumar, Tanguturi Naga Trisha," INTELLIGENT VIDEO CONTENT GENERATION USING DEEP LEARNING", International Journal of Engineering Science

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and Advanced Technology (IJESAT) Vol 25 Issue 12,2025, www.ijesat.com, https://doi.org/10.64771/ijesat.2025.044, Page 357 to 364, ISSN:2250-3676, 2025.

[8] J.V. Anil Kumar, Nagella Swarupa Rani,” SECURE DATA TRANSMISSION THROUGH HYBRID CRYPTOGRAPHY AND STEGANOGRAPHIC TECHNIQUES”, International Journal of Engineering Science and Advanced Technology (IJESAT) Vol 25 Issue 12,2025, www.ijesat.com, https://doi.org/10.64771/ijesat.2025.046, Page 373 to 383, ISSN:2250-3676, 2025.