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Flood Forecasting System Using Federated Learning

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Abstract: *Floods are among the most destructive natural disasters affecting millions worldwide. This paper proposes a federated learning-based flood forecasting system that enables decentralized model training while preserving data privacy. The system integrates environmental data such as rainfall, river levels, humidity, and temperature with machine learning and deep learning models including FFNN and CNN2D. The federated approach improves scalability, reduces communication overhead, and enhances prediction accuracy. Experimental evaluation shows reliable performance suitable for real-time disaster management systems.*

Keywords*: Floods*

I. INTRODUCTION

Flood prediction plays a crucial role in disaster management and early warning systems. Traditional centralized forecasting models face challenges such as data privacy risks, limited scalability, and delayed processing. With the rapid growth of IoT devices and environmental sensors, massive data is generated across multiple regions. Processing this data centrally is inefficient and insecure. Federated learning addresses these issues by enabling distributed model training without sharing raw data. This approach improves privacy, reduces latency, and enhances collaboration across multiple locations.

II. LITERATURE REVIEW

Earlier research focused on statistical techniques such as regression and time-series models for flood prediction. These methods provided baseline performance but lacked adaptability to complex patterns. Machine learning approaches like Decision Trees, Random Forest, and Support Vector Machines improved prediction accuracy by learning from historical data. Deep learning models such as CNN and LSTM further enhanced performance by capturing spatial and temporal dependencies. Federated learning has recently emerged as a privacy-preserving paradigm and has been successfully applied in healthcare and finance. However, its application in flood forecasting remains limited and requires further investigation.

III. DATASET DESCRIPTION

The dataset used in this study includes environmental parameters such as rainfall intensity, river water levels, humidity, and temperature. It contains 115 records with 12 features. Data preprocessing includes cleaning missing values, normalization, and feature scaling. The dataset is divided into training and testing sets in an 80:20 ratio. Proper preprocessing ensures better model generalization and reduces overfitting.

IV. SYSTEM ARCHITECTURE

The proposed system consists of multiple local nodes and a central aggregation server. Each node trains a local model using its own dataset. The local models include FFNN for baseline prediction and CNN2D for advanced feature extraction. The trained model updates are sent to the central server, where they are aggregated to form a global model. This architecture ensures data privacy, scalability, and efficient learning across distributed environments.

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Fig. 1. Dataset Upload Interface

V. METHODOLOGY

The methodology includes data collection, preprocessing, feature extraction, and model training. FFNN is used to establish baseline performance, while CNN2D extracts complex spatial features from input data. Federated learning aggregates model updates from multiple nodes without sharing raw data. The final global model is used for flood prediction and early warning generation, ensuring both accuracy and data privacy.

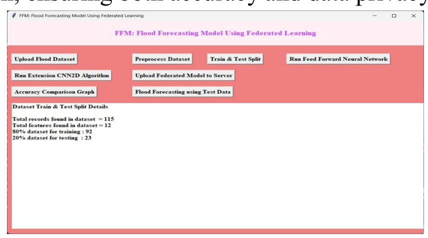

Fig. 2. Accuracy Comparison Graph

VI. RESULTS AND DISCUSSION

The experimental results demonstrate that CNN2D outperforms FFNN in terms of prediction accuracy and error reduction. The predicted water levels closely match actual values, indicating high reliability. Federated learning enhances performance by combining knowledge from distributed datasets while maintaining privacy.

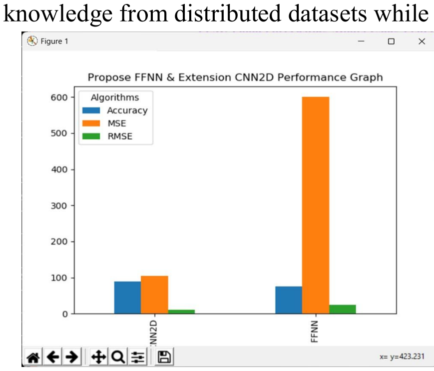

Fig. 3. Water Level Prediction Graph

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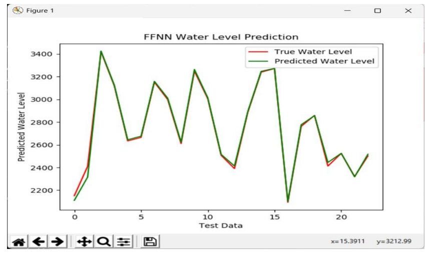

Fig. 4. Model Performance Visualization

VII. PERFORMANCE METRICS

The system is evaluated using Accuracy, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Accuracy measures the overall correctness of predictions, while MSE and RMSE quantify prediction errors. The results indicate high accuracy and low error rates, demonstrating the effectiveness of the proposed system.

VIII. APPLICATIONS

The proposed system can be deployed in disaster management agencies, government monitoring systems, smart cities, and early warning systems. It helps reduce risks, improve preparedness, and support decision-making during emergencies.

IX. FUTURE SCOPE

Future work includes integration with IoT sensors for real-time data collection, deployment of mobile applications for alert systems, and incorporation of advanced deep learning models such as LSTM and Transformers. Cloud-based federated learning can further enhance scalability and performance.

X. CONCLUSION

This paper presents a federated learning-based flood forecasting system that improves prediction accuracy while preserving data privacy. The integration of machine learning and deep learning models ensures reliable performance, making the system suitable for real-world deployment.

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