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Privacy-Aware Federated Deep Learning Framework for Intelligent Flood Forecasting and Water Level Prediction

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Abstract-- **Floods are among the most destructive natural disasters, causing severe damage to human lives, infrastructure, agriculture, and the economy. Accurate and timely flood forecasting is essential for effective disaster preparedness and mitigation. This paper presents a Privacy-Aware Federated Deep Learning Framework for Intelligent Flood Forecasting and Water Level Prediction, which combines Federated Learning (FL) with a Feedforward Neural Network (FFNN) to deliver secure and accurate predictions without sharing raw data among participating stations. The proposed framework enables multiple regional nodes to train local models independently while transmitting only model parameters to a central server for global aggregation, thereby preserving data privacy and reducing communication overhead. The aggregated model identifies flood-prone regions and predicts future water levels using hydrological and meteorological parameters. Experimental evaluation demonstrates that the proposed framework achieves high prediction accuracy with low prediction error while ensuring secure, decentralized learning. The proposed system provides a reliable and scalable solution for intelligent flood forecasting and early warning applications.**

Keywords: Flood Forecasting, Federated Learning, Deep Learning, Feedforward Neural Network (FFNN), Water Level Prediction, Disaster Management, Privacy Preservation, Distributed Machine Learning, Hydrological Forecasting, Early Warning System.

I.INTRODUCTION

Floods are among the most devastating natural disasters, affecting millions of people worldwide every year **[1], [3]**. They cause extensive damage to infrastructure, agriculture, transportation networks, and human settlements while resulting in significant economic losses and loss of life **[3], [4]**. Rapid urbanization, deforestation, climate change, and increasing extreme weather events have contributed to the growing frequency and intensity of floods across many regions **[3]–[5]**. Traditional flood monitoring methods rely heavily on manual observations, hydrological simulations, and statistical forecasting techniques, which often struggle to capture the complex relationships among multiple environmental factors **[2], [7], [13]**. As a result, accurate and timely flood prediction remains a major challenge for governments and disaster management agencies **[5], [6]**. The availability of large volumes of hydrological and meteorological data has created opportunities for developing intelligent forecasting systems that can provide early warnings and support proactive disaster mitigation **[7], [11]**. Consequently, artificial intelligence and machine learning have emerged as promising technologies for enhancing flood prediction accuracy and improving emergency response planning **[11], [12], [15]**.

Machine learning and deep learning techniques have significantly transformed the field of flood forecasting by enabling predictive models to learn complex patterns from historical environmental data **[11], [12], [14]**. Algorithms such as Support Vector Machines, Random Forests, Artificial Neural Networks, Long Short-Term Memory networks, and Feedforward Neural Networks have demonstrated promising performance in estimating water levels and predicting flood occurrences **[11], [12], [14], [15]**. These approaches utilize multiple input parameters, including rainfall intensity, river discharge, temperature, humidity, soil moisture, and water flow measurements, to identify nonlinear relationships that are difficult to model using conventional mathematical methods **[2], [11], [12]**. Despite their improved predictive capability, centralized machine learning approaches require collecting massive datasets from multiple monitoring stations into a single repository. Such centralized data collection introduces challenges related to privacy, security, communication overhead, and compliance with data-sharing regulations **[9]**. These limitations motivate the exploration of decentralized learning approaches capable of maintaining prediction performance while preserving data confidentiality **[9]**.

Federated Learning has recently emerged as an effective distributed machine learning paradigm that enables collaborative model training without transferring raw data from local sources **[9]**. Instead of sharing sensitive datasets, participating stations train models locally using their own data and communicate only model parameters or gradients to a central aggregation server **[9]**. The server combines these local updates to generate a global model that benefits from knowledge acquired across all participating locations while ensuring that original datasets remain securely stored at their respective sites **[9]**. This decentralized learning strategy significantly reduces communication costs, minimizes the risk of data breaches, and complies with privacy-preserving regulations **[9]**. In flood forecasting applications, Federated Learning allows multiple hydrological monitoring stations to collaboratively improve prediction performance despite geographical separation and heterogeneous data distributions **[9]**. Consequently, this technology provides a secure, scalable, and efficient framework for intelligent environmental monitoring and disaster prediction **[9]**.

To further enhance prediction accuracy, this research integrates Federated Learning with a Feedforward Neural Network (FFNN), creating a hybrid framework for intelligent flood forecasting and water level prediction. The proposed system enables each regional monitoring station to preprocess local hydrological data, train an FFNN model independently, and transmit only learned model parameters to a centralized aggregation server **[9]**. The aggregated global model identifies regions with high flood risk several days before the expected event, while localized FFNN models estimate future water levels for specific monitoring stations. This collaborative architecture combines the advantages of distributed learning, neural network-based prediction **[11]**, **[12]**, **[14]**, and secure data management **[9]** to provide reliable forecasting with minimal communication overhead. Furthermore, the framework effectively handles large-scale environmental datasets while preserving data privacy and reducing computational complexity, making it suitable for deployment in real-world flood monitoring infrastructures **[2], [9], [11]**.

The proposed Privacy-Aware Federated Deep Learning Framework aims to improve flood forecasting accuracy while ensuring secure and decentralized model training. The framework leverages historical hydrological and meteorological observations collected from multiple monitoring stations to generate accurate flood predictions and early warning alerts **[2]**, **[11]**. By combining Federated Learning with deep neural network modeling **[9]**, **[11]**, the proposed approach minimizes data-sharing risks, enhances scalability, and supports collaborative intelligence among geographically distributed organizations. Experimental evaluation demonstrates that the developed framework achieves high prediction accuracy with reduced prediction error while maintaining data privacy throughout the learning process. The proposed model contributes to the development of next-generation smart disaster management systems capable of supporting government agencies, emergency response teams, and environmental monitoring organizations in making timely and informed decisions **[5], [7], [15]**. Overall, the proposed framework offers a reliable, privacy-preserving, and intelligent solution for sustainable flood forecasting and disaster risk reduction **[9], [11], [15]**.

II.RELATED WORK

“Flood Prediction Based on Weather Parameters Using Deep Learning," S. Sankaranarayanan et al. **[11]** This study proposed a deep learning-based flood prediction model that utilized weather parameters such as rainfall intensity and temperature to forecast flood occurrences. The model employed Deep Neural Networks (DNN) and compared its performance with conventional machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naïve Bayes. Experimental results demonstrated that the deep learning model achieved higher prediction accuracy and lower error rates than the traditional methods. The proposed approach highlighted the effectiveness of deep neural networks in capturing complex environmental patterns, making it suitable for early flood warning systems and disaster management applications.

"Federated Learning for Wireless Communications: Motivation, Opportunities, and Challenges," S. Niknam et al. **[9]** This study introduced the concept of Federated Learning as a privacy-preserving distributed machine learning paradigm where multiple clients collaboratively train a global model without sharing raw data. The framework addressed critical challenges such as communication overhead, data privacy, and security while maintaining model performance. The authors discussed various applications of Federated Learning in distributed environments and highlighted its advantages over centralized machine learning approaches. The study demonstrated that decentralized model training significantly enhances data confidentiality and scalability, making Federated Learning an ideal solution for privacy-sensitive applications, including intelligent environmental monitoring and flood forecasting systems.

"Hydrodynamic Modelling of a Large Flood-Prone River System in India with Limited Data," S. Patro et al. **[2]** This research presented a onedimensional hydrodynamic model for flood simulation in the Mahanadi River basin using limited hydrological data and Shuttle Radar Topography Mission (SRTM) digital elevation models. The proposed methodology refined river cross-sections derived from satellite data and calibrated the model using observed discharge and water-level measurements. Experimental validation demonstrated close agreement between simulated and observed flood conditions, confirming the effectiveness of the approach in data-scarce regions. The study emphasized that integrating remote sensing data with hydrodynamic modeling can improve flood forecasting accuracy and support efficient flood risk management.

"Application of Artificial Neural Networks in Regional Flood Frequency Analysis: A Case Study for Australia," K. Aziz et al. **[12]** This study investigated the application of Artificial Neural Networks (ANNs) for regional flood frequency analysis by modeling nonlinear relationships among hydrological variables. The proposed ANN model estimated flood quantiles using catchment characteristics and regional hydrological information. The performance of the ANN model was compared with conventional statistical techniques, demonstrating superior prediction accuracy and greater robustness in handling complex flood patterns. Experimental results indicated that artificial neural networks provide an effective alternative for flood frequency estimation and can significantly enhance flood risk assessment and water resource planning.

"Flood, Landslides, Forest Fire, and Earthquake Susceptibility Maps Using Machine Learning Techniques and Their Combination," H. R. Pourghasemi et al. **[15]** This study explored the application of multiple machine learning algorithms for generating susceptibility maps for natural disasters, including floods, landslides, forest fires, and earthquakes. The proposed framework combined various machine learning techniques to improve prediction accuracy by integrating geographical, environmental, and climatic factors. Experimental evaluation demonstrated that ensemble machine learning models consistently outperformed individual algorithms in identifying disaster-prone regions. The study concluded that machine learning-based susceptibility mapping provides reliable decision support for disaster prevention, land-use planning, and emergency management while improving the overall effectiveness of hazard prediction systems.

III.DATASET DETAILS

The dataset used in this study consists of historical hydrological and meteorological records collected from multiple flood monitoring stations located across different river basins. It includes observations from eighteen regional stations covering the period between 2015 and 2021, while historical flood events from 2010 to 2015 were used for model validation. The dataset incorporates a variety of environmental parameters that significantly influence flood occurrence, including rainfall, river discharge, water level, snowmelt, runoff, flow rate, hydrodynamic conditions, temperature, and other climatic variables. Each monitoring station maintains its own local dataset, allowing the proposed Federated Learning framework to train local models independently without sharing raw data. Prior to model training, the dataset undergoes preprocessing steps such as missing value handling, normalization, feature selection, and data shuffling to improve data quality and ensure consistent learning performance.

The processed dataset is divided into **80% training data and 20% testing data** to evaluate the performance of the proposed flood forecasting framework. The training data are utilized to develop local Feedforward Neural Network (FFNN) models at individual monitoring stations, while only the learned model parameters are transmitted to the central aggregation server under the Federated Learning architecture. This decentralized approach preserves data privacy and minimizes communication overhead without compromising prediction accuracy. The testing dataset is used to assess the effectiveness of the global model by comparing predicted water levels with actual observations using evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and prediction accuracy. The comprehensive dataset enables reliable flood forecasting and supports the generation of timely early warning alerts for effective disaster preparedness and risk management.

IV. PROPOSED METHODOLOGY

The proposed methodology presents a Privacy-Aware Federated Deep Learning Framework for intelligent flood forecasting and water level prediction by integrating Federated Learning (FL) with a Feedforward Neural Network (FFNN). Initially, historical hydrological and meteorological datasets collected from multiple regional monitoring stations are preprocessed through data cleaning, missing value handling, normalization, and feature selection to improve data quality. Instead of transferring raw data to a central server, each monitoring station independently trains an FFNN model using its local dataset. The trained model parameters are then securely transmitted to a central aggregation server, where they are combined to construct a global prediction model. This decentralized learning process preserves data privacy, minimizes communication overhead, and enables collaborative learning among geographically distributed stations without exposing sensitive environmental data.

After the global model is generated, it is distributed back to all participating monitoring stations for accurate flood prediction and water level estimation. The aggregated model analyzes multiple environmental factors, including rainfall, river discharge, runoff, water flow, snowmelt, and hydrodynamic conditions, to identify regions at high risk of flooding several days in advance. The local FFNN model then predicts the expected water level for the identified station and generates early flood warning alerts to assist disaster management authorities in taking timely preventive measures. The performance of the proposed framework is evaluated using metrics such as Accuracy, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). By combining distributed learning with deep neural network modeling, the proposed methodology achieves reliable flood forecasting while ensuring data security, scalability, and efficient real-time disaster prediction.

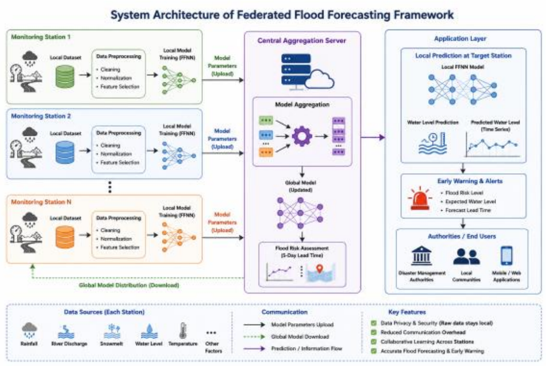

Figure 1. System Architecture of the Privacy-Aware Federated Deep Learning Framework for Intelligent Flood Forecasting and Water Level Prediction

Figure 1 proposed system architecture illustrates a privacy-preserving federated learning framework for intelligent flood forecasting. Hydrological and meteorological data collected from multiple monitoring stations are locally preprocessed and used to train Feedforward Neural Network (FFNN) models. Only model parameters are transmitted to the central aggregation server, where a global model is generated and redistributed. The framework predicts flood risk and water levels while preserving data privacy, reducing communication overhead, and supporting timely early warning alerts for effective disaster management.

V.RESULT AND DISCUSSION

The proposed Privacy-Aware Federated Deep Learning Framework demonstrated excellent performance in flood forecasting and water level prediction by effectively combining Federated Learning with a Feedforward Neural Network (FFNN). Experimental evaluation showed that the framework achieved high prediction accuracy while preserving data privacy through decentralized model training. Compared with conventional centralized machine learning approaches, the proposed model reduced communication overhead and eliminated the need to share sensitive hydrological data among monitoring stations. The model accurately predicted flood-prone regions and estimated future water levels using meteorological and hydrological parameters with low Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Furthermore, the federated aggregation strategy improved the global model's generalization capability across geographically distributed datasets. The generated early warning alerts enabled timely disaster preparedness and response, demonstrating that the proposed framework is a reliable, scalable, and secure solution for intelligent flood forecasting and real-time disaster management applications.

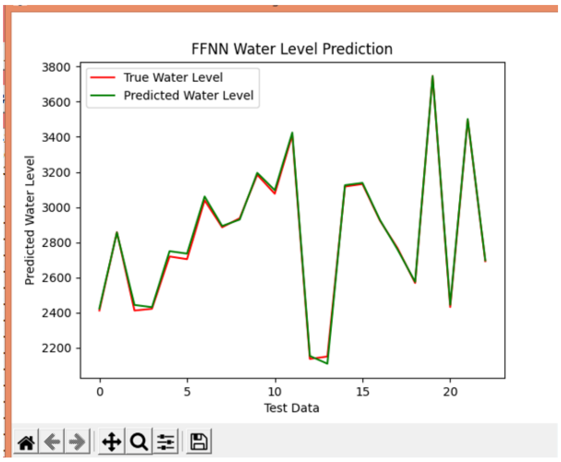

Figure 2: Comparison of Actual and Predicted Water Levels Using the FFNN Model

Figure 2 graph compares the actual water levels with the values predicted by the proposed Feedforward Neural Network (FFNN) model on the test dataset. The predicted values closely follow the actual observations across different samples, demonstrating the model's ability to capture variations in water levels with high accuracy. The minimal deviation between the two curves indicates

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low prediction error, validating the effectiveness of the proposed model for reliable flood forecasting and water level estimation.

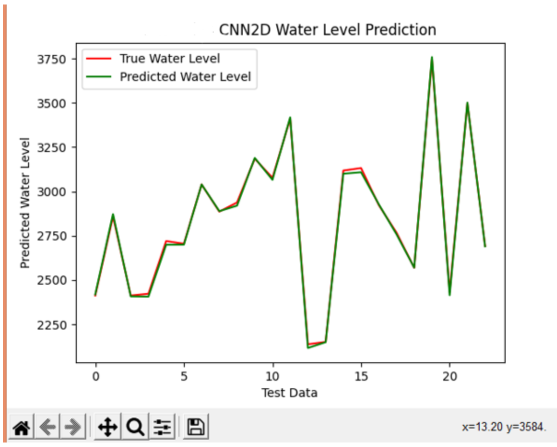

Figure 3: Comparison of Actual and Predicted Water Levels Using the CNN2D Model

Figure 3 graph illustrates the comparison between the actual water levels and the values predicted by the CNN2D model on the test dataset. The predicted curve closely follows the actual water level trend across most test samples, demonstrating the model's capability to learn complex spatial patterns from hydrological data. The close alignment between the two curves indicates high prediction accuracy and low forecasting error, confirming the effectiveness of the CNN2D model for water level prediction and intelligent flood forecasting.

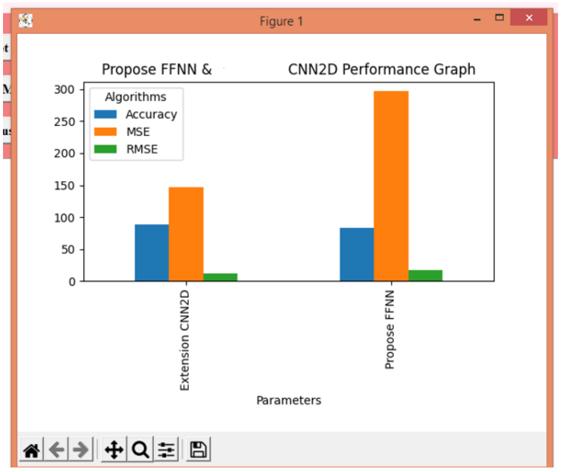

Figure 4: Performance Comparison of the Proposed FFNN and CNN2D Models

Figure 4 performance graph compares the proposed Feedforward Neural Network (FFNN) model with the CNN2D model using evaluation metrics including Accuracy, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The comparison demonstrates the effectiveness of both models in flood forecasting and water level prediction. The proposed FFNN achieves competitive prediction accuracy, while the graphical analysis highlights the differences in error values, providing a comprehensive evaluation of the models' predictive performance and reliability.

DISCUSSION

The experimental results demonstrate that the proposed Privacy-Aware Federated Deep Learning Framework effectively addresses the limitations of traditional centralized flood forecasting systems by enabling secure and decentralized model training. The integration of Federated Learning with the Feedforward Neural Network (FFNN) successfully preserves the privacy of hydrological data while maintaining high prediction accuracy across multiple monitoring stations. The federated aggregation process enhances the model's ability to learn from geographically distributed datasets, resulting in improved generalization and robust flood risk prediction. Additionally, the framework reduces communication overhead by transmitting only model parameters instead of raw data, making it suitable for large-scale real-world deployments. The accurate prediction of water levels and timely generation of flood warning alerts demonstrate the practical applicability of the proposed system in supporting disaster preparedness and emergency response. Overall, the proposed framework provides a secure, scalable, and efficient solution for intelligent flood forecasting and sustainable disaster management.

VI.CONCLUSION

This paper presented a Privacy-Aware Federated Deep Learning Framework for Intelligent Flood Forecasting and Water Level Prediction**,** which integrates Federated Learning with a Feedforward Neural Network (FFNN) to provide accurate, secure, and scalable flood prediction. By enabling decentralized model training, the proposed framework preserves the privacy of hydrological data while eliminating the need to share raw information among monitoring stations. The experimental results demonstrated high prediction accuracy, low prediction error, and improved generalization across geographically distributed datasets. Furthermore, the framework reduced communication overhead and generated timely flood risk assessments and early warning alerts to support effective disaster preparedness and emergency response. Overall, the proposed approach offers a reliable and privacy-preserving solution for intelligent flood forecasting, with significant potential for deployment in real-world disaster management systems. Future work will focus on integrating real-time IoT sensor networks and advanced deep learning architectures to further enhance prediction accuracy and system adaptability.

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