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FFM: Flood Forecasting Model Using Federated Learning

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ABSTRACT: Floods are one of the most common natural disasters that occur frequently causing massive damage to property, agriculture, economy and life. Flood prediction offers a huge challenge for researchers struggling to predict floods since long time. In this article, flood forecasting model using federated learning technique has been proposed. Federated Learning is the most advanced technique of machine learning (ML) that guarantees data privacy, ensures data availability, promises data security, and handles network latency trials inherent in prediction of floods by prohibiting data to be transferred over the network for model training. Federated Learning technique urges for onsite training of local data models, and focuses on transmission of these local models on the network instead of sending huge data set towards central server for local model aggregation and training of global data model at the central server. A local feed forward neural network (FFNN) model is trained at the client station where the flood has been expected. Flood forecasting module of local FFNN model predicts the expected water level by taking multiple regional parameters as input. The proposed flood forecasting model has successfully predicted previous floods happened in the selected zone during 2010 to 2015 with 84 % accuracy.

KEYWORDS: Hydraulic, meteorological, flood forecasting system, federated learning, feed-forward neural network.

I. INTRODUCTION

In recent years, rate of natural and man-made disasters has increased in the world. Global flood risk has raised due to hydrological extremities, increased urbanization and global warming. Floods are devastating natural disasters that result in severe life losses, significant destruction of infrastructure, agriculture and downfall of overall socioeconomic system of a country. Floods are common in all parts of the world but their intensity vary from region to region. In developing countries, flood occurrences inflict countless casualties every year and cause cruel economic crises, rising pecuniary problems. Global temperature escalation resulting in overall climate change cause an increased rate of snow melting and precipitation due to which floods are becoming more frequent and intense. It shows that frequency of flood occurrence in Pakistan is higher than other natural disasters. Floods have been observed to outnumber at all other calamities happened in the South Asian countries during 2021. To protect life and economic infrastructure, governments intensely need a reliable system that may predict floods before its occurrence so that necessary actions might be taken in time. Many statistical methods and techniques like the climatology average method (CLIM), flood frequency analysis (FFA), Bayesian forecasting models (BFM), artificial neural networks (ANN) and many more are used for flood prediction in literature. In these models, flood causing physical processes have been expressed through complex mathematical expressions.

It is the need of the time to present an unconventional flood prediction system that can not only predict flood but also enforce policies and legislations for preserving data privacy, guaranteeing data security, ensuring data availability, controlling data abundance, and handling latency in data communication. Federated Learning (FL) is the most recent technique of ML that do not need data to be transferred from its origination place rather empowering its clients to perform some pre-processing of data onsite and train their own local data model independently using local data. Local data models are transferred to central server through network for aggregation and training of global model. FL based setup reduced communication overhead to a minimum, while at the same time clients have enough data to render a good model. Privacy, security and communication threats offered by traditional ML models have been automatically eliminated as data is kept safe with the owner organization. Moreover, network issues have also been suppressed as the huge dataset is never being transferred over the network rather a small sized model trained from local data is travelling over the network reducing overheads. Privacy and data security issues related to traditional ML based solutions have enforced the application of FL technique for the training of secured and privacy protected flood prediction models. FL facilitated in the training of a decentralized learning model where user data is never sent to a central server.

II. RELATED WORKS

S. Niknam, H. S. Dhillon, and J. H. Reed [1] Federated learning for wireless communications. Motivation, opportunities, and challenges There is a growing interest in the wireless communications community to complement the traditional model-driven design approaches with data-driven machine learning (ML)-based solutions. While conventional ML approaches rely on the assumption of having the data and processing heads in a central entity, this is not always feasible in wireless communications applications because of the inaccessibility of private data and large communication overhead required to transmit raw data to central ML processors. As a result, decentralized ML approaches that keep the data where it is generated are much more appealing. Due to its privacy-preserving nature, federated learning is particularly relevant for many wireless applications, especially in the context of fifth generation (5G) networks. In this article, we provide an accessible introduction to the general idea of federated learning, discuss several possible applications in 5G networks, and describe key technical challenges and open problems for future research on federated learning in the context of wireless communications.

T. Li, A. K. Sahu, A. Talwalkar, and V [2] Federated learning: Challenges, methods, and future directions Smith Federated learning involves training statistical models over remote devices or siloed data centers, such as mobile phones or hospitals, while keeping data localized. Training in heterogeneous and potentially massive networks introduces novel challenges that require a fundamental departure from standard approaches for large-scale machine learning, distributed optimization, and privacy-preserving data analysis. In this article, we discuss the unique characteristics and challenges of federated learning, provide a broad overview of current approaches, and outline several directions of future work that are relevant to a wide range of research communities.

R. Sadiq, M. A. Al-Zahrani, A. K. Sheikh, T. Husain, and S. Farooq [3] Performance evaluation of slow sand filters using fuzzy rule-based modelling Most chemical and biological systems are not linear in nature. To account for the non-linearity of the processes in slow sand filters, fuzzy rule-based system with classification was used to model slow sand filter in Siddhipur Water Treatment Plant, Lalitpur. Membership functions were created using regular hierarchy, and rule conclusions were generated by using the values which have the most matching degree. A total of 82 data rows of inlet turbidity, filter runtime and outlet turbidity was collected for 3 filter cycles for the modeling. The modeling showed accuracy of 75.6 % over all the data rows. For validation, the model showed accuracy of 81.25 %. The observed and inferred outlet turbidities showed a value of mean absolute error of 0.2561. Open-source software FISPRO was used for fuzzy modeling.

III. PROPOSED WORK

Flood Forecasting Model (FFM) has been developed to forecast floods in multiple rivers and barrages of the selected region. The proposed model is composed of five layers as presented in the proposed system. Flood prediction involves a huge amount of multidimensional data. In physical layer, data collection centers are present at the edge, where sensors have been used to collect and transmit data to the local client station for local model training. These sensors include rain gauge sensors, water flow calculating sensors and water level sensors. In the proposed model hydrological and meteorological dataset of a region selected from Central Asia have been processed. The algorithm that is used in the FFM is Feed forward neural network (FFNN).

Feed Forward Neural Network (FFNN) A Feed Forward Neural Network is an artificial Neural Network in which the nodes are connected circularly. A feed-forward neural network, in which some routes are cycled, is the polar opposite of a Recurrent Neural Network. The feed-forward model is the basic type of neural network because the input is only processed in one direction. The data always flows in one direction and never backwards/opposite. In its most basic form, a Feed-Forward Neural Network is a single layer perceptron. A sequence of inputs enter the layer and are multiplied by the weights in this model. The weighted input values are then summed together to form a total. If the sum of the values is more than a predetermined threshold, which is normally set at zero, the output value is usually 1, and if the sum is less than the threshold, the output value is usually -1. The single-layer perceptron is a popular feed-forward neural network model that is frequently used for classification. Single-layer perceptrons can also contain machine learning features.

3.1 System Design and analysis:

A federated learning approach empowers flood forecasting by leveraging data from geographically dispersed sensor networks while safeguarding data privacy. Sensors deployed across the target region continuously collect real-time environmental data like rainfall, water levels, and soil moisture. This data remains secure on the individual sensor

devices themselves. Each sensor device becomes a mini training ground, housing a local machine learning model that utilizes the federated learning technique to train on its locally collected data. This local model collaborates with a central server, acting as the coordinator. Instead of sending raw data, devices transmit model updates (weight adjustments) to the server. The server then aggregates these updates from all devices, creating a refined global model. This improved global model is then distributed back to the local devices, fostering a continuous learning cycle. Secure communication is vital. A dedicated layer ensures only model updates are transmitted, minimizing data transfer and protecting sensitive information. Encryption further strengthens the integrity of these updates during transmission.

Input Design plays a vital role in the life cycle of software development, it requires very careful attention of developers. The input design is to feed data to the application as accurate as possible. So inputs are supposed to be designed effectively so that the errors occurring while feeding are minimized. According to Software Engineering Concepts, the input forms or screens are designed to provide to have a validation control over the input limit, range and other related validations. Input design is the process of converting the user created input into a computer-based format.

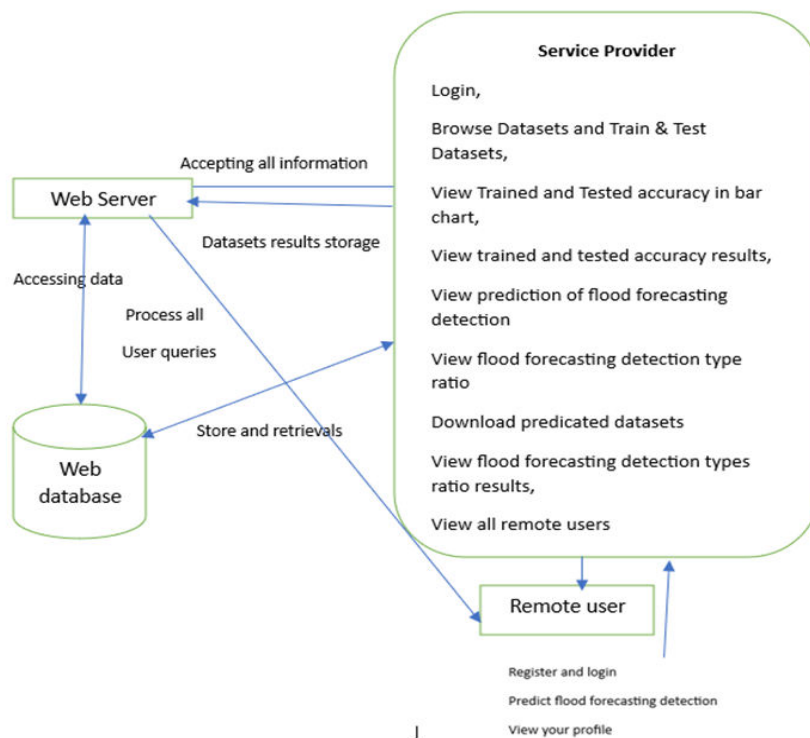


Fig1. System Design

3.2 Module Implementation:

Flood forecasting model using federated learning architecture will have majorly three modules to work with. All these three modules are supposed to perform different tasks and would have a significance. The modules of the application are:

- The Web Server
- The Database
- Remote User

Each module plays a distinct role in ensuring the functionality and efficiency of the system.

The Remote User Module represents users accessing the system remotely, offering functionalities like registration, login, profile management, and access to system features. It includes components for authentication, profile management, and interaction with other modules. User interfaces are designed for different roles, and security measures like authentication and encryption are implemented to protect user data and privacy. The Remote User Module provides functionalities for remote users to interact with the system, including registration, login, and profile management. It

ensures secure authentication and data encryption to protect user privacy. The module's organization focuses on user-friendly interfaces and efficient communication with other system components.

The Web Server Module :

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Flood Forecasting Detection, View Flood Forecasting Detection Type Ratio, Download Predicted Data Sets, View Flood Forecasting Detection Type Ratio Results, View All Remote Users.

The Web Server Module serves as the front-end component responsible for handling web-based interactions with users. It receives user requests, manages logins, and delivers web pages. This module incorporates components for user authentication, session management, and routing requests. Following the MVC pattern, the codebase is structured into controllers, middleware, and views, facilitating organized development and maintenance. The Web Server Module interacts with the Database Module to retrieve and store data, ensuring seamless communication between the front-end and back-end components. It utilizes secure authentication and encryption to protect data integrity and confidentiality. The modular design enables scalability and maintainability, allowing each module to focus on specific tasks while integrating smoothly with others.

The Database Module (Web Database) :

The Database Module (WEB Database) stores healthcare datasets, user information, and analysis results, ensuring data persistence and retrieval. It includes components for schema definition, data manipulation, and query processing, utilizing a suitable data storage solution such as an RDBMS. The module's organization involves designing tables, defining relationships, and optimizing queries for efficient data handling. The Database Module serves as the backend storage mechanism, ensuring data persistence and retrieval. It incorporates robust security measures to protect data integrity and confidentiality. The module's organization involves designing efficient database schemas, optimizing queries, and implementing backup and recovery procedures.

Remote User Module :

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGINPREDICT FLOOD FORECASTING DETECTION, VIEW YOUR PROFILE.

IV. RESULTS AND DISCUSSION

Results

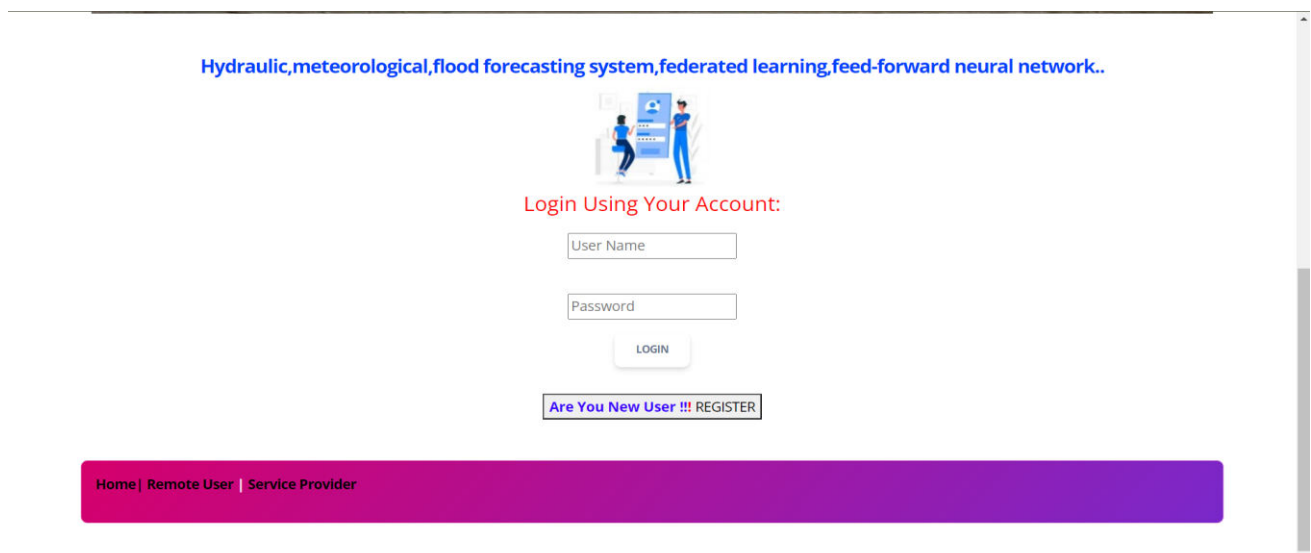


Fig2. Login Page

Hydraulic, meteorological, flood forecasting system, federated learning, feed-forward neural network..



REGISTER YOUR DETAILS HERE !!!

Username	User Name	Password	Password
E-Mail Id	Enter Email	Address	Enter Address
Gender	---Select Gender ---	Mobile Number	Enter Mobile Number
Country Name	Enter Country Name	State Name	Enter State Name
City Name	Enter City Name	REGISTER	

Registered Status ::

Home | Remote User | Service Provider

Fig3. Registration page

View Flood Forecasting Prediction Type Details !!!

id	Human_Displaced	Animal_Fatality	Description_of_Casualties_injured	Extent_of_damage	Event_Source	Event_Souce_ID	Prediction
	NA	NA	NA	About 900 people of 135 villages affected..	IMD	NA	Cyclone and Flood
	NA	NA	3 persons died in Sonitpur & Baksa	NA	IMD	NA	Heavy Rain
				₹ 5,76,537			

Source: PTI P

Fig4. Prediction details

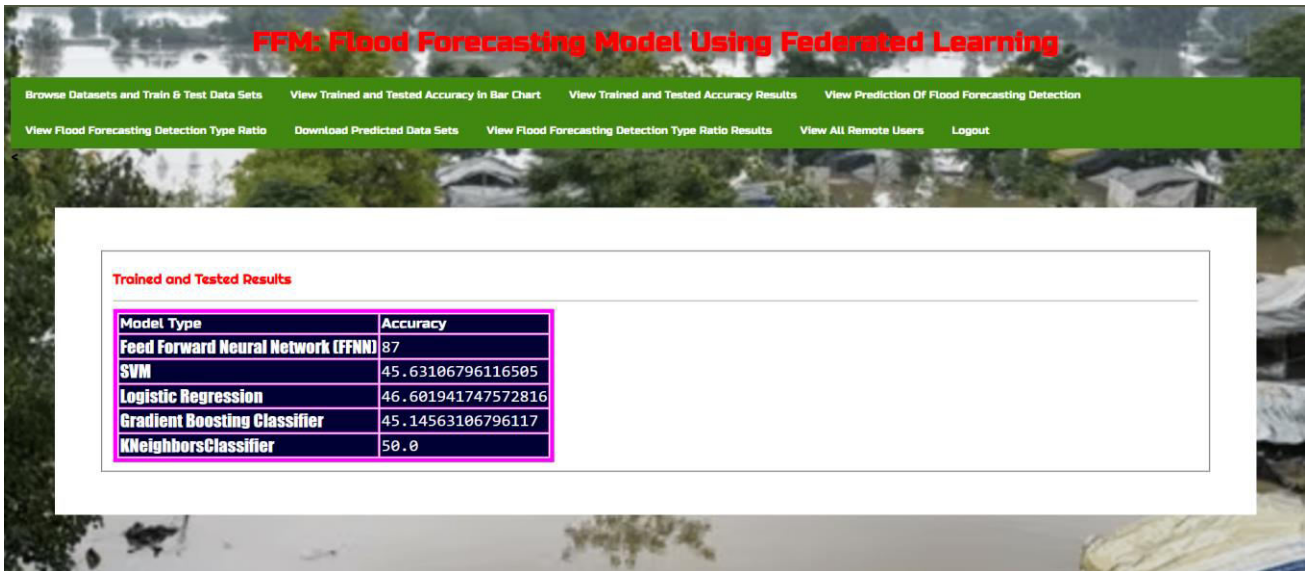


Fig5. Accuracy

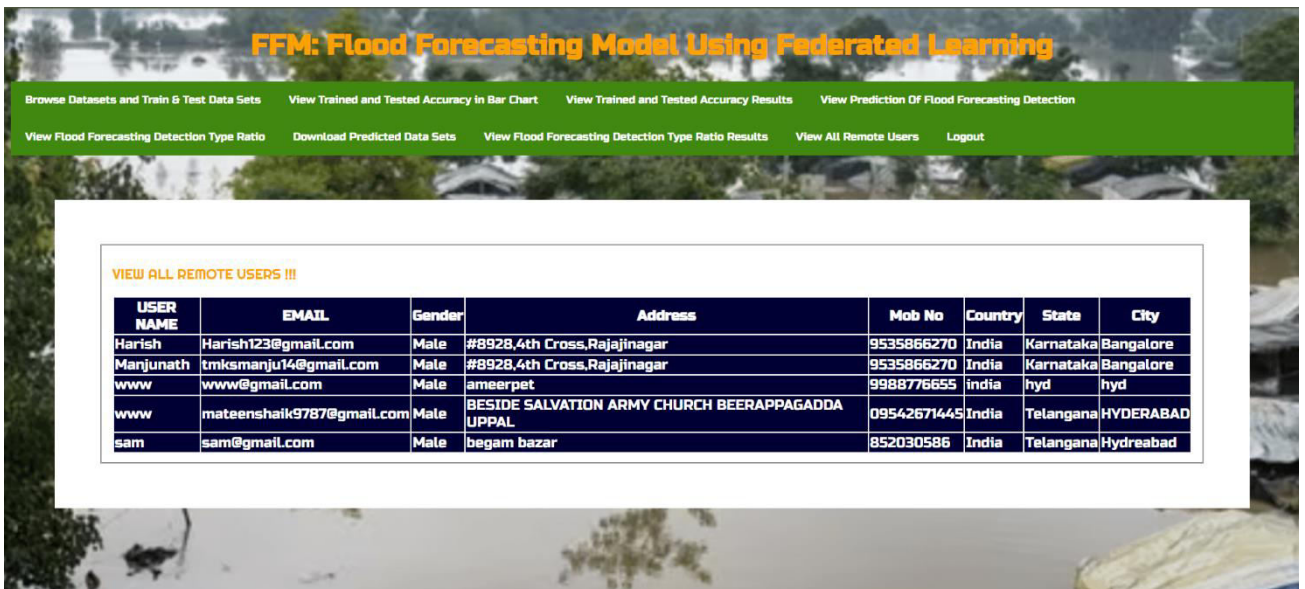


Fig6. All remote users

V. CONCLUSION

In this research, a flood forecasting model (FFM) has been presented that works in two modules. In first module, eighteen local stations have been monitored for training and transmitting local data models to central server. Central server trains global model that has been capable enough to determine the local station where flood is expected within net five days by analyzing multiple parameters extracted from local models. In second module of FFM, feed forward neural network model is trained at the local station where flooding has been predicted to determine the expected raise in water level during flood. Hydraulic and metrological data at eighteen local stations have been locally processes to preserve data privacy, guarantee data security and ensure data availability. The proposed FFM also issues flood alert to flood mitigation department for taking necessary actions towards disaster prevention and response. The proposed system has also been evaluated for prediction of historic floods encountered in the selected region from 2010 to 2015. The proposed FFS predicted the historical floods with 86% accuracy. Currently FFM has been trained on regional data of the selected zone but in future, it can be expanded to predict floods in other regions of the world using

their datasets. federated learning presents a significant advancement in flood forecasting. It tackles the challenge of leveraging geographically distributed data while maintaining data privacy. Local sensor stations can train models on their own readings and share only the refined model updates with a central server. This collaborative approach fosters more accurate flood predictions compared to individual, isolated models.

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