FFM: FLOOD FORECASTING MODEL USING CNN2D AND FFNN MODELS

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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. In this article, the proposed model integrates locally trained models of eighteen clients, investigates at which station flooding is about to happen and generates flood alert towards a specific client with five days lead time. 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 dataset of five different rivers and barrages has been collected from 2015 to 2021 considering four aspects including snow melting, rainfall-runoff, flow routing and hydrodynamics. The proposed flood forecasting model has successfully predicted previous floods happened in the selected zone during 2010 to 2015 with 84 % accuracy. As extension we used advanced algorithms like Convolution2D Neural Network which gain popularity in all domains for its accurate and successful prediction accuracy of more than 90%. So to enhance accuracy we have used CNN2D as extension for flood forecasting.

Index Terms - Hydraulic, meteorological, flood forecasting system, federated learning, feed-forward neural network., Convolution2D Neural Network

1. INTRODUCTION

In recent years, rate of natural and man-made disasters has increased in the world [1]. Global flood risk has raised due to hydrological extremities, increased urbanization and global warming [2]. 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 [3]. In developing countries, flood occurrences inflict countless casualties every year and cause cruel economic crises, rising pecuniary problems [4]. 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 [5]. Figure 1 shows that frequency of flood occurrence in Pakistan is higher than other natural disasters [6]. Floods have been observed to outnumber at all other calamities happened in the South Asian countries during 2021 [7].

In the face of escalating threats posed by floods to both human life and economic infrastructure, governments are in critical need of reliable predictive systems to enable timely and effective interventions [8]. Despite numerous global and regional methodologies, models, and strategies proposed for flood prediction, the inherent complexity of this natural disaster has impeded substantial improvements in accuracy [9]. Established statistical methods such as climatology average method (CLIM), flood frequency analysis (FFA), Bayesian forecasting models (BFM), and artificial neural networks (ANN) have utilized complex mathematical expressions to represent flood-causing physical processes [11-14].

The advent of machine learning (ML) has significantly advanced flood prediction systems by offering enhanced performance and cost-effective solutions. Hydrologists increasingly favor ML methods, seeking more accurate and efficient prediction models through novel ML techniques and hybridization of existing ones [15-16]. However, ML's dependency on extensive data for model training poses challenges, as concerns related to data privacy, security, and regulatory restrictions hinder data sharing among authorities [17-18]. Traditionally, flood forecasting systems have employed centralized setups, concentrating both the prediction model and data in a single location for training before dissemination to all clients. Despite its convenience, this approach introduces latency, connectivity issues, and potential security and privacy risks [19-20].

2. LITERATURE REVIEW

[16] In this they introduce a hybrid recurrent neural network with convolution kernel smoothing, time series attention, and multivariate autoregressive integrated moving average for accurate urban reservoir flood forecasting, validated in Ankang Reservoir. The proposed hybrid model effectively predicts urban reservoir floods, outperforming traditional hydrological models and other machine learning networks, demonstrated through accurate real-time forecasting in Ankang Reservoir. Dependency on accurate upstream data, potential sensitivity to threshold adjustments, and computational complexity could limit the system's robustness in different scenarios. Adapting to diverse geographical conditions, ensuring real-time data availability, and addressing uncertainties in rainfall predictions pose challenges for the proposed flood forecasting system. Limited by the specific geographical characteristics of Ankang Reservoir, generalizability to different regions may require additional calibration and validation processes.

[21] In this paper a real-time flood forecasting model employs back-propagation networks with self-organizing map cluster analysis, enhancing accuracy by creating ensemble forecasts during typhoon events in the Wu River Basin, Taiwan. The ensemble model,

integrating back-propagation networks and self-organizing map clustering, outperforms individual models in accurately forecasting flood values and intervals during typhoon events in the Wu River Basin. Dependence on accurate typhoon data, potential sensitivity to cluster selection, and computational complexity are challenges that may affect the robustness of the proposed system. Adapting to diverse typhoon characteristics, ensuring real-time data availability, and addressing uncertainties in rainfall predictions pose challenges for the proposed real-time flood forecasting system. The model's applicability might be limited to the specific characteristics of the Wu River Basin, requiring careful consideration and validation for broader geographical use.

[23] An integrated XAJ-MCQRNN model, combining Xinanjiang conceptual model and Monotone Composite Quantile Regression Neural Network, enhances short-term flood probability density forecasting, addressing error propagation and accumulation challenges. The XAJ-MCQRNN model outperforms the MCQRNN, demonstrating improved accuracy and reliability in short-term flood probability density forecasting, benefiting flood mitigation and early warning systems. Potential complexities in integrating conceptual and machine learning models, sensitivity to input data quality, and computational demands may pose challenges in deploying the proposed system. Adapting to diverse hydrological conditions, ensuring timely rainfall data availability, and addressing uncertainties in rainfall-runoff modeling present challenges for the proposed short-term flood probability density forecasting system. Applicability may be limited to catchments similar to Jianxi River, necessitating careful consideration for different hydrological contexts and extended validation.

[24] In this they proposed a ConvLSTM model combining CNN and LSTM processes spatial-temporal hydrological data, achieving accurate flood prediction in Xi County, China, surpassing recent models. ConvLSTM demonstrated superior performance in predicting flood arrival time and peak discharge, offering a promising alternative for accurate and timely flood prediction. Potential drawbacks include computational complexity, resource-intensive training, and sensitivity to the quality and quantity of input data. Implementation challenges may arise in optimizing model parameters, ensuring data quality, and integrating real-time monitoring for dynamic flood prediction. The model's effectiveness may vary in different geographic regions, and its generalizability might be limited by specific environmental conditions and data availability.

[25] They introducing a flood prediction and extent mapping model utilizing multispectral, radar, and LIDAR remote sensing technologies, addressing gaps identified in current methods for enhanced accuracy. Remote sensing technologies play a crucial role in flood prediction, offering valuable insights for disaster management, though challenges and limitations persist in their application. Challenges include high equipment costs, limited accessibility to advanced technologies, and potential inaccuracies in data interpretation affecting flood prediction precision. Implementation challenges involve integrating diverse remote sensing data, ensuring real-time data acquisition, and addressing issues related to data resolution and accuracy for robust flood prediction. Despite advancements, limitations in remote sensing

technologies, such as weather dependence and data interpretation uncertainties, may impact the model's overall effectiveness in flood prediction scenarios.

3. METHODOLOGY

i) Proposed Work:

The proposed Flood Forecasting Model (FFM) employs Federated Learning (FL) and a Feed Forward Neural Network (FFNN) to enhance flood prediction accuracy while preserving data privacy. In the initial step, multiple clients collaboratively train local models, and data is transmitted to a central server for aggregation. Subsequently, a global model is trained based on local models, predicting flood occurrences at specific client stations with a 5-day lead time. The final step involves training a local FFNN on the identified station, estimating water levels, and triggering authorities for flood preparedness. The research's motivation is humanitarian, aiming to prevent loss of life and widespread damage. To further improve accuracy, an extension incorporates Convolutional Neural Network [24] (CNN2D) alongside traditional FFNN, measuring performance through accuracy, Mean Square Error (MSE), and Root Mean Square Error (RMSE). This combined approach represents a novel and comprehensive strategy for flood forecasting.

ii) System Architecture:

The proposed Flood Forecasting Neural Network (FFNN) model comprises three layers of hidden nodes designed to predict floods five days in advance. The system architecture integrates input from various models, including the snow melting model, rainfall runoff model, flow routing model, and hydrodynamic model. These models collectively generate essential information for flood forecasting.

In the first step of the architecture, the results from the snow melting model, rainfall runoff model, and flow routing model are combined. This consolidated information serves as input data for the FFNN model, specifically populating the inner hidden nodes. The FFNN model, with its three layers of hidden nodes, transforms this input into predictions for flood forecasts. The second step involves incorporating the hydrodynamic model results into the FFNN, further enhancing the model's ability to capture complex interactions in the hydrological system.

To optimize the spatial-temporal aspects of the input data, an extension of the Convolutional Neural Network [24] (CNN2D) algorithm is employed in the third step. This algorithm allows the FFNN model to effectively process the multidimensional input data, extracting spatial features critical for accurate flood forecasting. By integrating these diverse models and leveraging the FFNN architecture with CNN2D, the proposed system aims to enhance the accuracy of flood predictions by considering multiple hydrological factors and their complex interactions.

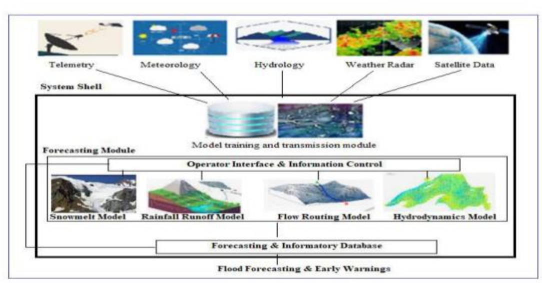


Fig. 1 Proposed Architecture

iii) Dataset:

In the proposed flood prediction study, the author employs a dataset compiled from 18 stations or rivers, utilizing it to locally train the Feed Forward Neural Network (FFNN) algorithm. This dataset, consisting of essential information, becomes the basis for training the FFNN model, allowing it to learn and make predictions about water levels at various locations. After the local training phase, the trained FFNN model is transmitted to a centralized server for global updates. While the author has not made the original dataset publicly available on the internet, an alternative is sought, leading to the utilization of the KERALA flood dataset [25] accessible on the Kaggle website. This Kaggle dataset encompasses records of monthly rainfall, with the first row specifying column names and the subsequent rows containing dataset values. Significantly, the last column in the dataset holds crucial information about water level recordings, playing a pivotal role in predicting and managing flood risks. The predictions derived from the trained FFNN model aid authorities in informing citizens about potential flood events based on the forecasted water levels.

Despite the efficacy of the traditional Feed Forward Neural Network (FFNN) algorithms employed in the proposed work, the study recognizes the potential for further accuracy enhancement by incorporating more advanced techniques. While the original work did not leverage Convolutional Neural Network [24] (CNN2D), the extension of the model now integrates this advanced algorithm. CNN2D has gained popularity across diverse domains for its superior accuracy compared to FFNN. This inclusion aims to improve prediction precision by capturing intricate spatial relationships and patterns within the dataset, showcasing a forward-thinking approach to flood forecasting that aligns with contemporary advancements in neural network methodologies.

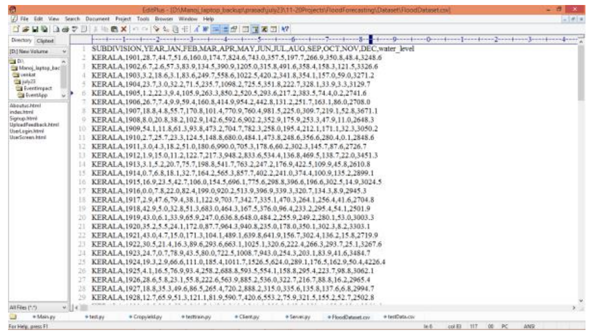


Fig. 2 Dataset

In above dataset screen first row represents dataset column names and remaining rows represents dataset values where dataset has recordings of monthly rainfall and last column contains Water Level and based on predicted water level authorities will inform citizens about flood.

iv) Pre – processing Dataset:

In this project, the "Pre-process Dataset" module serves as a crucial precursor to the implementation of a hybrid predictive model that combines traditional Feed Forward Neural Network (FFNN) algorithms with an extension utilizing Convolutional Neural Network with 2D layers [24] (CNN2D). The primary objective is to enhance the accuracy and robustness of flood prediction by effectively handling the dataset before model training.

The pre-processing module encompasses three key steps. Firstly, the identification and removal of missing values are crucial to ensuring the integrity of the dataset. Missing values, if not addressed, could introduce bias and inconsistencies during model training. Following this, the dataset undergoes a normalization process, where features are scaled to a standardized range. Normalization prevents certain features from disproportionately influencing the model due to varying scales, promoting fair and unbiased learning.

The final step involves shuffling the dataset, introducing randomness to the order of data instances. This step is particularly significant in preventing the model from learning patterns based on the order of input data, mitigating the risk of overfitting and ensuring better generalization to unseen data.

Subsequently, the pre-processed dataset is used to train a hybrid model that combines the strengths of a traditional FFNN with the spatial-awareness capabilities of CNN2D. This innovative approach aims to capture complex spatial relationships within the dataset, offering a more accurate and context-aware flood prediction model. The integration of CNN2D as an extension aligns with contemporary advancements in neural network methodologies, showcasing a forward-thinking strategy for improving flood forecasting accuracy.

v) Training & Testing:

In the "Train & Test Split" module of this project, the dataset is divided into two subsets – a training set and a testing set – to facilitate model training and evaluation. The primary purpose of this module is to assess the model's performance on unseen data, ensuring its ability to generalize beyond the training set.

The process involves allocating 80% of the dataset for training the predictive model, allowing it to learn patterns, relationships, and trends within the data. This substantial portion of the dataset is crucial for the model to capture the underlying features and variations necessary for accurate predictions. The remaining 20% is reserved for testing the trained model. This separate test set serves as a simulated real-world scenario, allowing the assessment of the model's predictive capabilities on data it has not encountered during training.

The utilization of an 80-20 split is a common practice in machine learning, providing a balance between having enough data for effective model training and maintaining a significant portion for rigorous evaluation. This division helps in detecting potential issues such as overfitting, where a model performs well on the training set but struggles with new, unseen data. By evaluating the model on the test set, the project ensures a more reliable assessment of its generalization performance and predictive accuracy, contributing to the robustness and reliability of the flood forecasting system.

vi) Algorithms:

Feed Forward Neural Network:

A feedforward neural network is one of the simplest types of artificial neural networks devised. In this network, the information moves in only one direction—forward—from the input nodes, through the hidden nodes (if any), and to the output nodes. There are no cycles or loops in the network. Feedforward neural networks were the first type of artificial neural network invented and are simpler than their counterparts like recurrent neural networks and convolutional neural networks.

Architecture of Feedforward Neural Networks

The architecture of a feedforward neural network consists of three types of layers: the input layer, hidden layers, and the output layer. Each layer is made up of units known as neurons, and the layers are interconnected by weights.

- **Input Layer:** This layer consists of neurons that receive inputs and pass them on to the next layer. The number of neurons in the input layer is determined by the dimensions of the input data.

- **Hidden Layers:**

These layers are not exposed to the input or output and can be considered as the computational engine of the neural network. Each hidden layer's neurons take the weighted sum of the outputs from the previous layer, apply an activation function, and pass the result to the next layer. The network can have zero or more hidden layers.

- **Output Layer:** The final layer that produces the output for the given inputs. The number of neurons in the output layer depends on the number of possible outputs the network is designed to produce.

Each neuron in one layer is connected to every neuron in the next layer, making this a fully connected network. The strength of the connection between neurons is represented by weights, and learning in a neural network involves updating these weights based on the error of the output.

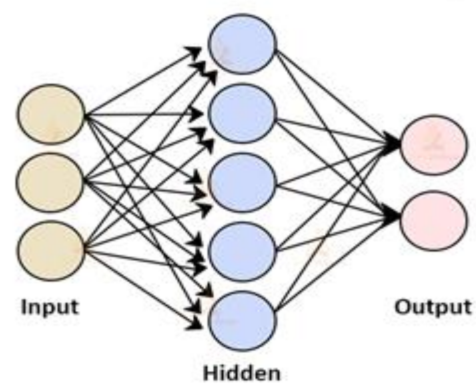


Fig 3 Architecture of Feed Forward Neural Network

Extension CNN2D Algorithm:

The Convolutional Neural Network (CNN or ConvNet) is a class of deep neural networks that is particularly effective in processing and analyzing visual data. The Convolution2D layer is a fundamental building block within a CNN, responsible for applying convolutional operations to input data.

Convolutional Neural Network (CNN) [24] is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. For example visual datasets like images or videos where data patterns play an extensive role.

CNN architecture

Convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.

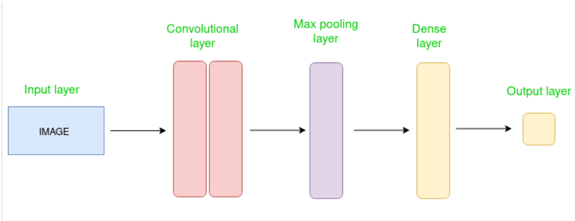


Fig 4 CNN Architecture

The Convolutional layer applies filters to the input image to extract features, the Pooling layer downsamples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

S. NO	ALGORITHM	ACCURACY%
1	FFNN	82.76%
2	CNN2D	87.86%

MSE: The measure of mean squared error needs a target of prediction or estimation along with a predictor or estimator, which is said to be the function of the given data. MSE is the average of squares of the "errors".

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE = mean squared error
n = number of data points
Y_i = observed values
$\hat{Y}_i$ = predicted values

S. NO	ALGORITHM	MSE%
1	FFNN	296.96%
2	CNN2D	147.22%

RMSE: The root mean square error (RMSE) is a very frequently used measure of the differences between value predicted value by an estimator or a model and the actual observed values. RMSE is defined as the square root of differences between predicted values and observed values. The individual differences in this calculation are known as "residuals". The RMSE estimates the magnitude of the errors. It is a measure of accuracy which is used to perform comparison forecasting errors from different estimators for a specific variable, but not among the variables, since this measure is scale-dependent.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

$\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are predicted values
$y_1, y_2, \ldots, y_n$ are observed values
n is the number of observations

S. NO	ALGORITHM	RMSE%
1	FFNN	17.23%
2	CNN2D	12.13%

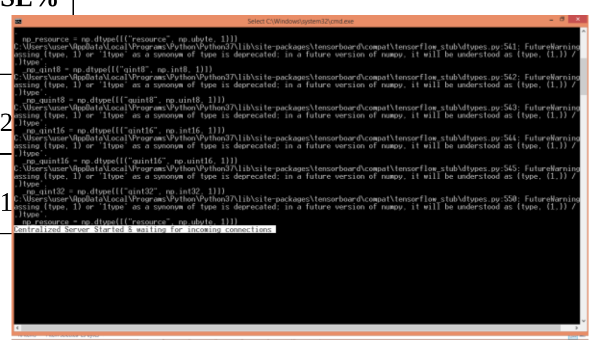
Performance Evaluation Table:

S. NO	ALGORITHM	ACCURACY%	MSE%	RMSE%
1	FFNN	82.76%	296.96%	17.2
2	CNN2D	87.86%	147.22%	12.1

Comparison graph:

Fig 5 Comparison graph of FFNN & CNN2D algorithm

First double click on 'runServer.bat' file to start centralized server and get below output



In above screen Centralized server started and now let it run and then double click on 'run.bat' file to start client which will train model locally by uploading local dataset and get below output

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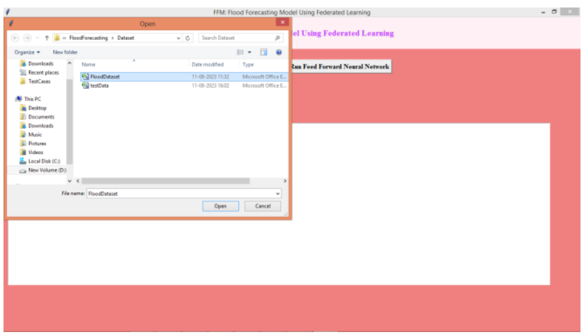
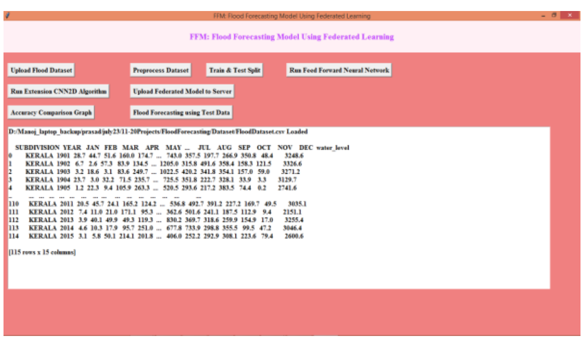
In above screen click on ‘Upload Flood Dataset’ button to load dataset and get below screen



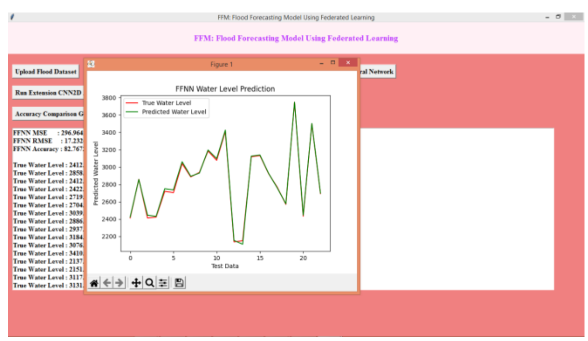
In above screen selecting and uploading ‘Flood Dataset’ and then click on ‘Open’ button to load dataset



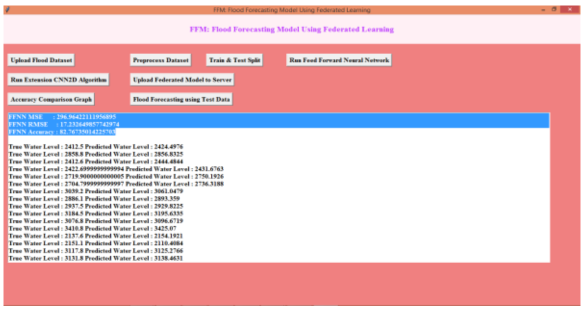
In above screen dataset loaded and now click on ‘Pre-process Dataset’ button to process dataset and get below output

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

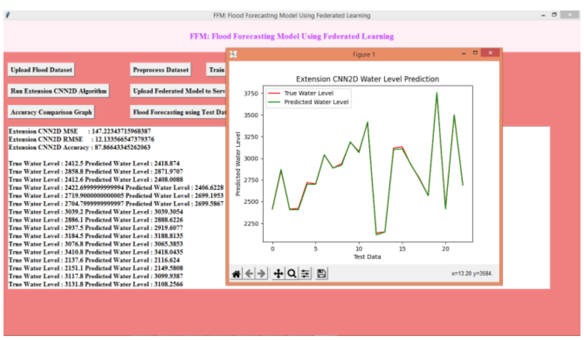
In above screen displaying dataset size and then displaying train and test size and now click on ‘Run Feed Forward Neural Network’ button to train propose FFNN algorithm and get below output



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



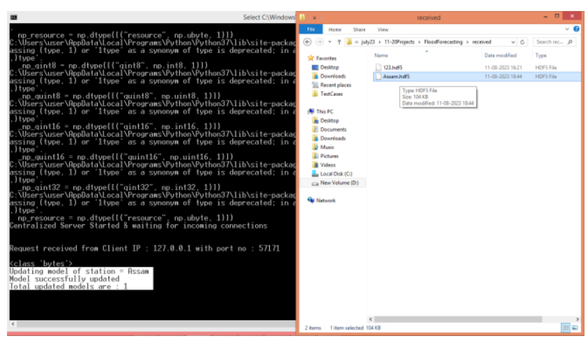
In above screen in first 3 lines we can see FFNN algorithm MSE, RMSE and accuracy values and then we can see true and predicted water levels for future days and now click on 'Run Extension CNN2D Algorithm' button to train extension algorithm



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



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.

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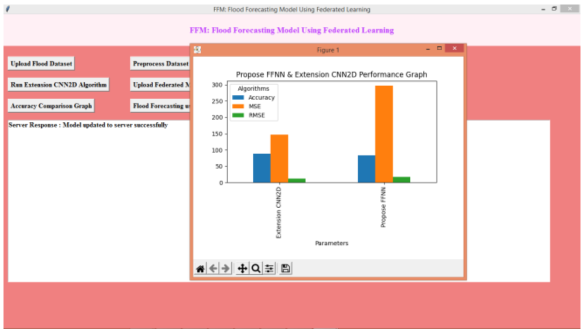
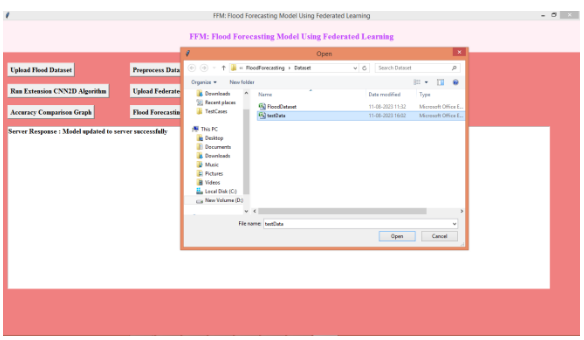
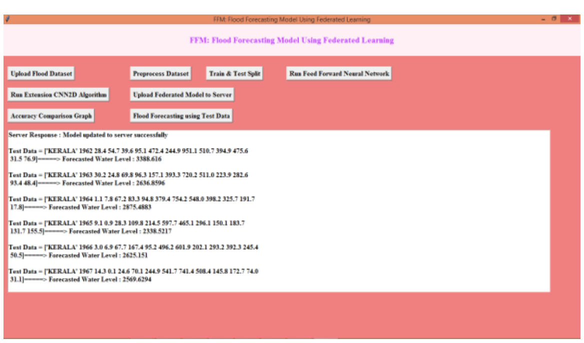


In above comparison graph x-axis represents algorithm names and y-axis represents accuracy and MSE values and we can see for extension algorithm accuracy is high and MSE, RMSE error is lower compare to propose FFNN algorithm and now close above graph and then click on 'Flood Forecasting using Test Data'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

5. CONCLUSION

In conclusion, the presented Flood Forecasting Model (FFM) exhibits a two-module approach for enhanced flood prediction and mitigation. The first module establishes a network of eighteen local monitoring stations, training and transmitting data models to a central server. This central server, in turn, constructs a global model capable of forecasting floods within the next five days by analyzing diverse parameters from the local models. The second module utilizes a Feed Forward Neural Network at the predicted flood location to estimate the expected rise in water levels. Privacy, security, and data availability concerns are addressed by locally processing hydraulic and meteorological data. The FFM demonstrates its efficacy by issuing timely flood alerts to the flood mitigation department, aiding in proactive disaster prevention and response. The evaluation on historical floods from 2010 to 2015 showcases a commendable accuracy of 82.76%. Moreover, the extension of the model with CNN2D significantly improves accuracy to 87.86%.

6. FUTURE SCOPE

The future scope of the Flood Forecasting Model (FFM) envisions its expansion to predict floods globally by incorporating datasets from diverse regions. The system's demonstrated adaptability to regional data positions it as a promising tool for proactive flood forecasting on a broader scale. Through continued development, collaboration, and integration of international datasets, the FFM holds the potential to contribute significantly to global disaster management efforts, offering timely predictions and insights for various regions susceptible to flooding.

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