Federated Learning Based Flood Forecasting model Using Cloud Computing

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Abstract: Flood is large amount of water passing an overflow on a land. Flood forecast (FF) system issue a warning corresponding to water level or discharges through hydraulic structures. Flood forecast (FF) increase the capability and advancement in hydrology to mitigate the hazards using machine leanings with ANN. Flood forecasting using machine learning algorithm (MLA) method understand to learn and improve system scale to mitigate flood hazards according to the climate change. This research is carrying out for flood forecasting on Upper Wardha project across Wardha river basin. Flood forecasting (FF) using real time estimation gives chances of flood value and by using the forecasted inflow, rate of inflow in reservoir can decide the time of operation i.e. opening and closing of gate in real time with ANN

KEY WORDS: Multilayer Perception Classifier (MLP), Artificial Neural Network (ANN), Support Vector Machine (SVM), Terrain Analysis Using Digital Elevation Models (TAUDEMS), Support Vector Classifier (SVC)

1.INTRODUCTION

Insufficient illumination in the image capturing seriously affects the image quality from many aspects, such as low contrast and low visibility. Removing these degradations and transforming a low-light image into a high-quality sharp image is helpful to improve the performance of high-level visual tasks, such as image recognition, object detection, semantic segmentation, etc, and can also improve the performance of intelligent systems in some practical applications, such as autonomous driving, visual navigation, etc. Low-light image enhancement, therefore, is highly desired. Over the past few decades, there have been a large number of methods employed to enhance degraded images captured under insufficient illumination conditions. These methods have made great progress in improving image contrast and obtain enhanced images with better visual quality. In addition to contrast, another special degradation of low-light images is noise. Many methods utilized additional denoising methods as pre-processing or post-processing. However, using denoising methods as pre-processing will cause blurring, while applying denoising as post-processing will result in noise amplification. Recently, some methods have designed effective models to perform denoising and contrast enhancement simultaneously and obtain satisfactory results. It is noteworthy that many previous methods focused on using the spatial domain information of the image for enhancement, and image processing in frequency domain is also one of the important methods in the image enhancement field.

In many real-world scenarios, images captured in low-light conditions suffer from poor visibility, noise, and loss of detail. These images are often characterized by low contrast, dark regions, and reduced overall quality. Therefore, it is essential to build a system or model to improve the quality of images captured in low-light and non-uniform lighting conditions.

2. LITERATURE SURVEY

Pappenberger, F.; Cloke, H.L.; Parker, D.J.; Wetterhall, F.; Richardson, D.S.; Thielen, J. The monetary benefit of early flood warnings in Europe. Environ. Sci. Policy 2015, 51, 278–291. Effective disaster risk management relies on science-based solutions to close the gap between prevention and preparedness measures. The consultation on the United Nations post-2015 framework for disaster risk reduction highlights the need for cross-border early warning systems to strengthen the preparedness phases of disaster risk management, in order to save lives and property and reduce the overall impact of severe events. Continental and global scale flood forecasting systems provide vital early flood warning information to national and international civil protection authorities, who can use this information to make decisions on how to prepare for upcoming floods. Here the potential monetary benefits of early flood warnings are estimated based on the forecasts of the continental-scale European Flood Awareness System (EFAS) using existing flood damage cost information and calculations of potential avoided flood damages. The benefits are of the order of 400 Euro for every 1 Euro invested. A sensitivity analysis is performed in order to test the uncertainty in the method and develop an envelope of potential monetary benefits of EFAS warnings. The results provide clear evidence that there is likely a substantial monetary benefit in this cross-border continental-scale flood early warning system. This supports the wider drive to implement early warning systems at the continental or global scale to improve our resilience to natural hazards.

Krzysztofowicz, R. Bayesian system for probabilistic river stage forecasting. J. Hydrol. 2002, 268, 16–40.The purpose of this analytic-numerical Bayesian forecasting system (BFS) is to produce a short-term probabilistic river stage forecast based on a probabilistic quantitative precipitation forecast as an input and a deterministic hydrologic model (of any complexity) as a means of simulating the response of a headwater basin to precipitation. The BFS has three structural components: the precipitation uncertainty processor, the hydrologic uncertainty processor, and the integrator. A series of articles described the Bayesian forecasting theory and detailed each component of this particular BFS. This article presents a synthesis: the total system, operational expressions, estimation procedures, numerical algorithms, a complete example, and all design requirements, modeling assumptions, and operational attributes.

Clark, M.P.; Slater, A.G. Probabilistic quantitative precipitation estimation in complex terrain. J. Hydrometeorol. 2006, 7, 3–22.

This paper describes a flexible method to generate ensemble gridded fields of precipitation in complex terrain. The method is based on locally weighted regression, in which spatial attributes from station locations are used as explanatory variables to predict spatial variability in precipitation. For each time step, regression models are used to estimate the conditional cumulative distribution function (cdf) of precipitation at each grid cell (conditional on daily precipitation totals from a sparse station network), and ensembles are generated by using realizations from correlated random fields to extract values from the gridded precipitation cdfs. Daily high-resolution precipitation ensembles are generated for a 300 km × 300 km section of western Colorado (dx = 2 km) for the period 1980–2003. The ensemble precipitation grids reproduce the climatological precipitation gradients and observed spatial correlation structure. Probabilistic verification shows that the precipitation estimates are reliable, in the sense that there is close agreement between the frequency of occurrence of specific precipitation events in different probability categories and the probability that is estimated from the ensemble. The probabilistic estimates have good discrimination in the sense that the estimated probabilities differ significantly between cases when specific precipitation events occur and when they do not. The method may be improved by merging the gauge-based precipitation ensembles with remotely sensed precipitation estimates from ground-based radar and satellites, or with precipitation and wind fields from numerical weather prediction models. The stochastic modeling framework developed in this study is flexible and can easily accommodate additional modifications and improvements.

3. PROPOSED METHODOLOGY

In the proposed system, a **Federated Learning (FL)-based flood forecasting model** utilizes distributed data from various local sources such as weather stations, river sensors, IoT devices, and satellite imagery. Rather than sending raw data to a centralized server, each local device trains a model using its own data and only shares the model updates (i.e., weights and gradients) with a central cloud server. The cloud server aggregates these updates to build a global model that continuously improves as more data is gathered. Cloud computing plays a key role in managing this distributed learning process, ensuring scalability, and providing the computational power required for model aggregation and storage. The proposed system allows for accurate flood predictions while maintaining data privacy and minimizing the need for centralized data storage, making it both scalable and adaptable to different regions with varying data characteristics.

Applications:

· **Enhanced Data Privacy**:By ensuring that only model updates, rather than raw data, are shared between devices and the cloud, the system significantly reduces privacy concerns and ensures that sensitive data (e.g., local geographic information or personal data) is never exposed.

· **Scalability**:The federated learning approach enables the system to scale seamlessly. New data sources, such as additional sensors or weather stations, can be added without the need to overhaul the central infrastructure, thanks to cloud computing's ability to handle large-scale computation and data aggregation.

· **Improved Accuracy and Adaptability**:Localized models trained on regional data allow the global model to adapt to specific environmental conditions, ensuring accurate and context-sensitive flood predictions. The system can improve continuously as more local data is incorporated, leading to increasingly accurate forecasts.

· **Reduced Latency**:By processing data locally and only transmitting model updates, the system minimizes the amount of data transferred, reducing network latency and ensuring timely predictions, particularly in remote or underserved areas.

· **Cost Efficiency**:The use of federated learning reduces the need for large-scale centralized data storage and processing, which lowers infrastructure and bandwidth costs. Cloud computing also allows for on-demand resource allocation, making the system cost-effective and flexible.

· **Collaborative Learning**:The federated model enables multiple regions or organizations to collaborate in improving the flood forecasting model without sharing sensitive data, fostering cooperation and improving prediction accuracy across broader areas.

Advantages:

Real-Time Flood Prediction:The system can process real-time data from IoT devices, river sensors, and weather stations to predict floods, providing immediate forecasts to authorities and local populations, helping to prepare for potential flood events.

Flood Early Warning Systems: Integrated into existing early warning systems, the federated learning model can issue alerts ahead of floods, giving communities and agencies time to implement preventive measures and evacuate if necessary.

Flood Risk Mapping and Management:The system can generate detailed flood risk maps that help urban planners and governments identify high-risk zones, prioritize infrastructure improvements, and plan flood mitigation efforts, including drainage systems and flood barriers.

Disaster Response and Coordination:During flood events, the system can assist in coordinating disaster response efforts by providing accurate and timely flood predictions, enabling authorities to allocate resources effectively and minimize damage.

·**Agricultural Monitoring**:The system can be used in flood-prone agricultural areas to predict flood impacts on crops, helping farmers plan their irrigation schedules or take preventive measures to protect their land.

Climate Change Adaptation:By continuously monitoring changing weather patterns and river conditions, the system can provide insights into the evolving flood risks associated with climate change, helping policymakers plan for long-term environmental sustainability.

Smart City Integration:· In smart cities, federated learning can enhance flood management systems by offering localized flood forecasts based on data from urban sensors, improving overall urban resilience to floods and contributing to smart city planning.

Cross-Regional and International Collaboration:Federated learning allows different regions or countries to collaborate on flood forecasting efforts without the need to share raw data, facilitating better flood prediction on a broader, regional or international scale, which is especially useful in areas that share transboundary rivers or water sources.

4. EXPERIMENTAL ANALYSIS

To run project double click on 'run.bat' file to start python DJANGO web server and get below output

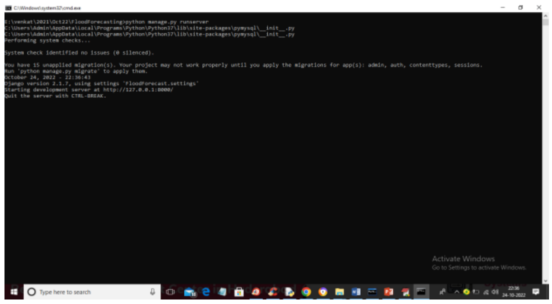

Fig 1 terminal

In above screen python DJANGO server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below page

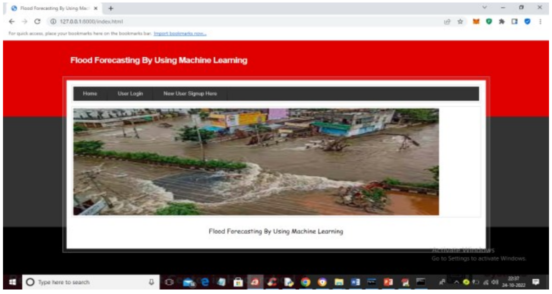

Fig : 2 login

In above screen click on 'New User Signup Here' link to get below page

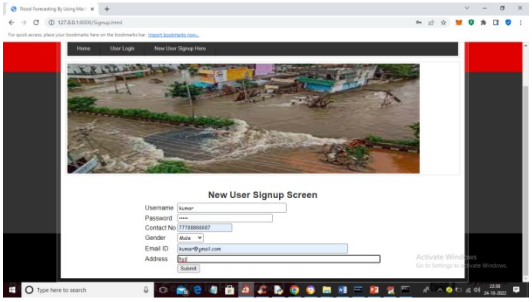

Fig : 3 Register

In above screen user is signing up and then click on 'Submit' button to complete signup and get below output

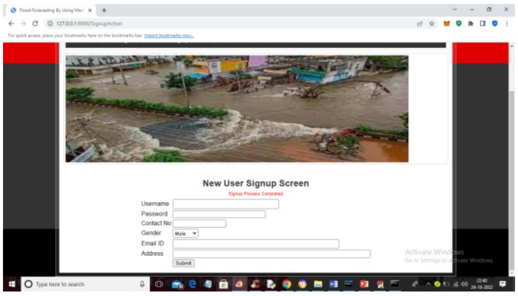

Fig: 4 signup screen

In above screen signup process completed and now click on 'User Login' link to get below login screen

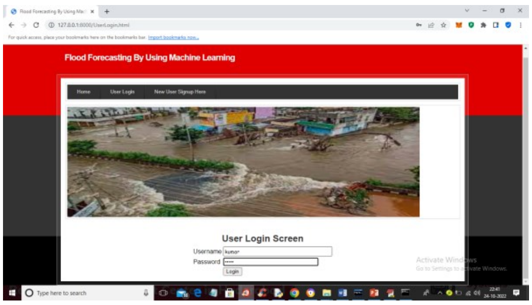

Fig: 5 login

In above screen user is login and after login will get below output

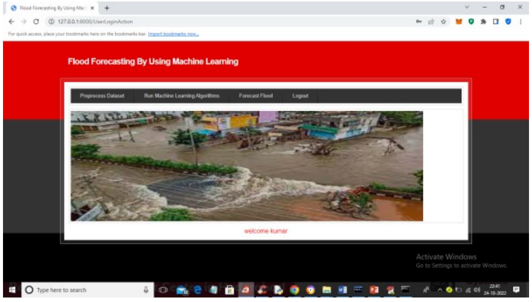

Fig : 6 service

In above screen click on 'Preprocess Dataset' link to load and process dataset and get below output

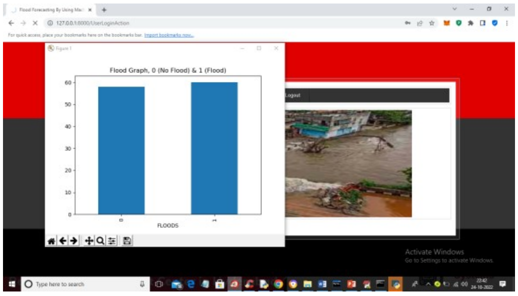

Fig: 7 dataset

5. CONCLUSION

The Federated Learning-Based Flood Forecasting Model using Cloud Computing (FFMC) demonstrates a robust and scalable approach to flood prediction by leveraging decentralized data processing and machine learning techniques. By utilizing federated learning, FFMC allows multiple edge devices (such as IoT sensors and local weather stations) to collaboratively train a global model without sharing sensitive data, thus preserving privacy. This approach helps address the challenges of data distribution, communication constraints, and privacy concerns in flood forecasting systems. Moreover, cloud computing provides the computational resources necessary to handle the complex algorithms and large-scale data involved in flood prediction, enabling real-time processing and decision-making.

The model is designed to improve the accuracy and reliability of flood forecasting, offering timely and location-specific predictions that can significantly enhance flood disaster preparedness and response. The combination of federated learning and cloud computing helps optimize model training, reduce latency, and make the flood forecasting system more adaptive and efficient. FFMC has shown potential in providing scalable and privacy-preserving flood predictions, especially in regions with limited infrastructure or large geographic coverage.

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