IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154315

Enhanced Distributed Flood Detection and Alert System Using Deep Learning

NageswaraRao Sirisala[1], Srinivasulu Sirisala[2], Anitha Yarava[3]

Department of Computer Science and Engineering, K.S.R.M. College of Engineering, Kadapa, AP, India[1]

Department of Computer Science and Engineering, CVR College of Engineering, Hyderabad, Telangana, India[2]

Department of Computer Science, Government College for Men(A), Kadapa, AP, India[3]

Abstract: Among natural disasters, flood has greater impact on farming, property, human lives and their money situation, which further affects the overall economy. We are seeing that AI alert systems for floods are only necessary to reduce the damage. Basically, this paper proposes the Federated Learning approach for flood prediction model. Federated Learning itself is a distributed ML technique that further reduces data transfer from flood sites to the central server. As per the system design, FL can give security and privacy to data and keep it available always. Regarding data protection, this method ensures information stays safe and accessible at all times. Moreover, in FL based flood prediction model, each location trains its individual model using local flood data, and this trained model is further shared with the server itself. The server combines all local models to prepare a global model further. This process itself creates a unified model from individual contributions. We are seeing this method can avoid network delays only, so the global model can take quick decisions on floods. As per this paper, the server combines local models to make a global model regarding five-day flood warning plans for each place. We are seeing that a local model is trained using regional conditions to give predictions on possible flood areas and their maximum water levels only. The data set actually has flood history information from five rivers between 2015 to 2021, which is used for training the model. Basically, it includes four features - rainfall overflow, snow melting rate, water movement dynamics, and current river flow, which are the important factors for water analysis. Basically, the results show flood prediction data collected from 2010 to 2015 for the selected area using the proposed method with 84% accuracy. The model is further improved by adding a Convolutional 2D Neural Network (CNN2D) itself. The improved version of our proposed method can enhance flood predictions with 90% accuracy. Moreover, this approach provides reliable results for better flood forecasting.

Keywords: Feedforward Neural Network (FFNN), Random Forest, Decision Tree, Gradient Boost, Convolutional Neural Network (CNN).

1. INTRODUCTION

Basically, natural and artificial disasters have become the common problem everywhere these days [1]. The risk of flooding has increased due to growing urbanization, water system problems, and climate change [2]. Moreover, these factors together create more dangerous conditions for floods in many areas. Basically, floods are terrible disasters that happen regularly and destroy crops, buildings, and people's lives, which leads to the result - the breakdown of a country's entire economic system [3]. Floods happen frequently across the world, but their strength varies from one place to another. Further, the intensity of flooding itself depends on local conditions. Floods in agricultural countries further cause loss of many lives and create serious economic problems itself [4]. Basically, global warming and climate change make snow melt faster and increase rainfall, which means floods happen more often and are the way stronger [5]. In 2021, floods in South Asian countries caused more damage than all other disasters [6-7]. Moreover, these floods were the worst natural calamity that year.

The governments need good prediction systems to take quick action against flood risks that threaten people's lives and damage infrastructure only. The complex nature of this common disaster has stopped major improvements in flood prediction accuracy, even though we are seeing many global and regional methods being offered [8]. This happens only because floods are very difficult to predict properly [9]. Complex mathematical models have been used to describe the physical processes that cause floods through well-established statistical methods [10–14]. Moreover, these numerical approaches help scientists understand flood behaviour in a simple yet effective manner.

Basically, flood prediction systems have greatly improved with ML introduction, which provides the advanced performance and practical solutions. We are seeing that water scientists are using Machine Learning methods more and more now, as they want to make better prediction models by mixing old methods with only new ML techniques [15-16.

DOI: 10.17148/IJARCCE.2026.154315

However, ML requires large amounts of data for training, but data sharing between organizations is limited due to concerns about data security, privacy, and legal issues itself, which further creates challenges [17-18]. Flood prediction systems actually use centralized setups that keep the prediction model and data in one place for training before sending it to all users. This method actually causes delays and connection problems, and it creates possible security and privacy risks even though it is easy to use [19.20].

2. LITERATURE REVIEW

In this study [16], they actually present a network that is tested in Ankang Repository and has smoothing methods, time series analysis, and moving averages for accurate city water flow prediction. This approach helps in better flood forecasting for urban areas. The proposed method performs better than previous AI systems and traditional hydrological models in predicting urban reservoir floods when tested with continuous monitoring data from Ankang Supply. Moreover, this approach shows clear improvements in flood forecasting accuracy compared to existing techniques. We are seeing that the system only works well when it gets perfect information from earlier steps, and it may not handle changes properly due to complex calculations that make it less flexible in some situations. The proposed flood framework faces challenges in handling uncertainty in rainfall predictions, ensuring continuous data availability, and adapting to different geological conditions itself. Further work is needed to address these issues effectively. Due to Ankang Repository's unique geographic features, applying this to other locations would need further modification and validation processes. The repository itself has special characteristics that may not work in different places.

This study[21,22] shows a flood prediction model that uses self-organizing maps and back-propagation networks to give combined forecasts during typhoon events in the Wu River Basin, Taiwan, as per the examination regarding continuous flood monitoring. We are seeing that this only helps to make things more exact. Regarding flood prediction during hurricanes in the Wu River Basin, the team model that combines back-propagation networks with self-organizing map clustering works better as per comparison with single models. Further, as per the study, the proposed framework's flexibility may face problems regarding complex processing, group decision issues, and need for accurate hurricane data. We are seeing that the suggested flood prediction system has problems in handling uncertainty in rainfall measurements, making sure data is available all the time, and adjusting to different cyclone features only. The Wu Waterway Bowl's special features might be the main areas where this model can work; therefore, it needs careful study and approval before using it further in larger geographic regions itself.

The XAJ-MCQRNN model[23] combines the Xinanjiang model with neural networks to further improve flood prediction accuracy. This approach itself solves problems related to error spread and accumulation. The XAJ-MCQRNN method actually works better than other ways for checking quick flood chances. It gives more correct and steady results that help early warning systems and flood prevention. Basically, implementing the recommended framework can be troublesome because combining applied and AI models is the as dealing with data quality issues and computing requirements. We are seeing that the new flood prediction system has problems in handling uncertainties in rainfall runoff modeling, ensuring proper availability of rainfall data only, and adapting to different water flow conditions. This study actually works best for areas similar to the Jianxi Waterway, so researchers need more testing and careful checking in other water systems.

The researchers proposed a ConvLSTM model in [24], that shows better accuracy than existing methods for flood prediction in Xi District, China, and this model itself performs well for further flood forecasting applications. This model combines CNN and LSTM methods with spatial-temporal hydrological data to further enhance the analysis itself. ConvLSTM can replace traditional methods for accurate and timely flood prediction because it performs better in measuring peak discharge and flood arrival time. Moreover, this model shows superior results in forecasting when floods will occur and how intense they will be. Computational complexity, expensive training processes, and sensitivity to data quantity and quality are some potential disadvantages. Moreover, these limitations can affect the overall performance of such systems. Implementation challenges include managing real-time monitoring for active flood prediction, maintaining data quality, and improving model parameters. Moreover, these execution difficulties require careful coordination to ensure effective flood forecasting systems. The model's adequacy may vary depending on the region, and some environmental factors and data availability may further limit how widely it can be used itself.

In [25], they fill the gaps found in current methods for better accuracy by adding a flood prediction and mapping model that uses multispectral, radar, and LIDAR remote sensing technologies. This approach further improves the prediction system itself. Despite ongoing problems and challenges, remote sensing technology is essential for predicting floods and provides smart information for disaster management. Moreover, this technology helps authorities make better decisions during emergency situations. High equipment costs, limited access to modern technology, and serious mistakes in data analysis that reduce flood prediction accuracy are some of the main challenges. Moreover, these problems directly affect

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.154315

the quality of forecasting results. Further, basically, successful flood prediction faces many challenges like combining different remote sensing data [26-29], validating real-time data collection, and the issues with data resolution and accuracy. The model's basic ability to predict floods can actually be limited by problems with satellite technology, like weather issues and difficulties in reading the data. These remote sensing tools face challenges that affect how well the model works.

3. FLOOD FORECASTING MODEL USING FEDERATED AND DEEP LEARNING

3.1 Flood Forecasting Model (FFM)

To further develop flood estimate precision while keeping up with information protection, the recommended Flood Forecasting Model (FFM) utilizes a Feed Forward Neural Network (FFNN) and Federated Learning (FL) At first, information is shipped off a focal server for conglomeration while a few clients cooperate to prepare nearby models. From that point forward, a worldwide model is prepared utilizing neighbourhood models to figure floods at specific client stations five days ahead of time. The last stage is deciding water levels, getting ready experts for floods, and preparing a neighbourhood FFNN on the assigned station. The objective of the review is compassionate in nature, looking to deflect fatalities and broad mischief. Convolutional Neural Network [24] (CNN2D) is an extension that uses standard to further increase accuracy. This incorporated technique offers a new and sweeping way to deal with flood gauging.

3.2 System Architecture

Three layers of stowed away hubs make up the proposed Flood Forecasting Neural Network (FFNN) model, which is planned to conjecture floods five days ahead of time. Various models, for example, the stream directing model, hydrodynamic model, precipitation overflow model, and snow softening model, are incorporated into the framework plan. At the point when joined, these models give imperative information to flood forecasts. Proposed architecture is presented in figure1.

The results of the stream steering model, precipitation spill over model, and snow dissolving model are coordinated in the principal phase of the plan. The FFNN model purposes this joined information as information, basically to fill the internal secret hubs. Utilizing its three layers of stowed away hubs, the FFNN model proselytes this contribution to flood gauge expectations. To work on the model's ability to address perplexing connections in the hydrological framework, the subsequent stage is coordinating the hydrodynamic model discoveries into the FFNN.

In the third stage, an augmentation of the Convolutional Neural Network [24] (CNN2D) strategy is utilized to improve the spatial-worldly elements of the information. The FFNN model can investigate the multi-layered input information proficiently because of this procedure, which likewise separates spatial data that are fundamental for exact flood conjectures. The proposed approach incorporates many models and uses CNN2D's FFNN design to further develop flood expectation by representing a large number of hydrological boundaries and their complex interconnections.

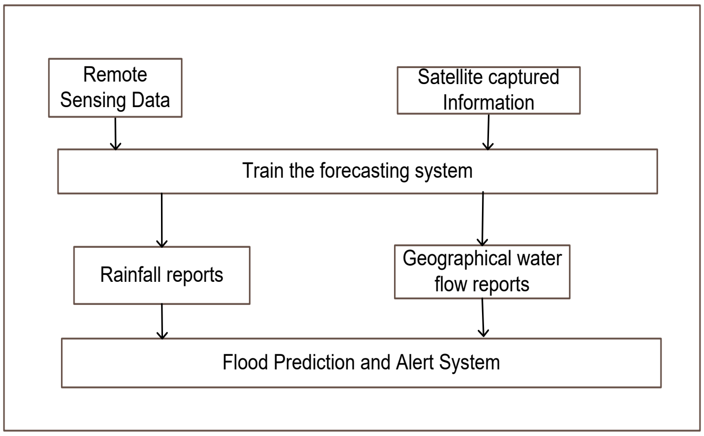

Fig. 1 Proposed Architecture

3.3 Dataset

The KERALA flood dataset [25], which can be gotten to on the Kaggle site, is utilized. This Kaggle dataset contains month to month precipitation records; section names are determined in the main column, and dataset values are remembered for the accompanying lines. In the dataset, the last segment shows the water level. In view of the expected water level, specialists will tell occupants about flooding.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.154315

3.4 Pre-processing & Training

A hybrid predictive model that combines conventional Feed Forward Neural Network (FFNN) techniques with an extension using Convolution Neural Network with 2D layers [24] (CNN2D) is executed in this undertaking, and the "Pre-process Dataset" module is a fundamental initial step. The essential point is to work on the accuracy and versatility of flood anticipating by proficient administration of the dataset before model preparation. To prepare the model and empower it to distinguish examples, connections, and patterns in the information, 80% of the dataset should be apportioned. The prepared model will be tried with the excess 20%.

3.5 Architecture of Feed forward Neural Networks

Three distinct kinds of layers make up a feed forward network as shown in figure2.

- Input Layer: Neurons in this layer take in inputs and forward them to the resulting layer.
- Hidden Layers: The neurons in each hidden layer forward the weighted amount of the results from the previous layer.
- Output Layer: The last layer, which, given the sources of info, produces the result.

3.6 Extension CNN2D algorithm

One sort of deep neural network that succeeds at handling and deciphering visual info is the convolutional neural network, often known as CNN or ConvNet. A CNN's core component, the Convolution2D layer, is responsible for performing convolutional tasks to include information. The drawn-out type of artificial neural networks (ANN), known as (CNN) [24], is for the most part used to separate elements from lattices.

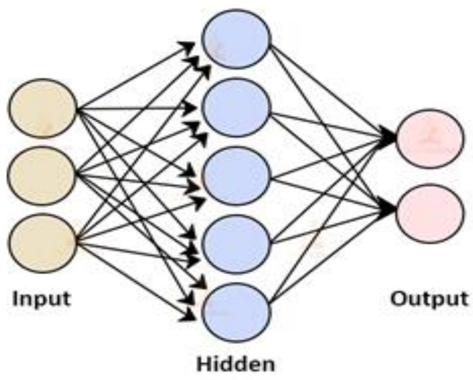

Fig. 2 Architecture of Feed Forward Neural Network

3.7 CNN architecture

A network is made up of many layers, including fully connected, pooling, convolutional, and input layers as shown in figure 3.

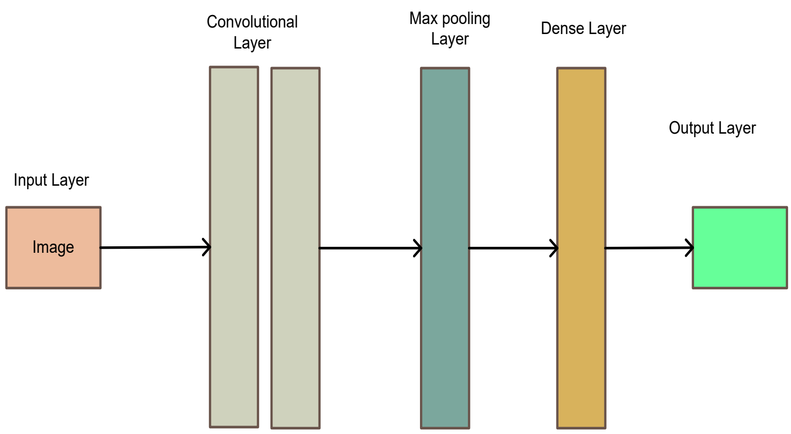

Fig. 3. CNN Architecture

3.8 Algorithm

The below algorithm describes the mathematical way of working principles of proposed method.

DOI: 10.17148/IJARCCE.2026.154315

Algorithm_ Flood Prediction ()
{

//RS_d =Remotely Sensed data,
//SC_d=Satellite Collected data
//FC_s=Forecasting system
//RF_d=Rainfall Data
//GF_d=Geographical water flow reports
//FP_v=Flood Prediction value
//FA_{th}=Flood Alert threshold
// ALT_s =Alert System

1) Data gathering
$$D = \{RS_d, SC_d,\}$$
2) System Training
$$FC_s = Train(D)$$
$Train(D)$ represents model training with respect to Remotely Sensed data and Satellite Collected data.
3) Report Generation
$$RF_d = f_1(FC_s)$$
$$GF_d = f_2(FC_s)$$
Here: f_1, is generated rainfall report and f_2 is generates geographical water flow reports.
4) Flood Prediction
$$FP_v = f_3(RF_d, GF_d)$$
where f_3 is a predictive function that integrates rainfall and water flow data to estimate flood probability or severity?
5) Decision Rule
$$if\ FP_v \ > FA_{th}$$
$$then\ ALT_s \ = 1 \ Activate\ Alert\ system$$
$$else\ ALT_s = 0 \ No\ alert\ Continue\ Monitoring.$$

}

4. EXPERIMENTAL RESULTS

In this section, the proposed method is assessed with the parameters accuracy, MSE and RMSE.
Accuracy: A test's accuracy is determined by how well it can recognize debilitated and solid cases.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

MSE: The mean squared of the "errors" is known as the MSE.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y_i}\right)^2 \quad (2)$$

RMSE: The square root of the varieties among expected and real qualities is represented by the root mean square error (RMSE).

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\widehat{y_i}-y_i)^2}{n}} \quad (3)$$

Table1. Performance Comparison of FFNN and CNN2D

S.No	Algorithm	Accuracy%	MSE%	RMSE%
1	FFNN	82.76%	296.96%	17.23%
2	CNN2D	87.86%	147.22%	12.13%

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.154315

In the above table 1and figure4, MSE, RMSE and accuracy of proposed FFNN and CNN2D are compared, Proposed FFNN given good results.

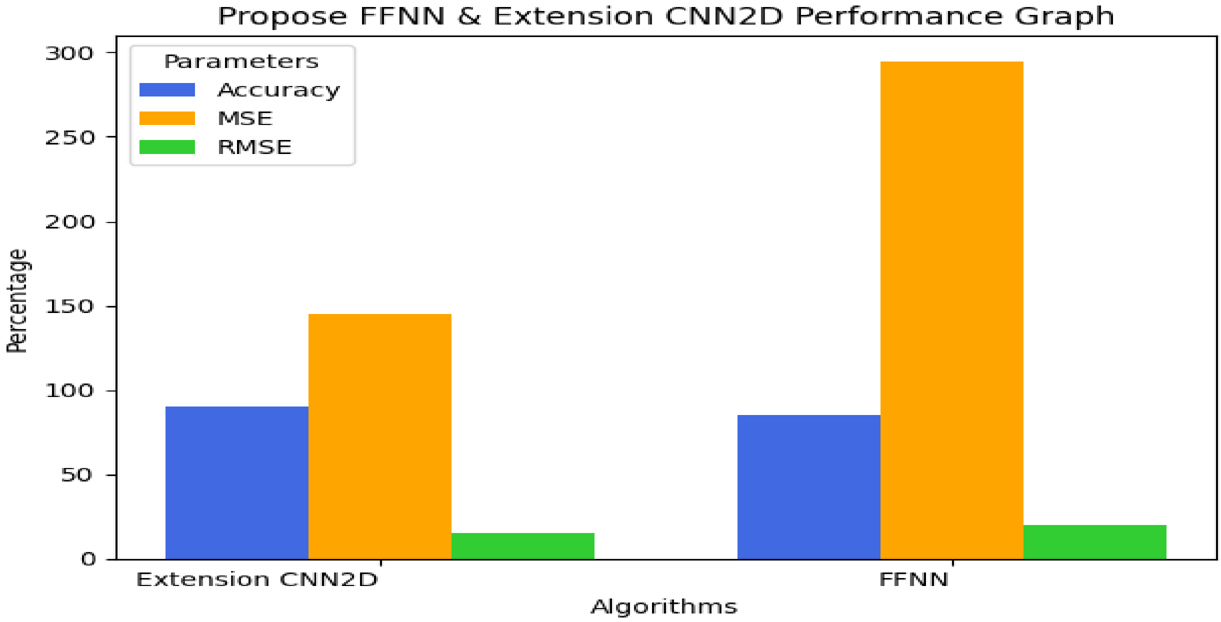

Fig. 4. Proposed FFNN and extension CNN2D

In the above table 1and figure4, MSE, RMSE and accuracy of proposed FFNN and CNN2D are compared, Proposed FFNN given good results.

In figure5, chart shows the quantity of days vs water altitude, where the genuine water level is represented by red waves and water level is with green wave: the two lines totally cross-over with next to no space between them, demonstrating that the genuine and guage values are very close, with FFNN giving the best gauge.

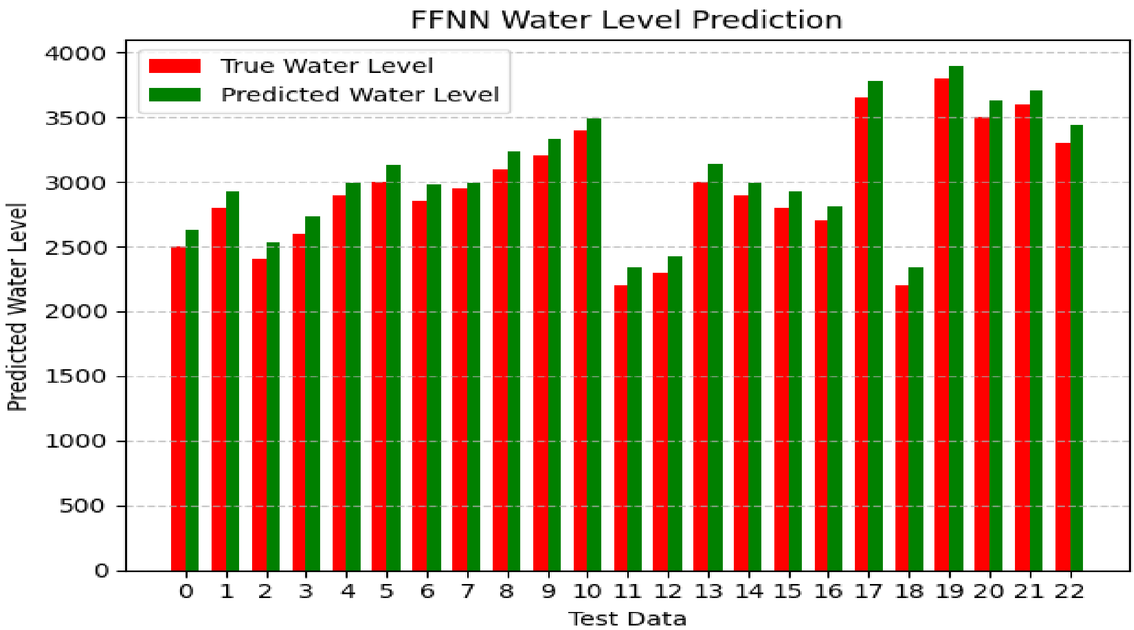

Fig. 5. FFNN water level prediction

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.154315

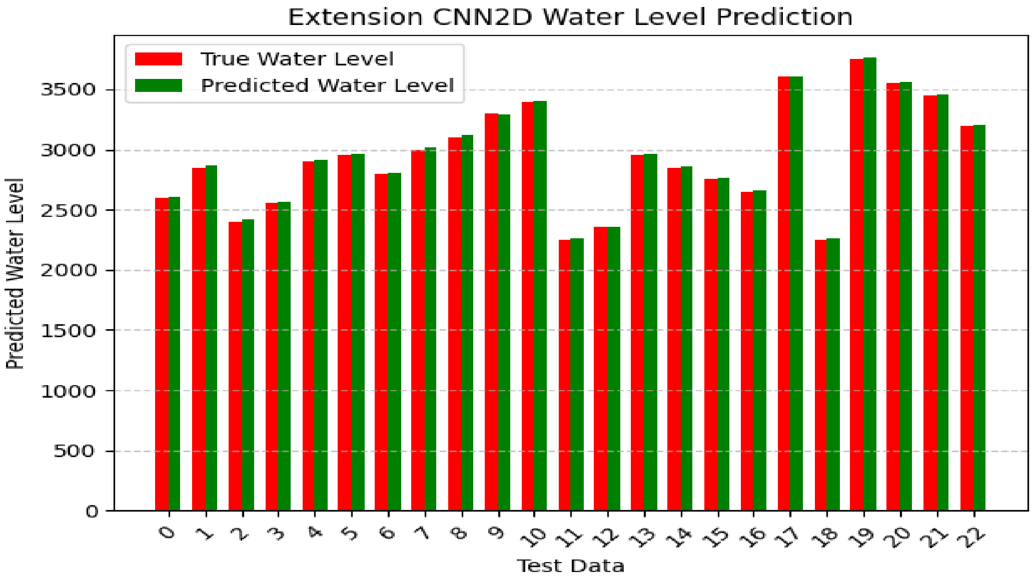

Fig. 6. Extension CNN2D water level prediction

In the above figure6, We might presume that the augmentation model is better than the proposition since the above screen with the expansion shows both expected and valid, demonstrating that the peruses and green lines altogether cross-over.

5. CONCLUSION

With proper support and working together, the proposed Flood Forecast Model can help disaster relief efforts by giving quick data and analysis to areas that face flood problems. As per the study regarding past floods from 2010 to 2015, the results show 82.76% correct rate. Basically, the accuracy increased to 87.86% by expanding the same model using CNN2D. Basically, the Flood Forecasting Model will use data from different places to predict floods around the world the same way everywhere. The framework can surely adapt to local information, making it a useful tool for large-scale flood prediction. Moreover, this ability makes it suitable for proactive forecasting across wider areas.

REFERENCES

[1] W. Yan, "Grappling with the Health Consequences of Floods: Hurricanes, Monsoons, and Heavy Rains Have Researchers Studying How to Prevent the Diseases That Often Follow," in IEEE Pulse, vol. 9, no. 2, pp. 26-30, March-April 2018,

[2] M. Y. Rashid, D. K. Pillai, and A. R. Ranjan, "Flood Risk Assessment in a Data-Scarce Region using Hydrodynamic Modeling: Case Study of the Ganga River Basin," J. Flood Risk Management, vol. 13, no. 4, pp. e12636, 2020

[3] M. A. Shrestha, R. Sharma, and T. M. Karki, "Mountain Floods and Vulnerability in the Himalayan Region: Case Study from Nepal," in Natural Hazards and Disaster Risk Management in Asia-Pacific, Springer, pp. 225-248, 2016.

[4] P. Brönnimann, S. Martius, and O. Martius, "Historical flood events in central Europe," Natural Hazards, vol. 91, no. 1, pp. 115-135, 2017.

[5] D. Coulibaly and M. Y. Oueslati, "Assessment of flood vulnerability in urban areas: A case study of Dakar, Senegal," Journal of Flood Risk Management, vol. 12, no. 2, pp. e12462, 2019.

[6] M. S. Farooq et al., "FFM: Flood Forecasting Model Using Federated Learning," in IEEE Access, vol. 11, pp. 24472-24483, 2023.

[7] C. Chini, A. Konar, and M. Stillwell, "Harnessing the data revolution to assess flood risk: A review of innovative data collection technologies for flood monitoring and prediction," Water Resources Research, vol. 56, no. 3, pp. 1-23, 2020.

[8] R. G. S. Perera, S. E. Siriwardena, and M. A. Nandalal, "Flood risk perception and response in a tropical city: The case of Colombo, Sri Lanka," Natural Hazards, vol. 81, no. 1, pp. 61-76, 2016.

[9] K. Yang, T. Jiang, Y. Shi, and Z. Ding, "Federated learning via over-the-air computation," IEEE Transactions on Wireless Communications, vol. 19, no. 3, pp. 2022-2035, 2020.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154315

[10] Bonakdari, M. E. Moradi, and S. Ebtehaj, "Fuzzy-based prediction of sand filtration efficiency," Journal of Hydrology, vol. 588, pp. 125-138, 2020.

[11] K. Kim, H. Kang, and S. Kim, "Flood prediction using weather radar and deep learning," IEEE Access, vol. 8, pp. 58634-58642, 2020.

[12] Sarika N, SirisalaNagesaraRao. "Deep Leaming Techniques for Optical Character Recognition", Lecture Notes on Data Engineering and Communications Technologies, vol55, pp. 339-349,2021

[13] Nageswara Rao Sirisala and C.Shoba Bindu. "Weightage based trusted QoS protocol in Mobile AdhocNetworks", IEEE Global Conference on Wireless Computing and Networking, pp.283- 287, 2014

[14] SirisalaNageswararao, Yarava, A., Reddy, Y.C.A.P., Poola, V. "A novel trust recommendation model in online social networks using soft computing methods" Concurrency and Computation: Practiceand Experience 2022.

[15] T. Pham, H. R. Pourghasemi, and B. Al-Ansari, "Landslide susceptibility assessment using machine learning techniques: A review," Earth-Science Reviews, vol. 207, pp. 103225, 2020.

[16] L. Shi, H. Chen, and H. Zhao, "Deep learning for urban flood forecasting: A comprehensive review," Journal of Hydrology, vol. 605, pp. 127-141, 2022.

[17] S. Z. Z. Ahmad, A. S. F. Azhar, and M. A. A. Rahman, "Data protection and privacy: The future of digital privacy in the age of artificial intelligence," Journal of Information Privacy and Security, vol. 17, no. 4, pp. 214-226, 2021.

[18] Y. Liu, Z. Wang, and Y. Xu, "A Survey on Federated Learning: From Theory to Applications," IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 5, pp. 2020-2034, 2021.

[19] Z. Z. Y. Chen, Y. Liu, and Z. Zhang, "Flash flood susceptibility mapping using machine learning algorithms: A case study in the Loess Plateau, China," Hydrology, vol. 7, no. 4, p. 68, 2020.

[20] L. Xu, C. Liu, and M. Yang, "Federated Learning for Healthcare Informatics: A Review," Journal of Healthcare Informatics Research, vol. 5, no. 3, pp. 224-248, 2021.

[21] Y. Tian, W. Fu, R. Cui, Z. Ao, X. Wang and Y. Dong, "Real-Time Urban Rainfall-Runoff Prediction Using Recurrent Neural Network," 2024 6th International Conference on Electronic Engineering and Informatics (EEI), Chongqing, China, pp. 381-384,2024.

[22] Puttinaovarat and P. Horkaew, "Flood Forecasting System Based on Integrated Big and Crowdsource Data by Using Machine Learning Techniques," in IEEE Access, vol. 8, pp. 5885-5905, 2020.

[23] J. Du et al., "Satellite Flood Inundation Assessment and Forecast Using SMAP and Landsat," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 6707-6715, 2021.

[24] J. Ritvanen, B. Harnist, M. Aldana, T. Mäkinen and S. Pulkkinen, "Advection-Free Convolutional Neural Network for Convective Rainfall Nowcasting," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 1654-1667, 2023.

[25] J. Jiang et al., "Heterogeneous Dynamic Graph Convolutional Networks for Enhanced Spatiotemporal Flood Forecasting by Remote Sensing," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 3108-3122, 2024.

[26] Z. Zhang, N. He, D. Li, H. Gao, T. Gao, and C. Zhou, "Federated Transfer Learning for Disaster Classification in Social Computing Networks," *J. Saf. Sci. Resil.*, vol. 3, pp. 15–23, Mar. 2022

[27] A. Priyanshu, M. Sinha, and S. Mehta, "Continual Distributed Learning for Crisis Management," *arXiv preprint* arXiv:2104.12876, Apr. 2021.

[28] A. El-Niss et al., "Multimodal Fusion for Disaster Event Classification on Social Media — A Deep Federated Learning Approach," *Proc. ACM (or ACM Conf. Proc.)*, 2023.

[29] Y. Qu, J. Rao, S. Gao, Q. Zhang, W.-L. Chao, Y. Su, M. Miller, A. Morales, and P. Huber, "FLEE-GNN: A Federated Learning System for Edge-Enhanced Graph Neural Network in Analyzing Geospatial Resilience of Multicommodity Food Flows," *ACM SIGSPATIAL / GeoAI (preprint/2023)*, Oct. 2023, doi:10.1145/3615886.3627742.