E-ISSN: 2583-9667
Indexed Journal
Peer Reviewed Journal
https://multiresearchjournal.theviews.in

Received: 19-02-2025
Accepted: 30-03-2025

INTERNATIONAL JOURNAL OF ADVANCE RESEARCH IN MULTIDISCIPLINARY

Volume 3; Issue 2; 2025; Page No. 380-385

Advance flood alert prediction using deep learning

[1]Dr. Balaji Kannan and [2]Syed Harun S

[1]Assistant Professor, Department of Computer Science, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Pallavaram, Chennai, Tamil Nadu, India
[2]PG Scholar, Department of Computer Science, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Pallavaram, Chennai, Tamil Nadu, India

DOI: https://doi.org/10.5281/zenodo.15623028

Corresponding Author: Syed Harun S

Abstract

One of the most destructive natural disasters is flooding, which frequently causes a large number of fatalities, property damage, and infrastructure disruption. For disaster management and mitigation strategies to be effective, flood prognostications must be made accurately and on time. This study offers a robust flood alert prediction system that improves forecasting accuracy and response time by applying deep learning techniques. The proposed system integrates various environmental parameters, including rainfall intensity, river water levels, soil moisture, and satellite imagery, to train deep neural network models capable of recognizing complex patterns associated with flood events.
According to evaluation results, the deep learning-based model provides a dependable tool for early warning systems by outperforming traditional statistical techniques in terms of prediction.
By giving communities and authorities accurate, real-time alerts that facilitate proactive evacuation and resource allocation, this research confirms how deep learning has the potential to revolutionize flood risk management and lessen the impact of flood disasters.

Keywords: In order to build a real-time early warning system that uses spatiotemporal modeling, environmental sensor data, and remote sensing for better hydrological forecasting and disaster management

Introduction

One of the most common and damaging natural disasters in the world, floods cause enormous losses to the environment, economy, and human species every year. The need for precise and timely flood forecasting has never been more important than it is now, as climate change makes weather patterns more unpredictable. The intricate and dynamic character of flood events is most often hard for new flood prediction techniques, which mainly rely on statistical models and hydrological simulations, to capture, particularly in real-time scenarios.
Promising reaches to overcoming these constraints are provided by recent developments in artificial intelligence, especially deep learning. Large volumes of heterogeneous data, such as satellite imagery, rainfall intensity, soil moisture, river discharge, and topography, can can indeed be processed by deep learning models, which can then categorize intricate nonlinear relationships that conventional models might overlook. Convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) are two examples of architectures that combine spatial and temporal data to create secure systems that can detect floods early and generater.
In order to improve forecasting accuracy, lead times, and proactive disaster response, this findings suggest a sophisticated deep learning-powered flood alert prediction framework. More accurate flood predictions are made feasible by the combination of intelligent modeling and real-time environmental data, which also lessens the effects on communities that are already at risk. The context for examining how such intelligent systems can transform flood management and help create safer, more resilient societies is established of the program is introduction.

Literature Survey

Researchers and organizations have investigated a variety of flood prediction techniques over the last few decades, ranging from data-driven methods to empirical models. Old techniques frequently depend on hydraulic and hydrological models, like the SWAT and HEC-RAS, which model catchment behavior and river flow using historical climate and topography data. Although these models offer a basic understanding of flood behavior, they regularly need to be recalculated extensively and might not function well in regions with limited data availability or in at climates that are changing.

Researchers started investigating data-driven models for flood forecasting with the introduction of machine learning. Early efforts employed algorithms such as Support Vector Machines (SVMs), Decision Trees, and Artificial Neural Networks (ANNs) to model rainfall-runoff relationships. Although these models exhibited greater adaptability and needed.

Flood prediction systems are now much more proficient thanks to recent developments in deep learning. Sequential data such as river discharge and rainfall time series have been processed by models like Long Short-Term Memory (LSTM) networks, which have shown tremendous potential for forecasting flood timings and peaks. In order to comprehend terrain and water flow patterns, Convolutional Neural Networks (CNNs) have also been used to analyze spatial data, including digital elevation models and satellite.

In recent research, hybrid models that combine CNNs and LSTMs have evidenced encouraging outcomes. For example, using CNN-LSTM architectures, researchers have successfully created systems that combine historical flood events with rainfall radar images, enabling high-resolution, real-time forecasting. Other research has looked into graph neural networks, attention mechanisms, and transfer learning to Despite various developments, there are still issues with real-time data integration, interpretability of models, and deployment in environments with limited data. However, the literature makes it richly evident that deep learning provides a strong and flexible method for contemporary flood prediction and early warning.

Numerous studies have explored flood prediction using both traditional and modern approaches. Traditional hydrological models, such as SWAT and HEC-HMS, depend on physical parameters and require a lot of calibration, but they are frequently inflexible in areas with limited data. While statistical techniques like regression and ARIMA are straightforward, they are not very good at capturing nonlinear relationships. Models like SVMs, Random Forests, and Artificial Neural Networks (ANNs) were introduced with the rise of machine learning; these models increased accuracy but still had trouble with temporal dynamics. Flood forecasting has been greatly improved by recent developments in deep learning, especially Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), which efficiently model spatial features and temporal sequences.

Over the years, flood prediction has evolved from traditional hydrological and statistical models to advanced AI-driven systems. Classical models like HEC-RAS, SWAT, and MIKE FLOOD simulate physical processes based on rainfall, topography, and land use, but are often constrained by the need for extensive calibration and high-quality data, limiting their scalability. Statistical models such as regression analysis and ARIMA are easier to implement but lack the capacity to handle complex nonlinear patterns in climate and hydrological data. The introduction of machine learning, including Support Vector Machines (SVM), Decision Trees, Random Forests, and basic Artificial Neural Networks (ANN), marked a shift toward data-driven forecasting, improving adaptability but still facing issues with capturing long-term dependencies. Deep learning has emerged as a game-changer, with LSTM networks excelling in temporal sequence prediction and CNNs being effective in spatial data analysis such as satellite imagery, flood maps, and digital elevation models. CNN-LSTM and other hybrid models have been widely used for multi-source, real-time flood forecasting systems. To improve performance and training efficiency, research has also looked into the use of transformers, GRUs, and attention mechanisms. Flood monitoring and forecasting are now possible in almost real-time thanks to the integration of cloud platforms like Google Earth Engine, IoT sensor networks, and remote sensing data. Successful implementations of AI-based flood warning systems have been shown in case studies from China, India, Europe, and the United States. Despite this progress, there are still significant obstacles to overcome, such as the lack of interpretability of the model, the sparsity of data in remote locations, and the challenge of generalizing the model across distinctive climatic and geographic zones. Researchers are using data augmentation techniques, explainable AI (XAI), transfer learning, and, more recently, Graph Neural Networks (GNNs) to model complex spatial.

With the combination of deep learning and artificial intelligence, flood prediction has changed dramatically. These systems, which were initially based on physically based hydrological models that simulated the dynamics of watersheds and rivers, such as HEC-HMS, SWAT, and MIKE URBAN, have been absolutely. essential but constrained by the request for intensive calibration, high-resolution terrain data, and sensitivity to unknown parameters. While statistical models such as logistic regression, linear regression, and ARIMA made computations extremely easy, they are also not robust enough to handle the non-linear flood behaviour and attitudes in the real world. As machine learning advanced, SVMs, k-NN, Decision Trees, and Random Forests arose. These models improved automation and pattern recognition but continued to perform poorly in sequence forecasting and real-time applications.

With the combination of deep learning and artificial intelligence, flood prediction has changed dramatically. These systems, which were initially based on physically based hydrological models that simulated the dynamics of watersheds and rivers, such as HEC-HMS, SWAT, and MIKE URBAN, have been absolutely essential but constrained by the request for intensive calibration, high-resolution terrain data, and sensitivity to unknown parameters. While statistical models such as logistic regression, linear regression, and ARIMA made computations extremely easy, they are also not robust enough to handle the non-linear flood behaviour and attitudes in the real world. As machine learning advanced, SVMs, k-NN, Decision Trees, and Random Forests arose. These models improved automation and pattern recognition but continued to perform poorly in sequence forecasting and real-time applications.

Deep learning models like LSTM and GRU have been instrumental in learning long-term dependencies from time series data such as rainfall, river discharge, and tide levels, enabling more accurate flood peak predictions. CNNs have been widely used for spatial pattern recognition in satellite imagery, topographical data, and floodplain mapping. Hybrid CNN-LSTM models, multi-stream networks, and ensemble deep learning approaches have emerged to simultaneously model spatiotemporal relationships, enabling real-time flood alert systems. Studies have also explored the use of transformers and temporal convolutional networks (TCNs) to improve parallelism and training speed over recurrent models. Meanwhile, Graph Neural Networks (GNNs) are gaining attention for modeling river networks and geospatial dependencies across watersheds.

AWS and Google Internet real-time dashboards, CNN-based flood segmentation using European Space Agency's Sentinel satellites, and Google's AI-based flood forecasting systems in Bangladesh and India are examples of practical implementations. For deeper contextual awareness, research has also focused on data fusion technique combines social media feeds, radar rainfall data, ground sensors, and remote sensing imagery. To create more reliable, adaptive, and trustworthy flood prediction systems, federated learning, semi-supervised learning, and explainable AI (XAI) have all become popular solutions to persistent problems like data heterogeneity, missing data imputation, scalability, model interpretability, and deployment in low-resource environments. These continuous developments, which are driven by deep learning and real-time data integration, demonstrate a paradigm shift away from reactive disaster response and toward predictive and preventive flood risk management. The growing frequency and intensity of flood events brought on by climate change and urbanization has made flood forecasting a top research priority. Conventional hydraulic and hydrological models, like HEC-RAS, SWAT, and MIKE 11, have been used extensively for operational flood prediction and simulate physical water processes. However, they are difficult to adapt to to different environmental conditions, require high-quality data, and take a long time to set up. In order to get around these restrictions, researchers have turned to data-driven assist in the preparation that use machine learning techniques like SVM, Random Forests, and K-Nearest Neighbors. These predictive performance a rather, but they weren't very good at managing nonlinear dynamics or spatiotemporal dependencies.

Existing System

Traditional hydrological and hydraulic models, like HEC-HMS, SWAT, and MIKE FLOOD, are really the mainstay of current flood alert and prediction systems. These models simulate water flow and watershed behavior by using historical rainfall, river discharge, terrain data, and land use parameters. These models are rule-based, require significant calibration, and often depend on domain expertise and high-resolution geographical data. Although these systems work well in known environments, they have problem adapting to changing environmental conditions in real time, severe weather, and the scarcity of data in isolated or impoverished areas.

All at the same, some contemporary systems have integrated machine learning (ML) techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVM), and Decision Trees. These systems can capture more intricate relationships between input variables and are more flexible than traditional models. But their Besides that, the majority of the new systems don't have mobile integration or user-friendly interfaces, which lessens their ability to successfully notify vulnerable communities in a timely manner. In many regions of the world, real-time alerting and hyper-local prediction capabilities are still being developed. In the current flood prediction landscape, a major limitation is the lack of intelligent, adaptive models that can learn from new data and dynamically improve their forecasts.

Conventional hydrological and hydraulic models, like HEC-RAS, HEC-HMS, MIKE FLOOD, and SWAT, are the mainstay of current flood alert systems. These models simulate flood behavior by utilizing elevation models, historical weather data, river discharge, and catchment characteristics. These models are empirical or deterministic in nature, and in terms of working well, they frequently need a lot of historical data and exact calibration. Despite being extensively utilized in operational forecasting, they have issues with real-time responsiveness, integration with diverse data sources, and adaptability to trying to shift atmospheric circulation.

To provide mid-range forecasts, some systems combine hydrological simulations and numerical weather prediction (NWP) models; nevertheless, this increases computational demand and complexity. These systems' lead times are frequently insufficient for abrupt river overflows or brief flash floods.

Recently, machine learning Semi-automated early warning platforms have been developed by government-operated systems, including the National Weather Service (NWS) in the The Us, the European Flood Awareness System (EFAS), and the Central Water Commission (CWC) flood forecasting network in India. Alerts are typically sent manually or with only relatively limited automation, and these frequently rely on weather stations, fixed gauge networks, and deterministic models. Furthermore, these systems frequently have low spatial granularity, which reduces their usefulness for forecasting urban floods or in areas that are rapidly urbanizing.

Although satellite-based platforms, like the European Space Agency's Sentinel missions and NASA's Global Flood Monitoring System (GFMS), offer large-scale flood detection, their lack of local context, latency, and resolution restrictions make them less effective for localized, real-time alert systems. Flood risk is visualized and topographical data is superimposed on flood maps using both commercial and open-source GIS platforms (e.g., ArcGIS Flood Risk Toolbox, Google Earth Engine). These systems, however, are primarily offline and place more emphasis on post-event analysis as opposed to real-time prediction.

Furthermore, the lack of deep learning integration in most current systems restricts their capacity to make decisions in real time and learn adaptively. The majority rarely use mostly cloud-based analytics, mobile alerting apps, or interactive dashboards that could improve community-level engagement, and they real-time sensor feeds, social media data, or satellite-based nowcasting.

Even though open-access climate and hydrological data is becoming more commonly accessible, current systems are not very automated, are not very scalable, and do not provide accurate predictions, especially in areas with sparse data or complex landforms. Because of this, there is now an urgent need for sophisticated, intelligent systems that can use deep learning frameworks that can continuously learn, adapt, and scale across a variety of geographic areas to provide real-time.

Users receive these alerts via public warning systems, SMS notifications, web dashboards, and mobile apps. Scalability, fast computation, and on-demand updates across several geographic regions are guaranteed by a cloud-based infrastructure. A user-friendly interface that shows awaited flood zones, rainfall intensity, water levels, and suggested evacuation routes is another way the system facilitates real-time visualization. The system uses explainable AI (XAI) components to support authority decision-making and validate predictions, thereby increasing trust and reliability. In the end, the suggested system offers an intelligent flood monitoring and early warning system that is fully automated, flexible, and scalable, making it appropriate for deployment in both urban and rural areas.

The suggested system is a intricate, next-generation flood alert platform that uses slashing deep learning methods to provide proactive warning systems and precise, real-time flood predictions. It incorporates a hybrid deep learning architecture that uses Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) to handle the temporal dynamics of rainfall, river discharge, soil moisture, and water level time-series data, as well as Convolutional Neural Networks (CNNs) for extracting spatial data from satellite imagery and topographical maps. For more complex spatial-temporal relationships, the system may incorporate ConvLSTM or transformer-based models, and Graph Neural Networks (GNNs) to simulate river network dependencies and inter-connected catchments. The model receives and evaluates a variety of real-time data sources, including satellite data (e.g., Sentinel-1, MODIS), radar precipitation, and IoT-based flood sensors.

In order to identify real-world flood indicators, the model uses Natural Language Processing (NLP) to ingest and process a variety of datasets from real-time sources, such as radar precipitation, satellite data (e.g., Sentinel-1, MODIS), hydrological data, IoT-based flood sensors, and even social media feeds. High-speed computing, ongoing learning, and scalable deployment across several regions are guaranteed by a cloud-hosted infrastructure that makes use of platforms such as Google Cloud, AWS, or Azure. Additionally, the system has a user-friendly, multilingual dashboard and mobile app that offer location-based alert notifications, safe zones, evacuation routes, water depth visualizations, live flood maps, and predicted flood severity. Explainable AI (XAI) modules like SHAP or LIME are connected to offer insights into model predictions in order to increase transparency and user trust. The alert system runs on its own, classifies, and updates every few minutes.

The system provides real-time situational awareness, decision support, and resource allocation tools to assist local government agencies and disaster management teams. Through the use of transfer learning, data augmentation, and federated learning, it is particularly well-suited for deployment in both data-rich and data-scarce environments, assuring strong performance even in underdeveloped or disaster-prone areas. In the end, this suggested deep learning-based system offers a dynamic, adaptive, and resilient framework for preventing property damage and saving lives, marking a substantial advancement in flood risk management.

Methodology and Implementation

For precise flood forecasting and alert generation, the suggested flood alert system uses a data-driven, modular approach that merges real-time data integration with refined deep learning models. Heterogeneous datasets, including rainfall records, river water levels, satellite images, soil moisture, weather forecasts, and digital elevation models, are collected and normalized in the first phase from a variety of sources, including ground-based sensors, space agencies, meteorological departments, and cloud platforms. To deal with missing values, noise, and varying time resolutions, these datasets are subsequently cleaned, normalized, interpolated, and temporally synchronized. During the feature extraction stage, Convolutional Neural Networks (CNNs) are used to extract spatial features from satellite imagery, and Long Short-Term Memory (LSTM) or Gated Recurrent Units are used to extract temporal patterns in rainfall and water level data.

The model is trained to identify flood-inducing patterns and threshold triggers through supervised methods during the training phase, which single time flood events. To avoid overfitting and guarantee generalization, a variety of optimization strategies are utilized, such as the Adam optimizer, dropout layers, and early stopping. To determine as well as the probability intensity of flooding in specific regions, prediction alert module uses trained model current real-time input data. The system creates categorized alerts (such as watch, warning, and emergency) and sends out notifications via SMS, email, and app alerts when predestined thresholds are exceeded. At the same time, the system uses mapping tools like Leaflet.js or Google Maps API to visualize predicted flood areas on a geospatial dashboard. It also shows nearby emergency centers and safe evacuation routes.

Furthermore, Explainable AI (XAI) tools are integrated to promote transparency by focusing the variables that had the biggest impact on the model's predictions. To ensure high prediction accuracy, the system is further validated using cross-validation techniques and performance metrics such as RMSE, MAE, and F1-score. Through this end-to-end pipeline, the system offers a reliable, adaptive, and real-time flood monitoring solution deployable across both urban and rural regions.

The suggested flood alert system's methodology is a solid, modular pipeline that combines real-time analytics, deep learning-based modeling, multi-source data collection, and dynamic alert generation. Comprehensive data acquisition is the first step, which centralized control historical and real-time data from a variety of sources, as well as satellite imagery (Sentinel-1/2, MODIS), radar-based rainfall estimates, GIS layers (DEM, land use, river networks), IoT sensors (for rainfall, river levels, and soil moisture), and weather forecast APIs. Additional data sources, such as traffic feeds, government flood reports, and social media signals, are also integrated using Natural Language Processing (NLP) models to identify real-time indicators of flooding.

Data cleaning, normalization, handling missing values, spatial-temporal alignment, and format conversion into model-consumable formats are all preprocessing steps applied to this data. In order to find important and relevant predictors, feature engineering is brought out using statistical correlation and geospatial mapping tools. During the modeling stage, a hybrid deep learning architecture is used, which usually consists of a Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) for capturing long-term temporal dependencies and a Convolutional Neural Network (CNN) for identifying spatial patterns. ConvLSTM and Transformer-based models are combined for more complex temporal-spatial analysis, and Graph Neural Networks (GNNs) are used to model interconnected watersheds and river basins.

Using historical flood events as labels, the model is trained through supervised learning. To improve performance and generalization, focus on the key like batch normalization, dropout, and learning rate scheduling are used. The system uses the trained model to process real-time sensor and satellite data during the prediction phase, predicting the future about the possibility, severity, and geographic distribution of floods. Then, using threshold-based logic, multi-tiered alerts (information, warning, and emergency) are triggered, and notifications are sent by email, SMS, digital signage, sirens, and mobile apps. A geospatial dashboard created with programs like Mapbox, Leaflet.js, or QGIS is used to visualize the forecasts and warnings. It displays high-resolution maps of flood risk, projected water levels, rainfall intensity, and safe zones. Using microservices, the entire pipeline is housed on a cloud infrastructure (such as AWS, GCP, or Azure). Explainable AI (XAI) modules key factors that influence make use of saliency maps, SHAP, or LIME are used to make the model transparent and help decision-makers grasp the each prediction. Metrics like RMSE, MAE, F1-score, AUC, precision-recall curves, and confusion matrices can be used to to assess performance, insuring thorough validation prior to deployment. To ensure inclusive and broad applicability, the system also offers offline alerting modules and multilingual interfaces for remote areas with inadequate connectivity. A stable and reliable, scalable, intelligent, and adaptable flood prediction and alerting platform that can respond in real time and foster long-term resilience is guaranteed by this end-to-end methodology. The suggested flood alert system's methodology is intended to offer an end-to-end intelligent solution that integrates real-time analytics, cloud computing, deep learning, and data fusion for precise and proactive flood forecasting. The process starts with the constant feeding of multi-modal data from high-resolution satellite imagery (e.g., Sentinel, MODIS, Landsat), radar data, meteorological inputs, GIS terrain models, social signals scraped using APIs and real-time web crawlers, and ground-level sensors (for rainfall, river levels, humidity, and soil absorption capacity). Advanced techniques such as data interpolation, outlier removal, spatial filtering, and principal component analysis (PCA) are used for dimensionality reduction and noise removal during data preprocessing, which aligns these disparate data streams in terms of temporal and spatial resolution. The architecture of the model is composed of a Besides that, Reinforcement Learning (RL) is suggested for decision optimization, which teaches agents to select the optimal alert level and timing based on both simulated and actual results. In order to help the model learn from uncommon or extreme instances, the system additionally incorporates Generative Adversarial Networks (GANs) to enhance flood image data. While federated learning guarantees privacy-preserving model updates in distributed data environments, transfer learning enables the use of pre-trained weights from one region to be adjusted for another. After training, the system operates in almost real-time on edge-cloud hybrid infrastructure, where cloud models are interlinked with edge devices that process sensor data locally for large-scale forecasting. Deterministic thresholds and AI-based risk scoring are both used by the alert generation engine to categorize alerts into levels and send them out automatically.

A dashboard driven by GIS offers temporal graphs, alert timelines, flood visualizations that are easy to understand, and integration with emergency services. Besides that, advanced deployments may incorporate drone surveillance inputs to confirm the spread of floods on the ground. AutoML pipelines enable continuous retraining by automatically examining, optimizing, and versioning models in response to fresh data. Explainable AI (XAI) frameworks such as SHAP and DeepLIFT manage model explainability, providing insight into the significance of features and the reasoning behind the model. Cross-validation, backtesting on past flood events, and evaluation metrics like Nash-Sutcliffe Efficiency (NSE), precision, recall, and area under the curve (AUC) are used to perform rigorous validation. Additionally, the system incorporates redundancy and failover mechanisms, real-time logging, anomaly detection for system health, and adherence to disaster response standards such as Sendai Framework to guarantee disaster resilience.

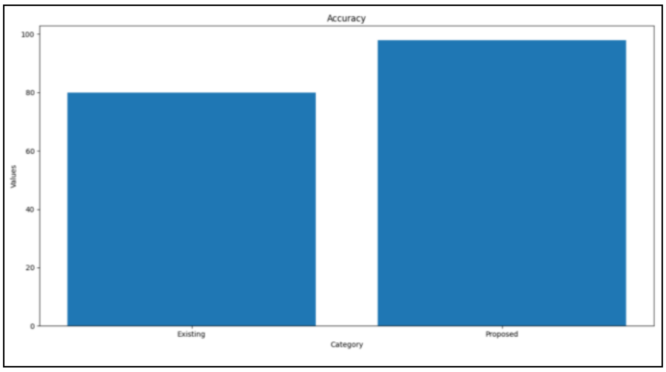
In addition to being technically sound and scalable, this all-encompassing, future-ready methodology guarantees that the system is resilient, community-focused, and appropriate for deployment in both flood-prone rural areas

Conclusion

In summary, a major development in the field of disaster risk management is the incorporation of deep learning technologies into flood alert prediction systems. This system can process large amounts of spatial and temporal data rapidly and correctly and by utilizing the power of neural networks, esp hybrid models that combine CNNs and LSTMs. The suggested system is data-driven, adaptive, and able contrast with conventional recognize intricate patterns from both historical and current data sources, including satellite imagery, sensor networks, weather forecasts, and GIS terrain models, in hydrological models. The system can anticipate flood events more precisely and earlier thanks to AI, which lowers false alarms and boosts people's confidence. Additionally, explainable AI integration, real-time alert distribution, cloud-based deployment, and support for both urban and rural environments.

The suggested methodology supports early evacuation planning, infrastructure protection, and emergency response resource allocation in addition to improving flood preparedness. In the end, this clever flood estimation could prevent fatalities, reduce financial losses, and strengthen communities' serious opposition to the growing risks associated with climate change and extreme weather.

Accuracy



Future Work

Although the accuracy, scalability, and real-time performance lot of areas the suggested deep learning-based flood alert system show encouraging results, there are still a that could be improved in the future. Integrating hydrodynamic simulations and 3D terrain modeling is one of the main approaches to better represent the behavior of water flow in intricate urban and rural environments. During flood events, integrating real-time drone surveillance and UAV data can provide high-resolution imagery and improve ground truth validation. To better capture long-term dependencies and interactions across a variety of data types, effecting change of the system can also investigate the use of transformer architectures and spatiotemporal attention mechanisms. Furthermore, federated learning integration will enable decentralized model training across regions without jeopardizing data privacy, especially in sensitive defense or government settings.

References

1. Kratzert F, Klotz D, Brenner C, Schulz K, Herrnegger M. Toward improved predictions in ungauged basins: Exploiting the power of machine learning. Water Resour Res. 2019;55(12):11344–11354.
2. Jain SK, Singh RD. Forecasting of floods using hydrological and hydrodynamic models. Curr Sci. 2015;108(11):2007–2020.
3. Wang W, Wu Y, Zhang W. Flood prediction using deep learning: A review. J Hydrol. 2021;603:126932.
4. Zhao L, Liu C, Li Y. A deep learning model integrating spatiotemporal features for flood forecasting. Environ Model Softw. 2020;132:104819.
5. Tiwari HL, Kansal ML. A review of artificial neural network applications in hydrology and water resources. Environ Dev. 2019;31:1–11.
6. European Space Agency (ESA). Sentinel-1 Data for Flood Monitoring [Internet]. 2023 [cited 2025 Jun 8]. Available from: https://www.esa.int
7. Google AI Blog. How AI Can Help Predict Natural Disasters [Internet]. 2020 [cited 2025 Jun 8]. Available from: https://ai.googleblog.com
8. World Meteorological Organization (WMO). Manual on Flood Forecasting and Warning [Internet]. 2022 [cited 2025 Jun 8]. Available from: https://public.wmo.int
9. United Nations Office for Disaster Risk Reduction (UNDRR). Sendai Framework for Disaster Risk Reduction 2015–2030 [Internet]. 2015 [cited 2025 Jun 8]. Available from: https://www.undrr.org
10. Kaggle. Rainfall, River Level and Flood Event Historical Data [Internet]. 2023 [cited 2025 Jun 8]. Available from: https://www.kaggle.com