Artificial Intelligence For Flood Forecasting: A Review

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Abstract- *Flooding remains one of India's most pressing natural hazards, with the National Disaster Management Authority reporting that over 12% of the country's landaround 40 million hectaresis vulnerable to inundation. In 2024, extreme rainfall and flooding events caused nearly 900 deaths and displaced thousands. Conventional hydrological models, though widely adopted, often face difficulties in delivering timely and accurate predictions. Progress in Artificial Intelligence (AI) has introduced new possibilities for enhancing flood forecasting, where machine learning and deep learning approaches can capture nonlinear hydrological relationships and improve response planning. This paper reviews both traditional modelling frameworks and modern AI-based strategies, including flood alert systems and geospatial mapping solutions, and evaluates their effectiveness in disaster preparedness. The findings indicate that AI holds strong potential for advancing resilience in flood-prone regions.*

Keywords- AI, Flood Forecasting,GIS, Hydrological Modelling, HEC-RAS, SWAT.

I. INTRODUCTION

The intensifying impacts of climate change have made disaster risk management a global priority. Among natural hazards, floods stand out as particularly destructive, accounting for substantial loss of life, large-scale displacement, and severe economic damage. Between 1998 and 2017, nearly two billion people were affected by flooding, with more than three-quarters of disaster-related deaths linked to such events [1]. Each year, droughts and floods together are estimated to claim over 8,000 lives, force millions from their homes, and inflict financial losses exceeding hundreds of billions of dollars [2]. Vulnerability is highest in low- and middle-income nations, where nearly 90% of the population most at risk of severe flooding resides [3].

Traditional forecasting methods, though effective to a degree, often struggle with the complexity of hydrological systems and the integration of real-time data [4]. Yet accurate and timely prediction is critical, since early warnings enable communities and governments to take protective measures [5]. Artificial Intelligence (AI) offers a new direction in this field. By learning from diverse data sources and adapting to dynamic conditions, AI-based algorithms can uncover nonlinear relationships and improve the accuracy of forecasts [6]. Beyond prediction, AI also strengthens disaster response by processing massive datasets rapidly, integrating geospatial information, and supporting informed decision-making [7]. This review highlights the growing role of AI in reshaping flood forecasting, comparing it with conventional models, and examining how these approaches can contribute to long-term resilience in the face of escalating climate threats.

II. TRADITIONALHYDROLOGICAL MODELS: HEC-RAS AND SWAT

Hydrological models form the backbone of water resource planning, flood prediction, and environmental assessment. Two of the most widely applied frameworks in this domain are the Hydrologic Engineering Centre's River Analysis System (HEC-RAS) and the Soil and Water Assessment Tool (SWAT).

HEC-RAS was developed by the U.S. Army Corps of Engineers to simulate river hydraulics and channel flows. It is commonly used for applications such as floodplain mapping, dam break studies, and infrastructure planning. The model can handle different flow regimessubcritical, supercritical, and mixedunder both steady and unsteady conditions [10]. Despite its versatility, HEC-RAS encounters numerical instabilities when applied to steep channels, highly dynamic systems, or stormwater networks where bed slopes exceed about 10% [11].

SWAT, on the other hand, is a process-driven model originally designed by the USDA Agricultural Research Service to examine the long-term impacts of land management on water and sediment yield in complex watersheds. It is capable of simulating runoff, evapotranspiration, groundwater interactions, and the transport of nutrients and chemicals. Due to its ability to represent land–climate interactions, SWAT is frequently used in climate change impact assessments [12]. However, the model demands extensive datasets and rigorous calibration, which can be both time-intensive and technically challenging. Moreover, because it was primarily designed for long-term watershed analysis rather than real-time forecasting, its suitability for rapid disaster response is limited [13].

III. FRAMEWORKS FOR FLOOD FORECASTING

a.   Machine Learning Approaches

Over the past two decades, machine learning (ML) has become an increasingly reliable tool for flood prediction, often outperforming traditional hydrological methods [14]. Regression modelssuch as linear and logistic regressionhave been used to estimate the probability of flooding by linking variables like rainfall, soil moisture, and river discharge. While straightforward and interpretable, these models are limited by their assumption of linearity, which restricts their ability to capture the complexity of real hydrological systems. Decision tree methods provide a rule-based alternative by recursively splitting data into categories. They are relatively easy to interpret and resilient to missing inputs, but single trees often overfit the data. Ensemble approaches such as Random Forests and Gradient Boosting mitigate this issue by combining multiple trees to improve accuracy and stability. Support Vector Machines (SVMs) extend model flexibility further by using kernel functions to map relationships into higher-dimensional spaces, enabling them to capture nonlinear patterns. However, the computational demands of SVMs increase substantially with larger datasets, limiting their practical use for real-time forecasting unless optimized.

Recent research shows that hybrid approacheswhere two or more models are combinedcan outperform standalone methods. For example, regression models have been paired with decision trees, and SVMs have been integrated with deep learning architectures, producing better generalization and predictive power [15]. The success of these models depends heavily on effective feature engineering, hyperparameter tuning, and the inclusion of diverse training data.

Looking ahead, ML-based flood forecasting is expected to benefit from real-time data assimilation, adaptive learning strategies, and the integration of emerging technologies such as satellite remote sensing, Internet of Things (IoT) sensors, and high-resolution climate models. These developments can help improve both the reliability and timeliness of flood predictions.

b.   Deep Learning for Hydrology

Deep learning has accelerated progress in flood forecasting by uncovering complex spatial and temporal relationships within hydrological data. Convolutional Neural Networks (CNNs) are widely applied to satellite imagery and hydro-meteorological datasets, where they excel at extracting spatial patterns for high-resolution flood mapping and the detection of vulnerable zones.

For sequential data, Recurrent Neural Networks (RNNs) have been employed to predict streamflow and flood occurrence. However, their effectiveness is restricted by the vanishing gradient problem, which reduces their ability to capture long-term dependencies. Long Short-Term Memory (LSTM) networks address this limitation through gated mechanisms, making them more suitable for hydrological time-series analysis.

More recently, Transformer architectures have introduced self-attention mechanisms that enable efficient modelling of long-range dependencies while processing multiple data sources in parallel. This advantage has led to hybrid designs, such as LSTM–Transformer combinations, which merge sequential learning strengths with attention-based adaptability. Optimizing these models through techniques like hyperparameter tuning has further improved accuracy, reduced predictive uncertainty, and supported near real-time forecasting.

Overall, the adoption of Transformer-based and hybrid architectures points toward a new generation of flood prediction models that are not only more accurate but also scalable and adaptable to diverse climatic and geographic settings.

c.   AI with Remote Sensing

The combination of artificial intelligence and remote sensing technologies has greatly improved the precision and efficiency of flood monitoring. Satellite imageryincluding multispectral data and synthetic aperture radar (SAR)provides detailed spatial information that is critical for mapping inundated areas. When integrated with Geographic Information Systems (GIS), these datasets can be processed into comprehensive flood assessments, supporting both prevention and response measures.

AI models, particularly deep learning frameworks, enhance this process by handling the vast volume and complexity of geospatial data. They are increasingly used to identify flood patterns, forecast rainfall impacts, and improve hydrological modelling. The ability of AI to extract meaningful insights from satellite data has made real-time disaster response more practical and effective.

A more recent advancement is Quantum Machine Learning (QML), which applies the computational strengths of quantum systems to predictive modelling. Studies comparing conventional AI models with quantum approaches in daily flood forecasting indicate that QML can achieve higher efficiency and stronger pattern recognition. Integrating

classical machine learning with quantum techniques is viewed as a potential pathway to more scalable and robust flood forecasting systems, aligning well with global goals of sustainability and resilience.

IV. CHALLENGES AND CONSTRAINTS

a. *Data availability and biases*

While machine learning methods have become central to flood prediction, their performance is often undermined by the quality of available data. In many flood-prone regions, historical hydrometeorological records are incomplete, inconsistent, or biased, which limits the generalizability of trained models [21]. Gaps in datasets can lead to forecasts that disproportionately misrepresent vulnerable areas, delaying evacuation and weakening response efforts. Addressing this issue requires more comprehensive data collection, the adoption of fairness-aware learning techniques, and greater transparency in model design.

b. *Computational Costs of Deep Learning Models*

Deeplearning models have shown remarkable predictive power, but their success depends heavily on access to diverse and reliable data. Missing or low-resolution records can reduce accuracy, while the models themselves often demand significant computing resources [22]. These requirements are difficult to meet in resource-constrained regions where flooding risks are highest. Approaches such as transfer learning, data augmentation, and the integration of high-resolution remote sensing can mitigate some limitations [23]. Nevertheless, the high processing costs not only restrict real-time forecasting but also raise concerns about energy consumption and sustainability [24]. Model profiling and predictive resource estimation may help select architectures that balance accuracy with efficiency [25].

c. *Ethical Challenges in AI-Driven Flood Prediction*

Embedding AI into flood forecasting raises ethical concerns related to fairness, accountability, and privacy. If models are trained on biased datasets, they may reproduce inequities in disaster warnings or resource allocation [26]. The opaque nature of many AI systems also makes it difficult to hold developers and agencies accountable for prediction errors. The use of explainable AI can improve trust and interpretability, but widespread data collection still presents challenges for privacy protection. A further complication is the "dual-use dilemma," where tools designed for disaster management could be misapplied in harmful ways [27]. Ensuring transparency, fairness, and ethical safeguards is therefore crucial for the responsible use of AI in flood forecasting.

V. FUTURE SCOPE

The integration of artificial intelligence into flood forecasting is shaping a new era in disaster risk management. As AI technologies continue to evolve, they are expected to improve the precision, speed, and adaptability of flood prediction systems [28].

By processing vast amounts of historical and real-time data, AIparticularly deep learning models can detect complex climatic patterns that traditional approaches often overlook. These insights enhance both short-term forecasting and long-term climate modelling. Real-time data assimilation from satellite imagery, hydrometric sensors, and IoT-based monitoring networks enables AI systems to provide rapid updates, strengthening preparedness and response strategies. Beyond technical advancements, AI also plays a growing role in community engagement. Platforms that combine local knowledge with data-driven insights foster participatory resilience planning. When linked with community-based initiatives, AI not only improves predictive frameworks but also ensures that mitigation strategies reflect local priorities [29]. For instance, AI can highlight vulnerable areas, simulate diverse flood scenarios, and guide region-specific resilience measures [30].

Looking forward, the most promising direction lies in merging advanced algorithms with community-driven planning and transparent, explainable AI systems. Such integration ensures that forecasting frameworks are not only technically sound but also socially sustainable, fostering long-term resilience at both institutional and grassroots levels.

VI. RESULT

The survey conducted by us highlights a transformative shift in flood forecasting brought about by artificial intelligence. Convolutional Neural Networks (CNNs), when combined with satellite imagery and real-time meteorological data, consistently demonstrated superior performance in predicting flood-prone regions. Across reviewed studies, CNN-based approaches achieved improvements in detection sensitivity of up to 20-30% over conventional hydrological and statistical methods, while also enabling near real-time predictions through faster processing. Deep learning architectures such as LSTMs and Transformers further enhanced temporal and spatial modelling, offering higher reliability in sequential flood prediction and integration of multi-source datasets.

However, the effectiveness of these models was found to be strongly dependent on the availability and quality of training data. High-resolution imagery and comprehensive historical flood records improved predictive accuracy, while data sparsity and inconsistencies led to reduced performance or overfitting. Additionally, computational demands posed a significant limitation, with deep learning models requiring considerable processing power, which may not be feasible in many flood-prone regions. Ethical considerations also emerged as a critical factor, particularly with respect to bias, transparency, and equitable distribution of resources in vulnerable communities.

Based on our review, we understand that AI-driven methodologies represent a significant advancement, but their real-world utility depends on addressing systemic challenges such as data gaps, computational scalability, and fairness in deployment. In our perspective, the most promising direction lies in combining advanced algorithms with community-driven strategies and explainable AI frameworks. Such an approach not only strengthens technical accuracy and operational speed but also ensures that flood forecasting remains socially sustainable and responsive to the needs of at-risk populations.

VII. CONCLUSION

In the past decade, flood forecasting has been greatly transformed by the adoption of artificial intelligence. Advances in machine learning regression models, deep learning architectures such as CNNs, LSTMs, and Transformers, together with remote sensing and GIS technologies, have enabled more precise flood mapping and improved disaster preparedness. These innovations have significantly strengthened predictive accuracy, supported real-time monitoring, and enhanced early warning systems, underscoring AI's growing importance in flood risk management.

Nevertheless, substantial challenges continue to hinder large-scale implementation. Limitations in data availability, the intensive computational resources required by deep learning models, and ethical issues surrounding bias and equitable access remain pressing concerns. Biased or incomplete datasets risk producing unreliable predictions that may disproportionately affect vulnerable regions.

To address these issues, future research should focus on optimizing AI methodologies for efficiency, developing adaptive and transparent models, and ensuring that forecasting systems are aligned with community-centered resilience strategies. Interdisciplinary collaboration and the wider use of

Explainable AI will be key to improving accountability and inclusivity. As climate change accelerates the frequency and intensity of flooding, advancing AI-based forecasting frameworks will be crucial in minimizing human and economic losses and in building a more sustainable and resilient future.

VIII. ACKNOWLEDGEMENT

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