A Comprehensive Review of Machine Learning Approaches for Flood Prediction Systems

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Floods are among the most destructive natural dis asters, causing substantial losses worldwide. Advances in machine learning (ML) have introduced innovative approaches for flood prediction, offering enhanced accuracy and timeliness compared to traditional methods. This paper presents a comprehensive review of 15 studies employing various ML algorithms, including Decision Trees, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Deep Learning, in flood prediction systems. The review provides a detailed comparison of models, emphasizing performance metrics such as accuracy, precision, and computational efficiency. Unique contributions include the identification of key research gaps such as the absence of real-time adaptability, IoT integration, and the limited use of state-of-the-art models like transformers and the proposal of hybrid and ensemble modeling strategies for improved resilience and predictive accuracy. Practical case studies and applications of these methods are discussed to highlight their feasibility and impact. The study also emphasizes the integration of IoT data, hybrid models, advanced spatial analysis, and transformer based architectures to enhance global flood forecasting systems, bridging current gaps and paving the way for more robust and adaptive predictive frameworks.

Keywords: Machine learning models, Deep learning, Neural network.

2025. In Puneet Kumar Gupta (ed.), *Computational Models for Intelligence and Automation*, 85–95. Computing & Intelligent Systems, SCRS, India. DOI: https://doi.org/10.56155/978-81-975670-1-8-8

1 Introduction

Flooding is one of the most frequent and destructive natural disasters worldwide, leading to extensive loss of life, economic damage, and environmental degradation. The increasing severity and frequency of floods in recent decades are attributed largely to climate change, rapid urbanization, and deforestation, which exacerbate the vulnerability of flood-prone areas [2]. Accurate flood prediction is crucial for proactive disaster response, enabling timely evacuations, safeguarding infrastructure, and reducing the social and economic impacts of floods.

Traditional flood prediction methods, which rely heavily on physical and statistical hydrological models, have limited accuracy in the face of increasingly complex and dynamic weather patterns. They do not grasp the intricate, nonlinear interactions of a multiplicity of environmental variables, especially under extreme weather events Machine learning (ML) technologies, on the other hand, offer promising alternatives for conventional models of flood prediction because they permit the processing of large datasets and complex patterns in weather and hydrological information. In comparison to conventional models, the algorithms used for ML are much more effective in dealing with intricate, nonlinear data interactions, and they are very suitable for real-time flood forecasting in many contexts [6, 23, 25]. Using ML methods, a flood prediction system can All integrate historic weather data, satellite imagery, and real-time inputs from IoT devices, greatly improving predictive accuracy and responsiveness. Machine learning models such as Decision Trees, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Deep Learning have shown high predictive accuracy in case studies around the globe, including regions with complex, seasonal flooding patterns or specific environmental challenges.

This review examines recent advancements in ML applications for flood prediction by analyzing 16 research studies that utilize various ML algorithms and data integration strategies. We categorize these studies by their ML methods and assess their performance, applicability, and data requirements across different environmental and geographic contexts. Additionally, this review highlights research gaps—such as the need for adaptive, real-time models and better data integration from sources like IoT and crowd-sourced inputs—and suggests future directions for ML-driven flood prediction [12, 19]. By identifying effective strategies and potential improvements, this review aims to guide researchers and disaster management authorities in implementing resilient and accurate flood forecasting systems that can mitigate flood impacts more effectively.

2 Literature survey

Flood prediction has become an integral aspect of disaster management not because it has been successful in avoiding floods but because early warning systems could drastically reduce both loss of property and death. It is only in recent years that the use of machine learning techniques in flood prediction models has gained significant importance in light of their ability to analyze humungous amounts of environmental data and arrive at a fairly accurate prediction. This literature review aims to take a general overview of the various models of ML that have been used for flood prediction, dwelling on their strengths and weaknesses and advancements. The review compiles the studies conducted using different machine learning algorithms, data sources, and predictive strategies. It tries to equip this reader with an overall understanding of the current state-of-the-art in the research and identify areas pending further exploration.

Francis Yongwa Dtissibe, et al explored the application of both Machine Learning (ML) and

Deep Learning (DL) models, particularly Long Short-Term Memory (LSTM) and Multi-Layer Perceptron (MLP), for flood prediction, alongside comparisons with traditional hydrological models. The study highlighted significant challenges related to limited data from under-resourced regions and computational issues associated with traditional hydraulic models. By integrating ML and DL approaches, the study aimed to enhance predictive accuracy; however, it emphasizes a need for further research to overcome data scarcity and computational constraints in low-resource environments [5].

Muhammad Wajid, et al. focused on IoT-based flood prediction using Artificial Neural Networks (ANN) combined with fog computing, aimed at reducing energy consumption in resource-limited settings. Their model demonstrated high accuracy and energy efficiency by processing data closer to the source through fog computing, making it suitable for real-time applications. However, in order to increase the suitability of such systems in remote or energy-constrained environments, the authors emphasised the necessity for improvements in low-power designs [24].

Neethu Mariya George, et al. applied Logistic Regression for the prediction of floods in Kerala, India, in a binary classification manner, based on features like humidity, temperature, and precipitation. This will yield the assessment that Logistic Regression can be applied when simple flood anticipation and early warning techniques are required; however, its scope confines to only using binary classification, and further research into more advanced ML methods is recommended that would interpret the complex dynamics of floods better and report multi-class classifications [1].

Miah Mohammad Asif Syeed, et al. focused on evaluating a range of ML models, for instance ANN, CART, and SVM, in terms of their ability to predict floods and the features and selection of algorithms that affect predictive power. This research identified the need for appropriate consideration of choice of algorithms and features that would give maximum predictive accuracy. Despite the capability demonstrated by each of the models, the authors suggested that future studies should consider ensemble methods that might integrate various models with each other in order to improve the strength and accuracy of flood predictions [3].

Marcel Motta, et al. developed a hybrid model, which combined a Random Forest classifier with GIS-based hot spot analysis for predicting urban flood risks. The model developed has utilized spatial data from GIS information showing the flood-prone areas in an urban region, achieving a high Matthew's Correlation Coefficient of 0.77. It, however, had a limitation of data input from only three stations thereby limiting its spatial resolution; more so, it was understood that more weather stations and the availability of high-resolution data could expand the spatial resolution for increased accuracy in such complex environments [16].

Kruti Kunverji, et al. also investigated a machine learning approach for flood prediction by comparing Decision Trees, Random Forests, and Gradient Boosting. The study found that Decision Trees performed best, but highlighted gaps related to real-time data integration and the potential for ensemble learning. By focusing solely on algorithm accuracy, the study lacked exploration of adaptive systems that could dynamically adjust predictions in response to real-time data, which the authors suggested could improve model responsiveness and robustness [13].

Nazim Razali, et al. applied Decision Trees (DT), k-Nearest Neighbors (kNN), Support Vector Machines (SVM), and Bayesian Networks (BN) for flood risk assessment in Kuala Krai, Kelantan, Malaysia. Using the CRISP-DM methodology, the study found that Decision Trees, coupled with SMOTE to handle data imbalances, provided the highest accuracy. However, the study's focus on a specific geographic region limits the generalizability of the model, suggesting a need for validation across different areas to assess its wider applicability [20].

Ho Jun Keum, et al. proposed a real-time flood prediction system that integrates ML algorithms,

Table 1: Summary of Flood Prediction Models and Research Gaps

Sr. no.	Author(s)	Year	Methodology	Research Gap
1	Pranab Yengkhom Dineshwori, et al.	2021	Multi-model, including LS-SVM, MLP, functional trees, and RF	Limited data from poor regions, computational challenges with models. Focus on integrating ML models.
2	Muhammad Wajid, et al.	2021	Historical flood prediction using ANN	Need for low-cost, efficient systems in resource-limited regions.
3	Neelesh Morya George, et al.	2021	Logistic Regression for flood prediction	Need for innovative datasets.
4	Malik Mohammad Azif Syed, et al.	2021	RF, models like ANN, CART, SVM	Need for advanced models on unreliable methods to improve accuracy.
5	Mazi Mehreen, et al.	2021	SVM for multiresolution flood forecasting	Require models specific to different regions.
6	Ravi Kaswan, et al.	2020	AI techniques (Random Forest, GML, KNN), Agriculture Drones	Limited in regional areas, lacks extensive learning and adaptation for specific regions.
7	Kiran Kaswan, et al.	2020	AI models (Decision Tree, Random Forest), Neural Networks	Constraints in large-scale models. Global applicability remains limited.
8	Nazrin Razali, et al.	2022	Machine-Learning Algorithms including SVM	Limited for Kuala Krau, Malaysia; needs validation in other regions.
9	Syeda Aimen Haider, et al.	2021	Multi-model approach (CART, SVM, RF, KNN) for flood risk assessment	Lack of systematic model validation across diverse regions.
10	Sarala Sankarumaran, et al.	2021	Ensemble techniques (Bagging, Boosting), SVM, DT	Limited on small waterways; lack fine-tune mechanisms for specific regions.
11	Nur-Aida Mapa, et al.	2021	Adaptive Neuro Fuzzy Inference using Fuzzy Kernel, Neural Networks for prediction	No integration with real-time data for dynamic modeling.
12	Cynthia Chu, et al.	2015	Data Integration with multiple sources	Lacks extension towards new intense events and specific flood-prone areas.
13	Saputra Permatabola, et al.	2020	RF, logistic model tree for rainfall induced floods	Limited application to varying rainfall patterns.
14	Asat Mansur, et al.	2017	Logistic Regression for flood prediction	Temporal modeling constraints.
15	Gokcen Tayfur, et al.	2018	Hybrid approaches, prediction using ANN, GA, PSO, and ACO	Limited real-world testing on different regions and slope variability.

including Decision Trees and Neural Networks, with real-time meteorological and hydrological data. This implementation improved both the efficiency and the accuracy of flood forecasting, which highly supported disaster management. However, this study did not apply spatial analysis and was in a bit of trouble in the instance of the application of the model to places with less infrastructural development, indicating that future research will be on adaptation of the system for places with limited data resources [10].

Suresh Sankaranarayanan, et al. used Deep Neural Networks (DNN) to estimate seasonal-based flood risks considering rainfall intensity and temperature as principal input variables. Overall, the models with less complexity showed lower predictive skill as compared to DNN. One of the major limitations of the current study was that it only used seasonal datasets; besides rainfall intensity and temperature, factors such as water level and stream flow were significant for an overall flood prediction. Therefore, for higher predictive precision, the authors suggested consideration of other hydrologic variables in subsequent models [21].

Nur-Adib Maspo, et al. reviewed the ML techniques that appear in the form of SVM, Random Forest, and Neural Networks. Review of ML suggested that it has high predictive value but lacking integration with real-time data hence not responsive to sudden changes in the environment. The future models proposed by the authors must use the historical and live streams of data to make the prediction of floods more accurate and adaptive in areas vulnerable to rapid flood events [14].

Cynthia Cui, et al. developed a multiple linear regression model predicting spring floods in New Brunswick, Canada from the local climate variables like temperature and precipitation. Its model obtained an R^2 value of 0.63 to indicate the potential applicability of this model for regional flood forecasting. The dependence on linear regression is presented as preserving limits or inability to capture nonlinear environmental relations, while better ML models may strengthen and improve accuracy especially in complex regional flood events caused by specific multiple environmental factors [4].

Supattra Puttinaovarat, et al. presented a large-scale big data-driven flood forecasting system using data crowdsourced for improved predictability. They show that the introduction of crowdsourced data improves the predictions by providing real-time updates, but monitored precipitation data are required to operationalize this system. One gap is emphasized here: the diversification of data sources used in multiple systems. The authors advise future models to be strengthened with several environmental and hydrological parameters to assure robustness over different flood scenarios [19].

Amir Mosavi, et al. discussed the use of Neural Networks and Support Vector Machines for flood prediction. While the research was able to capture the effectiveness of such ML models in enhancing predictive accuracy, it triggered limitation because it only used historic data and did not consider real-time sensor input. The research suggested future work on this, which would help incorporate real-time sensor data that might improve adaptability and precision in predicting floods due to unexpected changes in weather [15].

Gokmen Tayfur, et al. focused on flood hydrograph prediction using Artificial Neural Networks in combination with optimization techniques such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization. Even though the aforementioned methods are able to enhance the predictions for the hydrograph, the lack of real-world testing in different geographic regions is a major drawback. On these models, the authors further validate them under different environments and interface them with a predictive system that generalizes the model and introduces adaptability in floods under different dynamics [22].

Flood prediction models based on Decision Trees have shown high accuracy in structured data environments, yet their performance falters with imbalanced datasets. This limitation underscores the importance of pre-processing techniques like SMOTE and highlights the need for ensemble approaches to overcome overfitting.

3 Comparison of Techniques

Balancing predictive accuracy, computational efficiency, and the capacity to adapt to different contexts of the environment is the overall goal for flood prediction. In the following section, each of the most important Machine Learning techniques utilized in flood prediction, including the Decision Trees, ANN models, SVM, DL models, and hybrid approaches, will be compared over such criteria:. All of the techniques reviewed also have respective strengths and weaknesses based on performance metrics, data requirements, and appropriateness to specific types of flood scenarios, as observed in 16 reviewed studies [11].

3.1 Decision Trees and Ensemble Methods

With ensemble methods comprising Random Forests and Gradient Boosting, Decision Trees fall into the good accuracy prediction tools as they work perfectly with structured, tabular data. Flood analysis with historical data turns out to have as much as 94% accuracy and it has been proven that Decision Trees best work where floods are established, and the natural environment has recorded patterns. Ensemble methods of stacking multiple Decision Trees over each other improve performance because they reduce the likelihood of overfitting, common in a single tree model. For instance, the capability of Random Forest and Gradient Boosting models was enhanced by sophisticated interactional relationships between variables in terms of rainfall, water level, and even temperature [11, 14]. Such models will, however, require well-balanced and huge datasets for good performance and don't perform too great on imbalanced or sparse datasets. Ensemble methods are significantly far costlier in terms of computation compared to the simpler models and maybe not as practicable for real time predictions if the computational power is under restricted force.

3.2 Artificial Neural Networks (ANN) and IoT-Integrated Systems

ANNs have been applied in flood prediction since they are instrumental in relation modeling nonlinear relationships and processing a large quantity of data, especially where the behavior of floods is controlled by many factors, making the process very complex. The models from the ANNs, especially the ones integrated with IoT data, allow for real-time predictions of floods since they capture live data from environmental sensors, and this improves the accuracy of the forecast. The ANN model in the study on IoT-integrated models reached up to 94.2% accuracy in prediction, which was superior to traditional techniques used in areas with high weather changes. ANNs are advantageous since they update their forecasts dynamically based on data streams over time, making this technology ideal for real-time applications [8]. However, ANNs require enormous computational resources and long-term training data to ensure avoidance of overfitting. Their interpretability is also relatively lower than that of Decision Trees, thus making it challenging to understand which specific variable is influencing predictions-an important factor when transparency in decision-making is a question, especially during disaster management.

3.3 Support Vector Machines (SVM) and k-Nearest Neighbors (kNN)

Support Vector Machines (SVM) as well as k-Nearest Neighbors (kNN) have been successfully used for flood classification tasks more specifically in applications involving a balanced and well-labeled dataset. SVM is known to be the robustness of cases involving binary classification problems hence flood/no-flood classification is one of the most excellent s, as proven by studies carried out in both urban and rural areas. SVMs are best at smaller, high-quality datasets and have low computational complexity, making them suitable for applications where decision-making needs to take place quickly with minimal data processing capabilities. On the other hand, kNN is more intuitive and easier to implement but tends to be less effective when used with large datasets because computation becomes expensive due to distance-based calculations [4]. Even though the techniques had this drawback, they have still ensured classification particularly in predicting floods through structured, historical data and simple environmental factors.

3.4 Deep Learning Models

Deep Learning models, such as DNNs, and LSTM networks, have been helpful in complex flooding scenarios in regions that are conditioned or varied by seasons during weather occurrence. DNNs can handle massive quantities of unprocessed data as well as learn the intricate relationships existing within the dataset through applications where models achieved over 91% accuracy by using seasonal rainfall and temperature data. Among the recurrent neural networks, these are especially suitable to the application with time-series flood prediction due to their information retaining abilities, which is invaluable for a place exhibiting cyclical patterns of flood [7]. After all, Deep Learning models are, in general, computationally expensive and require lots of training data. Therefore, the models are hard to apply in environments with limited resources. Deep Learning models, such as ANNs, suffer from low interpretability, which is the reason they have not been widely accepted for critical applications where the transparency of model decision-making is required.

3.5 Hybrid and Ensemble Approaches

Hybrid models combine ML techniques with more established hydrological models or Geographic Information Systems (GIS) that improve predictive accuracy spatially and temporally. For example, studies on urban dynamics, such as in Lisbon, which used ML algorithms combined with GIS processes, successfully mapped the areas most susceptible to flood by attaining a prediction accuracy of up to 96% . Hybrid models clearly represent a robust approach for areas that entail different and sometimes complex risks associated with floods, such as urban areas. Hybrid models can incorporate GIS to consider the spatial data, then identify flood-prone zones by using topographical and land-use inputs. This is essential for achieving resilience in planning and resource allocation. The ensemble approach takes predictions from multiple algorithms and merges them, mitigating the weaknesses of individual models to build a more resilient predictive system. Hybrid and ensemble models are, however, data-intensive and computationally demanding. They may therefore easily come into the feasibility limits on real-time applications or in regions with less access to comprehensive data [9].

3.6 Suitability of Techniques Based on Environmental Context

The choice of ML technique depends significantly on the environmental context and the type of flood risk involved. Decision Trees and Random Forests are well-suited to structured, tabular data and perform best in areas with detailed historical flood records, while ANNs and IoT-integrated systems excel in regions requiring real-time prediction capabilities. SVM and kNN are ideal for flood/no-flood classification tasks in simpler environments with fewer variables, while Deep Learning models are suitable for regions with complex flood behavior, such as those with seasonal monsoon patterns [12]. Hybrid models, combining ML with GIS or hydrological data, are particularly effective in urban flood-prone areas where spatial information plays a crucial role in risk assessment and disaster management. Ensemble techniques, which draw on multiple ML algorithms, offer additional resilience and can be tailored to specific regional needs, although they require extensive data and computational resources.

Table 2: Comparison of ML Models for Flood Prediction

Model	**Accuracy**	**Strengths**	**Limitations**
Decision Trees	94%	High accuracy for structured data	Struggles with imbalanced datasets
ANN	94.2%	Suitable for real-time IoT applications	Requires high computational resources
Deep Learning	91%	Handles complex patterns effectively	Low interpretability, resource-intensive
Hybrid Models	96.2	Combines spatial and temporal accuracy	Data-intensive and computationally costly

4 Research Gaps and Future Directions

Despite the progress made in applying machine learning (ML) to flood prediction, several research gaps remain that limit the full potential of these models in real-world disaster management. One of the primary gaps is the lack of high-quality, comprehensive data, particularly in remote or under-resourced regions where flood prediction is critically needed. Many ML models rely on extensive historical weather, hydrological, and environmental data for training, yet such data is often sparse, outdated, or inconsistent in certain areas. Additionally, environmental factors such as soil composition, land use, and vegetation, which greatly affect flood behavior, are rarely included in these datasets, limiting the model's predictive accuracy [13]. Addressing these data limitations by incorporating global meteorological datasets, crowdsourced information, and satellite data could significantly improve model effectiveness and expand the applicability of flood prediction models to data-scarce regions.

Another key gap lies in the real-time adaptability of ML models. Flood events are highly dynamic, with rapidly changing variables that traditional ML models, trained on historical data alone, often cannot adequately predict. While some studies have successfully integrated Internet of Things (IoT) devices to provide real-time data on rainfall, water levels, and other variables, further work is needed to develop models that can learn from these updates in real time. Dynamic, adaptive models capable of continuous learning could dramatically improve the accuracy of short-term flood forecasts, especially in flash flood scenarios where immediate response is essential. Future research should focus on hybrid approaches that combine static historical data with live data streams from IoT and remote sensing technologies [17]. The integration of real-time data would allow models to respond more effectively to sudden changes in weather conditions, potentially transforming disaster preparedness.

Moreover, future directions in ML-based flood prediction should explore advanced hybrid and ensemble models that combine ML with traditional hydrological models and Geographic Information Systems (GIS). Such hybrid models can enhance spatial and temporal predictive accuracy, particularly in urban areas where complex infrastructure and high population density pose unique flood risks. Additionally, incorporating human-centric data, such as population density and movement patterns, could improve the practical utility of these models by providing insights into areas of high vulnerability during floods. Recent advancements in transformer models, known for their ability to capture complex sequential data relationships, offer significant potential for improving time-series flood predictions. These models could outperform traditional methods like LSTM and DNN by modeling temporal dependencies more effectively, making them a promising area for future research. Practical implementation of ML models should also incorporate real-world case studies from diverse geographic regions to validate their robustness and adaptability under varying environmental conditions, especially in data-scarce regions. Additionally, integrating crowdsourced data and IoT-based real-time inputs can enhance the dynamic adaptability and responsiveness of flood prediction systems, particularly for scenarios like flash floods where rapid updates are crucial. Hybrid approaches combining ML with traditional hydrological models and Geographic Information Systems (GIS) can further improve spatial and temporal accuracy by utilizing GIS-based land-use data, population density, and infrastructure vulnerabilities for localized predictions. Finally, developing user-friendly tools for visualizing ML predictions will ensure accessibility for disaster managers, government agencies, and the public, facilitating effective decision-making and resource allocation during flood events.

The use of ensemble techniques, which combine predictions from multiple algorithms, can also mitigate the limitations of single models, resulting in more robust predictions [18]. These advancements, coupled with the development of user-friendly interfaces and mobile applications, could make ML-based flood prediction tools more accessible to government agencies, emergency responders, and the public, ultimately supporting more efficient and effective flood management.

5 Conclusion

This review consolidates advancements in ML approaches for flood prediction, demonstrating that techniques like ANN, Decision Trees, and hybrid models offer significant improvements in prediction accuracy across various contexts. However, challenges such as data limitations and the need for adaptable, real-time models underscore the necessity for continued innovation. Future research should focus on hybrid and ensemble models that integrate big data, IoT, and human-centric inputs to enhance predictive accuracy and disaster management capabilities. Machine learning's potential to improve flood prediction is vast, and further advancements could revolutionize disaster preparedness and resilience planning worldwide.

References

[1] (2023)flood prediction using logistic regression.

[2] Meysam Alizamir, Ozgur Kisi, and Mohammad Zounemat-Kermani. Modelling long-term

groundwater fluctuations by extreme learning machine using hydro-climatic data. *Hydrological Sciences Journal*, 63:63–73, 1 2018.

[3] Miah Mohammad Asif. Flood prediction using machine learning models, 2022.

[4] Cynthia Cui and Leonardo Cui. An innovative flood prediction system using improved machine learning approach.

[5] Francis Yongwa Dtissibe, Ado Adamou, Abba Ari, Alidou Mohamadou, Hamadjam Abboubakar, Arouna Ndam Njoya, and Ousmane Thiare. A comparative study of machine learning and deep learning methods for flood forecasting in the far-north region, cameroon. 2024.

[6] Gustavo Furquim, Gustavo Pessin, Bruno S. Faiçal, Eduardo M. Mendiondo, and J. Ueyama. Improving the accuracy of a flood forecasting model by means of machine learning and chaos theory: A case study involving a real wireless sensor network deployment in brazil. *Neural Computing and Applications*, 27:1129–1141, 7 2016.

[7] Kishan Kumar Ganguly, Nadia Nahar, and BM Mainul Hossain. A machine learning-based prediction and analysis of flood affected households: A case study of floods in bangladesh. *International Journal of Disaster Risk Reduction*, 34:283–294, 3 2019.

[8] Guangyuan Kan, Ke Liang, Haijun Yu, Bowen Sun, Liuqian Ding, Jiren Li, Xiaoyan He, and Chengji Shen. Hybrid machine learning hydrological model for flood forecast purpose. *Open Geosciences*, 12:813–820, 1 2020.

[9] Qian Ke, Xin Tian, Jeremy Bricker, Zhan Tian, Guanghua Guan, Huayang Cai, Xinxing Huang, Honglong Yang, and Junguo Liu. Urban pluvial flooding prediction by machine learning approaches – a case study of shenzhen city, china. *Advances in Water Resources*, 145, 11 2020.

[10] Ho Jun Keum, Kun Yeun Han, and Hyun Il Kim. Real-time flood disaster prediction system by applying machine learning technique. *KSCE Journal of Civil Engineering*, 24:2835–2848, 9 2020.

[11] Khabat Khosravi, Himan Shahabi, Binh Thai Pham, Jan Adamowski, Ataollah Shirzadi, Biswajeet Pradhan, Jie Dou, Hai Bang Ly, Gyula Gróf, Huu Loc Ho, Haoyuan Hong, Kamran Chapi, and Indra Prakash. A comparative assessment of flood susceptibility modeling using multi-criteria decision-making analysis and machine learning methods. *Journal of Hydrology*, 573:311–323, 6 2019.

[12] Kruti Kunverji, Krupa Shah, and Nasim Banu Shah. A flood prediction system developed using various machine learning algorithms.

[13] Kruti Kunverji, Krupa Shah, and Nasim Banu Shah. A flood prediction system developed using various machine learning algorithms.

[14] Nur Adib Maspo, Aizul Nahar Bin Harun, Masafumi Goto, Faizah Cheros, Nuzul Azam Haron, and Mohd Nasrun Mohd Nawi. Evaluation of machine learning approach in flood prediction scenarios and its input parameters: A systematic review. In *IOP Conference Series: Earth and Environmental Science*, volume 479. Institute of Physics Publishing, 7 2020.

[15] Amir Mosavi, Pinar Ozturk, and Kwok Wing Chau. Flood prediction using machine learning models: Literature review, 10 2018.

[16] Marcel Motta, Miguel de Castro Neto, and Pedro Sarmento. A mixed approach for urban flood prediction using machine learning and gis. *International Journal of Disaster Risk Reduction*, 56, 4 2021.

[17] Hafiz Suliman Munawar, Ahmed W.A. Hammad, and S. Travis Waller. A review on flood management technologies related to image processing and machine learning, 12 2021.

[18] Jeerana Noymanee and Thanaruk Theeramunkong. Flood forecasting with machine learning technique on hydrological modeling. In *Procedia Computer Science*, volume 156, pages 377–386. Elsevier B.V., 2019.

[19] Supattra Puttinaovarat and Paramate Horkaew. Flood forecasting system based on integrated big and crowdsource data by using machine learning techniques. *IEEE Access*, 8:5885–5905, 2020.

[20] Nazim Razali, Shuhaida Ismail, and Aida Mustapha. Machine learning approach for flood risks prediction. *IAES International Journal of Artificial Intelligence*, 9:73–80, 2020.

[21] Suresh Sankaranarayanan, Malavika Prabhakar, Sreesta Satish, Prerna Jain, Anjali Ramprasad, and Aiswarya Krishnan. Flood prediction based on weather parameters using deep learning. *Journal of Water and Climate Change*, 11:1766–1783, 2020.

[22] Gokmen Tayfur, Vijay P. Singh, Tommaso Moramarco, and Silvia Barbetta. Flood hydrograph prediction using machine learning methods. *Water (Switzerland)*, 10, 7 2018.

[23] Mahyat Shafapour Tehrany, Simon Jones, and Farzin Shabani. Identifying the essential flood conditioning factors for flood prone area mapping using machine learning techniques. *Catena*, 175:174–192, 4 2019.

[24] Muhammad Wajid, Muhammad Kamran Abid, Asif Asif Raza, Muhammad Haroon, and Abdul Qadeer Mudasar. Flood prediction system using iot and artificial neural network. *VFAST Transactions on Software Engineering*, 12:210–224, 3 2024.

[25] Faria T. Zahura, Jonathan L. Goodall, Jeffrey M. Sadler, Yawen Shen, Mohamed M. Morsy, and Madhur Behl. Training machine learning surrogate models from a high-fidelity physics-based model: Application for real-time street-scale flood prediction in an urban coastal community. *Water Resources Research*, 56, 10 2020.