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IoT-Enabled Flood Monitoring and Early Warning Systems: A Systematic Review

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Abstract: Technology powered by the Internet of Things (IoT) and Machine Learning (ML) is transforming flood monitoring and disaster management. This study systematically examines key components including sensors, machine learning models, and communication networks within IoT-based flood detection and prediction systems. Using the PRISMA framework, the researcher evaluated 44 high-quality papers from IEEE Xplore, ScienceDirect, and other relevant databases. The review highlights ultrasonic sensors, rain gauges, water level, and flow sensors as the most effective hardware components, often paired with environmental sensors. In forecasting flood risks, machine learning algorithms, such as Random Forest (RF), had the highest accuracy, followed by K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP), Decision Trees (DT), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN), have also shown high predictive accuracy. Several protocols provide real-time data transmission, including LoRaWAN, Zigbee, GSM, and MQTT, while ThingSpeak, TagoIO, Grafana, and Blynk provide intuitive dashboards for monitoring and data visualization. IoT-driven systems enhance disaster response by providing early flood warnings, which allow authorities to act ahead of time. To reduce disaster risks and enhance community resilience to climate change, this study synthesizes current research on IoT-enabled solutions for floodwater level monitoring, prediction systems, and early warning systems. It outlines future directions for developing flood management solutions that are more resilient to disasters.

Keywords: Flood Monitoring, Flood Prediction, Internet of Things (IoT), Machine Learning, Early Warning Systems

I. INTRODUCTION

Floods rank among the most destructive natural disasters, leading to severe casualties and property damage [19,29,33]. According to the World Meteorological Organization (WMO), there were 11,778 weather-related disasters between 1970 and 2021, resulting in over 2 million deaths and economic losses exceeding $4.3 trillion (WMO, 2021). Asia recorded 3,612 disaster events, representing 47% of all weather-related disasters worldwide [14]. Developing nations, particularly in South and Southeast Asia, are disproportionately affected due to inadequate early warning systems and insufficient flood management infrastructure.

Traditional flood monitoring techniques primarily depend on manual water level measurements, satellite observations, and fixed flood barriers. Although researchers and authorities have used these methods for many years, they have several significant limitations. First, the reliance on manual data collection delays obtaining measurements, resulting in untimely flood warnings that compromise public safety. Second, many rural and remote locations lack adequate monitoring infrastructure, creating dangerous gaps in flood surveillance. Third, operational costs remain high due to physical sensor maintenance and manual data collection requirements. Finally, traditional static prediction models cannot effectively adapt to rapidly changing weather conditions or unexpected flood events, limiting their accuracy in forecasting sudden water surges. These shortcomings highlight the urgent need for more advanced, efficient, responsive flood monitoring solutions.

In addressing these limitations, digital technologies have become essential to disaster management, as demonstrated in a comprehensive review by [20]. While researchers have extensively studied digital transformation (DT) in industrial applications, IoT-based flood monitoring systems offer a promising but underdeveloped solution for disaster management. Modern flood monitoring systems increasingly use IoT sensors and machine learning. IoT technology facilitates instant, wireless data collection from critical locations such as riverbanks, urban drainage networks, and coastal zones. At the same time, ML algorithms enhance forecasting precision by processing historical trends and real-time environmental data. This integration offers significant potential for improving flood prediction and response systems.

Machine learning and IoT technology have revolutionized flood monitoring and prediction by providing innovative solutions for real-time data collection, transmission, and analysis [9,34,43]. IoT-based flood forecast systems have enabled cities to enhance their monitoring capabilities, improving public safety and resource allocation during flooding events [47]. This approach reduces operational costs while maintaining system efficiency [38]. IoT technology is transforming flood monitoring through its advanced capabilities. The system uses ultrasonic and water pressure sensors for real-time water level detection, while employing energy-efficient LoRaWAN and NB-IoT networks for long-distance data transmission. This collected data is processed and stored on cloud platforms like AWS IoT and Google Cloud, creating a centralized monitoring system. These IoT solutions automate flood monitoring processes, enabling continuous surveillance and significantly improving emergency response efficiency.

Machine learning algorithms significantly improve flood forecasting capabilities through multiple advanced techniques. In addition, recent studies have examined flood forecasting models for early warning systems (FEWS) [6,7,11,33,41]. Researchers have used machine learning algorithms and climate projections to assess flash flood susceptibility in Bangladesh's hilly regions [40]. These ML models employ sophisticated approaches like Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) to analyze and learn from historical flood patterns and trends. Flood forecasting with ES-LSTM/ANN models works well but encounters problems with data quality and sensors [26]. Random Forest and Support Vector Machine (SVM) algorithms process real-time sensor data streams efficiently. Additionally, ensemble methods like XGBoost and Gradient Boosting improve prediction accuracy and reliability by combining multiple models.

Together, these machine-learning techniques enable more precise flood forecasting by leveraging historical data patterns and current environmental conditions. In order to improve flood response, real-time data analytics can improve decision-making by efficiently processing data streams and delivering immediate insights. This study examines key flood monitoring technologies including sensors, communication systems, and online platforms and evaluates machine learning algorithms used in flood prediction models to assess their effectiveness and potential.

Research Questions

1) *What are the most commonly used IoT sensors for flood level monitoring?*

- The objective is to determine the type of sensors deployed in flood detection systems and assess their effectiveness in various environmental conditions (e.g., ultrasonic, pressure, radar).

2) *Which machine learning algorithms demonstrate the highest accuracy for flood prediction?*

- Analyze the performance of different predictive algorithms (e.g., LSTM, Random Forest, SVM) in processing sensor data and forecasting floods.

3) *How do existing flood monitoring systems handle real-time warning transmission, visualization, and communication?*

- To identify communication protocols (e.g., LoRaWAN, MQTT), online platforms (e.g., ThingSpeak), and alert mechanisms that enable effective flood monitoring and early warning dissemination.

II. METHODOLOGY

This study employed the Systematic Literature Review (SLR) methodology to examine IoT-based water level monitoring systems [4,10]. The study implemented Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [7,24] across four systematic research phases: (i) established precise research questions, defined objectives, and identified relevant search terms, (ii) select appropriate academic databases (such as ScienceDirect and IEEE) and developed systematic search strategies, (iii) screened and categorized studies according to predetermined inclusion and exclusion criteria, (iv) conducted in-depth analysis of the selected literature, extracting and synthesizing key findings. The review focused on peer-reviewed publications from 2020 to 2024 to capture the latest technological developments. This rigorous methodological approach enabled a comprehensive and transparent evaluation of existing evidence while strictly adhering to PRISMA standards throughout the research process.

A. *Eligibility Criteria*

To ensure quality and relevance, the researcher applied specific inclusion and exclusion criteria when selecting studies for this systematic review. In addition to selecting the best articles for analysis, these criteria ensured that the publications selected directly aligned with the research objectives.

1) *Inclusion criteria (IC)*

The researcher included articles that met all the following conditions:

IC1: Focused on IoT-enabled flood monitoring and prediction.

IC2: Published in peer-reviewed Scopus-indexed journals or other reputable journals, with detailed technical information about IoT sensor technologies, communication protocols, or prediction algorithms.

IC3: Published in English

2) *Exclusion criteria (EC)*

In excluding articles, the researcher excluded:

EC1: Non-IoT monitoring methods (such as manual gauges).

EC2: Unrelated topics discussed such as; Network security (DDoS attacks, intrusion detection), Computer vision for flood monitoring, and delay-tolerant network protocols.

EC3: Not peer-reviewed or did not meet scholarly standards

B. *Search strategy and identification*

The researcher searched ScienceDirect, IEEE Xplore, and peer-reviewed journals to identify relevant articles on IoT-based flood monitoring and prediction systems.

To ensure comprehensive coverage of IoT applications in flood monitoring and prediction, the author implemented a systematic search approach using boolean-optimized keyword combinations:

- *"IoT AND Flood"*
- *"Flood Water Level Monitoring OR IoT-based Flood Monitoring"*
- *"Flood Prediction Model AND Flood Prediction"*
- *"Flood Early Warning System OR Flood Alert"*

C. *Screening and selection*

The researchers implemented a two-stage screening process using established inclusion (IC1-IC3) and exclusion criteria. The initial title/abstract review selected 150 articles for full-text analysis, eliminating 1,579 irrelevant publications through systematic evaluation.

After this screening phase, the researcher excluded 17 additional articles and retained 133 high-quality studies for full-text review. This rigorous selection process guaranteed that only relevant, high-quality studies were included.

D. *Eligibility*

During full-text review, the researchers screened 133 articles using the predefined criteria. Of these, 89 were excluded, leaving 44 qualifying studies for systematic analysis. This process guaranteed the inclusion of only pertinent, high-quality research.

E. Full text reviewed

After a comprehensive full-text review, 44 articles met the predefined criteria and were deemed eligible. As a result, all 44 papers were reviewed and included.

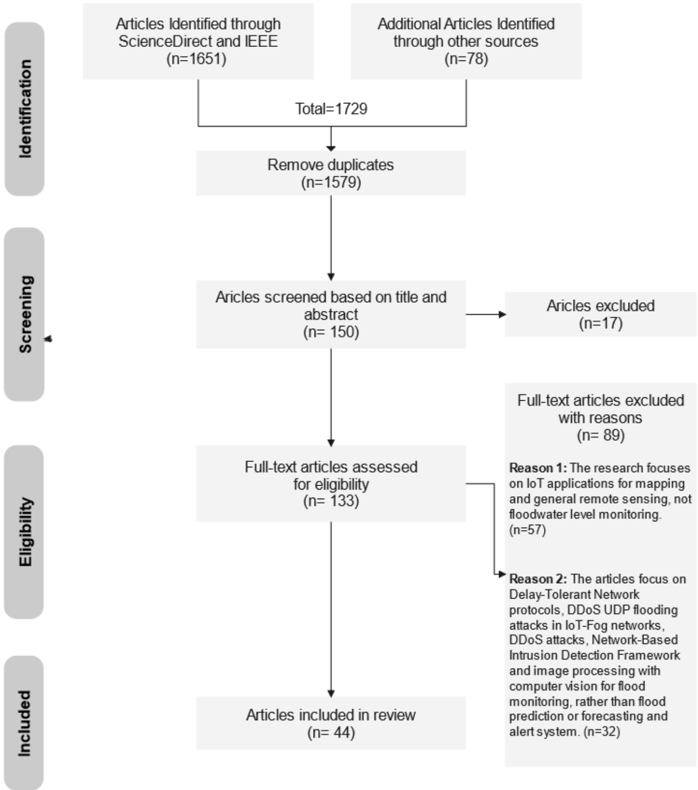

Fig. 1 A visual summary of study selection using the PRISMA framework

III. RESULTS AND DISCUSSION

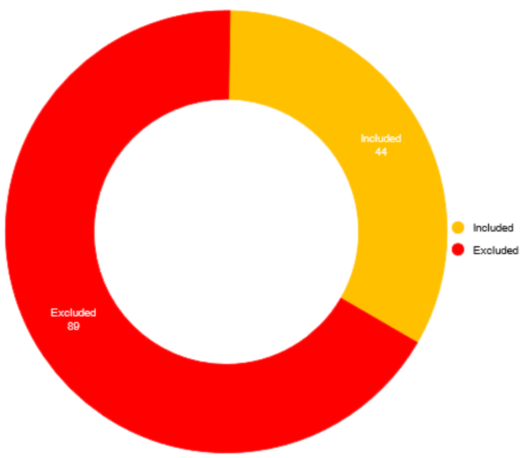

Fig. 2 Summary of the full-text articles evaluated for the Eligibility phase.

Fig. 2 illustrates the systematic screening process, which evaluated 133 articles for eligibility. Researchers excluded 89 studies that failed to meet the research criteria: 57 were removed for addressing general IoT applications in remote sensing/mapping without a specific focus on floodwater monitoring and 32 were eliminated for covering tangential topics (e.g., delay-tolerant networks, DDoS attacks, intrusion detection, or image processing) unrelated to flood prediction or early warning systems. The comprehensive analysis included

44 studies that met all selection criteria. Through this rigorous filtering process, the researchers ensured the review incorporated only the most relevant and methodologically reliable research on IoT-based flood monitoring and prediction systems.

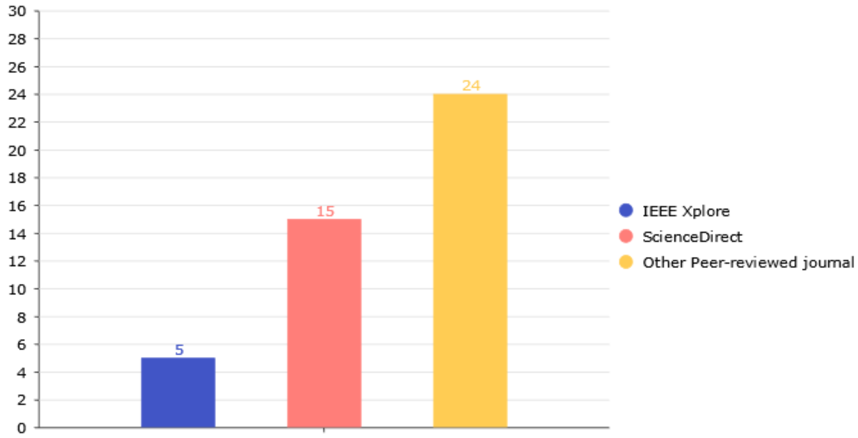

Fig. 3 Summary of the articles included and selected from reputable peer-reviewed journals.

This systematic review examined 44 peer-reviewed articles from high-quality sources, as shown in Figure 3. The dataset included 15 studies from ScienceDirect, five (5) from IEEE Xplore, and twenty-four (24) from other reputable journals. By incorporating research from multiple authoritative databases, this approach offers a comprehensive overview of current IoT-based flood monitoring and prediction systems.

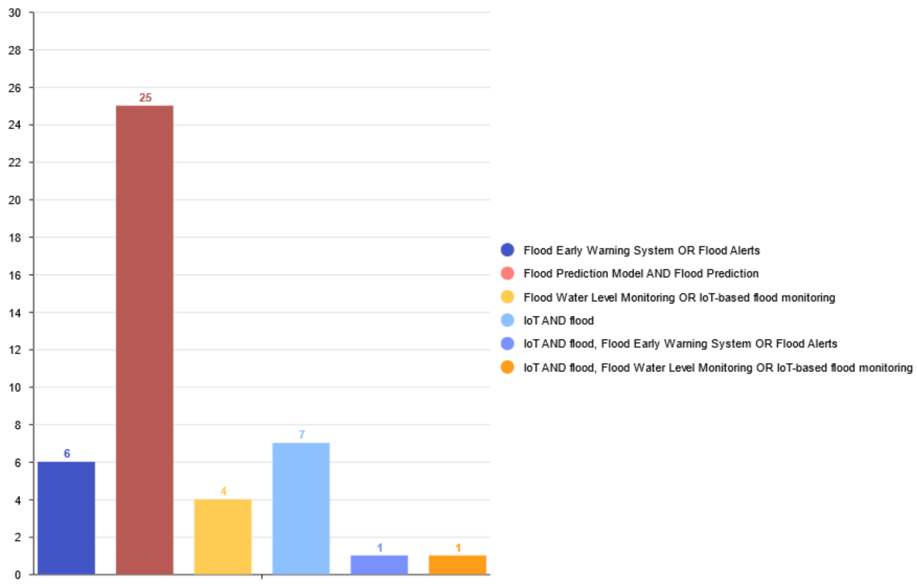

Fig. 4 Summary of articles selected for review based on keyword criteria

Fig. 4 presents the distribution of research articles obtained through systematic keyword searches. The most effective search string, "Flood Prediction Model AND Flood Prediction", retrieved 25 relevant articles. Other queries yielded fewer results: "IoT AND flood" returned seven (7) articles, "Flood Water Level Monitoring OR IoT-based flood monitoring" identified four (4) studies, and "Flood Early Warning System OR Flood Alerts" produced six (6) publications. Prominently, a precise search combining IoT with flood alerts and water level monitoring found just one matching article. These results demonstrate that search term precision critically influences both the quantity and relevance of publications in flood monitoring research.

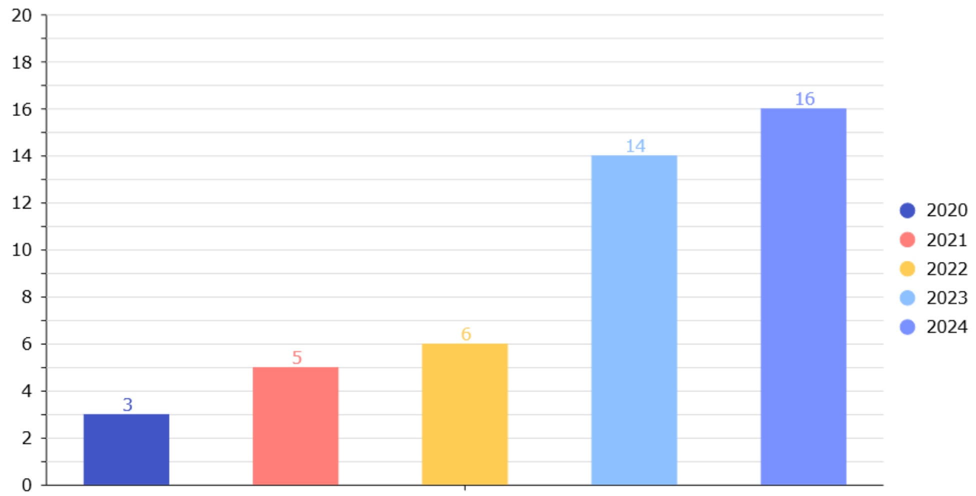

Fig. 5 Summary of reviewed articles by publication year

Figure 5 shows our systematic search of peer-reviewed journal articles (2020-2024) from ScienceDirect, IEEE Xplore, and other authoritative databases. The annual publication count reveals a sharp increase in research: 3 articles (2020), 5 (2021), 6 (2022), 14 (2023), and 16 (2024). This growth pattern reflects a rapidly expanding scholarly interest in IoT-based flood monitoring and prediction systems.

A. *IoT sensors commonly collect data and monitor floodwater levels.*

The table comprehensively analyzed various sensor types, their specific applications in flood detection, and their effectiveness in different hydrological conditions. This comparative assessment highlights the most deployed sensors, their measurement capabilities, and their suitability for flood monitoring scenarios.

TABLE I
A SYSTEMATIC REVIEW OF IOT SENSORS USED IN FLOOD WATER MONITORING SYSTEMS

Ref.	IoT sensor	Application
[2]	- LiDAR (Light Detection and Ranging) - Rain Gauge - Flow Rate Meter	This study utilized three specialized sensors to collect essential hydrological data for precise flood monitoring and forecasting: a LiDAR (Light Detection and Ranging) system measures water levels in feet, a rain gauge tracks rainfall in millimeters per hour, and a flow rate meter monitors water level variations in liters per hour.
[13]	Digital Barometric Air Pressure Sensor (DPS310)	This research incorporates a Digital Barometric Air Pressure Sensor (DPS310) into an IoT-based flood monitoring system. The sensor detects atmospheric pressure changes and wirelessly transmits the data to cloud platforms, enabling real-time analysis and flood risk assessment.
[22]	- Humidity and Temperature (DHT22) sensor - Rainfall Sensor (Ombrometer) - Water Flow Sensor - Ultrasonic sensor	This study employed an IoT sensor network for flood monitoring, integrating multiple environmental measurements: Temperature and humidity (DHT22 sensor), Rainfall intensity (ombrometer), Water flow velocity (flow sensor), and Water levels (ultrasonic sensors). This system enables real-time data collection and flood prediction.

[25]	Water level sensor	This study employs a water level sensor to classify water conditions into three categories: normal, above normal, and dangerous. The sensor converts analog measurements into digital signals, enabling efficient data processing and analysis.
[27]	- Water level - River flow sensor - Rain Gauge - Temperature and humidity (DHT11) sensor - Arduino Uno microcontroller	This study utilized an Arduino Uno microcontroller to collect and process data from various environmental sensors, including water level detectors, river flow sensors, rain gauges, and DHT11 temperature/humidity sensors. The system transmits all measured parameters to a central server for real-time analysis, enabling continuous monitoring of hydrological conditions. This integrated approach facilitates early flood detection and allows timely warning generation to mitigate potential risks.
[32]	- Temperature and Humidity sensor (DHT22) - Soil moisture sensor - Water level sensor	This study utilizes an integrated sensor system consisting of a DHT22 temperature/humidity sensor, a soil moisture sensor, and a water level sensor to monitor critical environmental parameters for agricultural management. The system collects real-time data, accurately evaluating crop conditions and irrigation needs. This approach facilitates optimized resource allocation and data-driven irrigation decisions.
[35]	- Rain Gauge (Flood Alert sensor) - Pressure sensor (BMP280) - Gas sensor (MQ2) - Air Quality sensor (MQ135) - Raindrop sensor - pH sensor - Turbidity sensor (SEN0189) - Temperature and Humidity sensor (DHT11)	This study integrates multiple sensors for comprehensive environmental monitoring: An ultrasonic rain gauge measures precipitation digitally A BMP280 sensor records temperature, humidity, barometric pressure, and altitude MQ2 and MQ135 sensors analyze air quality through gas detection (via resistance changes) A raindrop sensor monitors surface precipitation A multifunctional pH sensor assesses soil/liquid acidity, moisture, and light intensity SEN0189 turbidity sensors evaluate water quality alongside DHT11 sensors for temperature/humidity (in g/kg)
[37]	- Soil moisture sensor	This study incorporates soil moisture sensors to quantitatively measure groundwater saturation levels, generating essential data for flood risk assessment. These measurements

		substantially enhance the monitoring system's predictive capabilities, enabling timely flood warnings before surface flooding occurs.
[44]	- Pressure sensor - Electromagnetic - Capacitive - Resistive - Fiber Optic - Ultrasonic - Infrared - Acoustic - Wave - Float - Camera - Bio sensor - Microwave sensor - Radar sensor	This study employs multiple sensor technologies to enhance flood management across mapping and rescue operations. Each sensor type plays a unique role: pressure sensors detect water force variations, while radar sensors enable wide-area monitoring. Integrating these sensor networks with deep learning algorithms and Synthetic Aperture Radar (SAR) promises significant improvements in flood prediction. This approach aims to develop advanced, adaptive systems capable of autonomously analyzing complex environmental patterns for more effective flood forecasting and response.
[51]	- Flow sensor (YF-S201) - Float sensor	This study utilizes a YF-S201 flow sensor and float sensors to measure water levels and flow rates accurately. These sensors enhance flood monitoring precision, facilitating improved flood forecasting and more timely emergency response measures.
[52]	-Ultrasonic sensor (HC-SR04) with an Arduino microcontroller	Flood monitoring systems frequently use ultrasonic sensors for accurate, non-contact water level detection. These sensors are ideal for widespread implementation due to their consistent performance and minimal maintenance requirements.

Table 1 presents a systematic review of IoT sensors used in flood water monitoring systems. IoT-based flood monitoring systems utilize multiple sensor types to collect real-time hydrological data. These systems typically incorporate ultrasonic sensors [22,35,44,52], pressure sensors [35], and water level sensors [25,27,32], along with Rain Gauge [2,27,35] and environmental sensors for temperature and humidity (DHT11/DHT22) [22,27,32,35]. Additional components like water flow sensors [2,51], soil moisture sensors [32,37], and water quality monitors (turbidity, pH) [35] enable comprehensive flood risk analysis. At the same time, advanced implementations may include fiber optic, infrared, or acoustic sensors for specialized applications [44]. Microcontrollers process this sensor data, analyzing key parameters, including rainfall intensity, flow velocity, and atmospheric conditions. The integrated system enables remote monitoring and real-time alerts through web-based platforms. By pairing reliable sensor networks with cloud-based analytics, these IoT solutions deliver actionable flood data to decision-makers, ultimately strengthening community flood resilience.

B. Machine learning algorithms are most effective in analyzing sensor data for flood prediction.

This paper evaluates the effectiveness of Industry 4.0 technologies, particularly Machine Learning (ML) and Internet of Things (IoT) systems, in flood management applications [38]. The study of [3] evaluated four machine learning approaches: Random Forest (RF), K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP), and a novel GA-RBF-SVR hybrid model demonstrating how model fusion techniques can enhance prediction accuracy and spatial consistency for improved flood risk management.

Recent studies highlight the effectiveness of machine learning algorithms in flood prediction, particularly machine learning models such as Random forests, Naive Bayes, J48s, and convolutional neural networks (CNNs) that can handle complex hydrological data [25]. Comparative analyses show that Random Forest outperforms Support Vector Machines, Logistic Regression, and XGBoost across multiple accuracy metrics. At the same time, simpler models like Logistic Regression and Naive Bayes prove less effective for complex flood prediction tasks [31].

Advanced approaches include CNN-based models for efficient pluvial flood forecasting [21] and hybrid models (GA-XGBoost, DE-XGBoost) that surpass traditional methods like Random Forest and CART in multi-step water level prediction [36]. The paper also reviews Bayesian Model Averaging (BMA) and other probabilistic methods showing promise for hydrological applications [41].

TABLE 2
A SYSTEMATIC REVIEW OF MACHINED LEARNING ALGORITHMS USED FOR FLOOD PREDICTION

Ref.	Machine Learning Algorithm	Findings
[1]	-Long Short-Term Memory (LSTM) - Multilayer Group Method of Data Handling (ML-GMDH)	The evaluation demonstrates that LSTM and ML-GMDH deep learning models generate reliable river flow predictions. The LSTM model outperformed ML-GMDH, achieving higher accuracy (R^2 = 0.91 vs. 0.88) and lower RMSE values. While LSTM showed superior predictive performance for hydrological forecasting, ML-GMDH maintained strong forecasting capabilities.
[2]	- Multilayer Perceptron - Linear Regression	This study developed an accurate flood prediction system combining two machine learning approaches. A multilayer perceptron neural network achieved exceptional performance with 99% forecasting accuracy, while linear regression demonstrated strong predictive capability (88% accuracy) for processing sensor data. These methods form a robust framework for reliable flood risk assessment and forecasting.
[3]	- Multilayer Perceptron (MLP) - K-Nearest Neighbor (KNN) - Random Forest (RF) - GA-RBF-SVR hybrid model	The evaluation revealed distinct performance levels among the machine learning models: Multi-Layer Perceptron (MLP= 0.909), K-Nearest Neighbors (KNN= 0.904), Random Forest (RF= 0.942), and the GA-RBF-SVR hybrid model (0.945). By strategically integrating these models, the ensemble approach achieved superior performance (0.957), demonstrating that model fusion significantly enhances flood prediction accuracy.
[5]	-Long Short-Term Memory (LSTM) Bidirectional Long Short - Term Memory (BI-LSTM) - Deep Recurrent Neural Network (DRNN)	The Deep Recurrent Neural Network (DRNN) model enhanced with layer normalization and Leaky ReLU activation outperformed standard RNN, LSTM, and BI-LSTM architectures across multiple metrics, including lower MSE, RMSE and higher R^2 values. While DRNN achieved the highest accuracy, followed by LSTM and all models demonstrated comparable performance, with BI-LSTM showing only slightly reduced accuracy. These findings indicate that although DRNN's architectural improvements offer measurable advantages, traditional LSTM approaches remain highly effective for flood prediction.
[6]	- Artificial Neural Network (ANN) - Support Vector Machines (SVM) - Support Vector Regression (SVR) - Adaptive Neuro-Fuzzy Inference System (ANFIS) - Wavelet Neural Networks (WNN) - Decision Trees (DTs)	Machine learning models demonstrate unique strengths in flood prediction applications. Artificial Neural Networks (ANNs) effectively analyze complex historical flood data patterns, while Support Vector Machines (SVMs) specialize in binary flood classification of hydrological data. Support Vector Regression (SVR) reliably predicts continuous variables like water levels. The Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates neural networks with fuzzy logic to address data

		uncertainty. Wavelet Neural Networks (WNNs) effectively identify temporal-frequency patterns essential for flood behavior analysis. Decision Trees (DTs) provide transparent and interpretable models for various scenarios. Most notably, a hybrid WNN-ANFIS approach shows particular promise for long-term flood forecasting by combining WNN's time-frequency analysis with ANFIS's robust modeling capabilities, resulting in superior flash flood prediction accuracy.
[7]	- Copula and Bayesian Networks	This study highlights the widespread adoption of machine learning models in flood prediction due to their robust forecasting abilities. However, it underscores the critical role of probabilistic methods like Copula functions and Bayesian Networks in addressing uncertainty in flood risk evaluation. Given the inherently unpredictable nature of flooding, combining these probabilistic approaches with machine learning techniques could substantially improve the reliability of flood forecasting systems.
[12]	- Long Short-Term Memory (LSTM) - One-Dimensional Convolutional Neural Network (1D CNN) - Multilayer Perceptron (MLP)	The Long Short-Term Memory (LSTM) model demonstrated superior performance compared to other methods for both short- and long-term flood forecasting. Its recurrent neural network architecture effectively processes complex temporal patterns in rainfall and temperature data, which accounts for its exceptional predictive accuracy.
[17]	- Flood Forecasting Model (FFM) utilizes federated learning	The Flood Forecasting Model (FFM) demonstrated 84% accuracy in predicting historical floods between 2010-2015, indicating strong retrospective performance. This high accuracy suggests the model's potential for reliable future flood predictions in similar regions.
[18]	- Adaptive Neuro-Fuzzy Inference System (ANFIS) - Support Vector Machine (SVM) - Long Short-Term Memory Network (LSTM) - Radial Basis Function Neural Network (RBF-NN)	The evaluation showed that the Adaptive Neuro-Fuzzy Inference System (ANFIS) performed best among single models for 1-2 hour flood forecasts in the Kelantan River basin. However, the Intelligent Committee Machine Learning Flood Forecasting (ICML-FF) ensemble model outperformed all individual approaches, achieving greater accuracy with lower errors. By combining multiple models, ICML-FF produces more reliable flood predictions than any single model, demonstrating the advantage of integrated machine learning approaches for hydrological forecasting.
[21]	- Convolutional Neural Networks (CNNs)	The results demonstrate that Convolutional Neural Networks (CNNs) effectively transfer knowledge from training data to new terrains, proving their potential as efficient surrogate models for various flood prediction applications.
[23]	- Pyraformer - TimesNet - SegRNN	The deep learning models achieved exceptional flood prediction performance for the Wupper River region, with 99.7% accuracy and a 91% F1-score. These results demonstrate the models' effectiveness in accurately forecasting flood risks using hydrological data.
[25]	- Random Forest - Naive Bayes - J48	The water level forecasting evaluation showed notable performance variations among the tested algorithms. Random Forest outperformed others with 98.7% accuracy, while Naive Bayes (88.4%) and J48

		(84.2%) demonstrated lower but still significant accuracy. These findings establish Random Forest as the most effective method for water level prediction in this study.
[26]	- Exponential Smoothing-Long Short-Term Memory (ES-LSTM) - Artificial Neural Networks (ANNs) - Decision Tree (DT) Algorithm	The evaluation showed distinct strengths among the tested models: the ES-LSTM hybrid effectively analyzed precipitation time-series data, achieving minimal Mean Absolute Percentage Error (MAPE). At the same time, the Artificial Neural Network (ANN) approach demonstrated superior accuracy (96.65%) compared to Decision Trees (84.0%). These results position ANN as the most precise model for precipitation prediction, with ES-LSTM excelling specifically in time-series forecasting applications.
[28]	- Improved Principal Component Analysis (i-PCA) -1D-Convolutional Neural Network (CNN)	The study evaluates model performance using standard classification metrics: precision, accuracy, recall, and F1-score. Results demonstrate that the proposed model outperforms existing methods with 94.24% accuracy, an 8.24 percentage point improvement over the baseline 86% accuracy.
[29]	- Long-Short Term Memory (LSTM) - Artificial Neural Networks (ANN) - Random Forest (RF) - K-Nearest Neighbors (KNN) - Support Vector Machine (SVM)	The evaluation revealed significant variations in performance across different classifiers for high-risk flood classification. The LSTM model emerged as the top-performing single classifier, achieving a sensitivity of 0.925 during training/validation. However, its generalization capability was limited (testing sensitivity: 0.7). In contrast, SVM demonstrated the poorest performance with a sensitivity of just 0.057 (training) and 0.042 (testing). Accuracy assessments showed similar patterns: Training/Validation: LSTM (0.935) > KNN (0.867) > RF (0.807) > ANN (0.557) Testing: LSTM (0.81) > RF (0.65) > ANN (0.582) > KNN (0.538) Notably, ensemble classifiers substantially outperformed individual models. The LSTM and RF combination achieved exceptional validation accuracy (0.997) and maintained strong testing performance (0.811), while the ANN and RF ensemble showed robust results (validation accuracy: 0.956; testing: 0.737). The LSTM and RF ensemble excelled with an average testing sensitivity of 0.714, demonstrating superior predictive capability for flood risk assessment.
[31]	- Random Forest - Logistic Regression - Naive Bayes - K-Nearest Neighbors (KNN) - Decision Tree	The comparative analysis of flood prediction models revealed substantial accuracy differences. Random Forest performed best (95.90%), with K-Nearest Neighbors (KNN) close behind (95.13%). Decision Tree showed moderate accuracy (91.45%), while Logistic Regression (79.51%) and Naive Bayes (77.26%) were less effective. These results identify Random Forest and KNN as the top-performing algorithms for flood prediction among those tested.
[33]	- CNN - RF	This study evaluated multiple machine-learning approaches for flood prediction, revealing several

	- KNN with bagging, and a cubic classifier - Bayesian Linear model	key findings. The convolutional neural network demonstrated superior segmentation performance compared to the Random Forest classifier and NDWI threshold function. For flood susceptibility mapping, a KNN-cube ensemble model combining K-Nearest Neighbors, bagging, and a cubic classifier proved effective, notably enhancing its accuracy. Evaluation results identified the Bayesian Linear method as the top-performing model among all tested approaches, confirming its superior suitability for flood detection applications.
[36]	- GA-XGBoost - DE XGBoost - RF - CART	The study found that hybrid GA-XGBoost and DE-XGBoost models outperformed traditional Random Forest (RF) and CART methods for multi-step water level predictions. The hybrid approaches achieved greater accuracy, with relative errors of 2.18-9.21%, compared to RF's 3.76-10.41% and CART's 2.99-11.88% error ranges. These findings highlight the superior performance of hybrid models for hydrological forecasting applications.
[39]	- Decision Tree (DT) - K-Nearest Neighbors (KNN) - Support Vector Machine (SVM) - Bayesian Networks (BN)	The evaluation of four machine learning models showed Bayesian Networks (BN) achieved the highest accuracy (99.94%) on imbalanced data, followed by Decision Tree (DT: 99.89%), k-Nearest Neighbors (kNN: 99.50%), and Support Vector Machine (SVM: 98.23%). After applying SMOTE to address class imbalance, model performance improved significantly: Decision Trees (99.92%), k-Nearest Neighbors (99.86%), Bayesian Networks (99.68%), and Support Vector Machines (99.03%). These results demonstrate SMOTE's effectiveness, particularly for imbalance-sensitive algorithms like SVM, while confirming the consistent robustness of both Bayesian Network and Decision Tree approaches.
[40]	- Random Forest (RF) - XGBoost - Support Vector Machine (SVM) - Logistic Regression (LR)	The flood forecasting model evaluation showed notable accuracy differences: Random Forest (RF) performed best at 96%, followed by XGBoost (95%), while Support Vector Machines (SVM) and Logistic Regression (LR) both achieved 93%. These results establish RF and XGBoost as the most effective algorithms for flood susceptibility modeling among those tested.
[41]	- Hydrologic Forecast Merging (HFM) techniques - Bayesian Model Averaging (BMA)	The analysis reveals that Hydrologic Forecast Merging Techniques (HFM) techniques consistently achieve superior forecasting efficiency compared to standalone rainfall-runoff models. Of the various approaches examined, Bayesian Model Averaging (BMA) emerges as particularly noteworthy, demonstrating two key advantages: (1) minimizing prediction uncertainty, and (2) consistently reliable forecast performance. These characteristics have established BMA as the most widely adopted

		technique among the methods evaluated.
[47]	- LSTM-based machine learning model - ANN	This study shows that combining local sensor data with third-party weather forecasts significantly improves multi-step flood prediction accuracy. This advancement provides emergency responders and communities with reliable early warnings and enhanced preparation time against potential flood threats.
[48]	- Gradient Boosting Decision tree (GBDT) algorithm in Deep learning	The evaluation result confirms the GBDT regression model's effectiveness for real-time water monitoring, achieving a 19.77% relative error, an 82.00% qualification rate, and an outstanding 5.48% peak average relative error. These results demonstrate their strong predictive capability and practical value for flood forecasting.
[49]	- Random Forest algorithm	The study shows that combining GPS and Twitter data enhances flood prediction accuracy, with the integrated model outperforming conventional approaches by 8%. This article demonstrates the value of incorporating diverse data sources for more accurate forecasting.
[50]	- Random Forest (RF) - Multilayer Perceptron (MLP) - Support Vector Classifier (SVC)	The machine learning evaluation identified Random Forest (RF) as the top performer with near-perfect accuracy (0.99), closely followed by Support Vector Classifier (SVC) and Multilayer Perceptron (MLP) at 0.98 each. These results validate the effectiveness of advanced machine-learning techniques for flood forecasting.

Table 2 shows that the machine learning evaluation for flood prediction identified Random Forest as the most effective model, demonstrating superior accuracy. Performance rankings showed K-Nearest Neighbors (KNN) as the second-best approach, followed by Multilayer Perceptron (MLP), Decision Trees (DT), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN).

*C. **Machine learning algorithms are most effective in analyzing sensor data for flood prediction.***

Modern flood monitoring systems combine multiple technologies to gather, process, and distribute accurate hydrological data. These systems employ LoRaWAN for energy-efficient, long-range communication in remote locations and MQTT protocols for reliable connectivity. They integrate with IoT platforms such as TagoIO, ThingSpeak, and Blynk to analyze and visualize data, facilitating real-time flood level monitoring across four risk categories (safe, alert, cautious, dangerous) through computer and mobile interfaces. The systems deliver timely warnings via multiple channels including SMS alerts, web dashboards, audible alarms, LED indicators, and automated calls [52]. For enhanced situational awareness, Grafana provides high-frequency updates every 20 seconds, enabling precise trend analysis [13]. This comprehensive technological integration substantially strengthens flood preparedness by making critical risk information widely accessible.

TABLE 3
A SYSTEMATIC REVIEW OF APPLICATIONS, ONLINE PLATFORMS, OR COMMUNICATION PROTOCOLS

Ref.	Online platforms, Communication protocols	Function	Recommendation
[8]	- Sirens - Telephones - SMS - Social Network	This research aims to improve flood preparedness by addressing limitations in conventional risk assessment methodologies and extending early warning system capabilities to enhance protection for at-risk populations.	The study recommends integrating advanced technologies like mobile apps and real-time monitoring systems to deliver more accurate and timely flood warnings, enabling faster community response to impending threats.

[13]	- Grafana website	This research utilizes an interactive visualization tool compatible with mobile and desktop platforms, enabling users to analyze collected datasets.	The paper recommends optimizing IoT communication protocols through improved data transmission rates, reduced latency, and enhanced reliability to strengthen real-time monitoring capabilities. Furthermore, integrating machine learning-powered predictive analytics could enable flood forecasting by analyzing historical data, significantly improving disaster preparedness.
[15]	- Zigbee - Bluetooth and BLE - 6LOWPAN - Wi-Fi - LoRaWAN - EC-GSM-IoT	Early warning systems typically employ wireless and wired communication technologies for reliable data transmission of hazard alerts.	Future research should prioritize adopting advanced cellular technologies like 5G and NB-IoT to replace legacy GSM systems, significantly enhancing the performance and reliability of early warning networks.
[26]	MQTT protocol	The system transmits collected sensor data to the gateway for processing.	The paper emphasizes the need to enhance alert systems through supervisor notifications, to ensure proper alert verification and escalation by authorized personnel. This improvement would accelerate flood response times and optimize emergency decision-making during flood events.
[32]	- HTTP - Server-Sent Events (SSE)	This article presents a dynamically updated user interface that monitors irrigation conditions.	The paper proposes implementing the MQTT protocol to enable fast, efficient communication between field devices and the central server.
[37]	- ThingSpeak	The system enables real-time soil moisture monitoring through ThingSpeak's interface, providing visualization tools, historical data analysis, and customizable alert configurations for a complete flood detection solution.	The study emphasizes developing mobile applications to deliver direct flood alerts to end-users, significantly improving community engagement and ensuring timely risk communication.
[38]	- Long-range wide area network (LoRaWAN) - MQTT (MQ Telemetry Transport - Constrained Application Protocol	MQTT (Message Queuing Telemetry Transport) employs a publish/subscribe model ideal for IoT systems, particularly in low-bandwidth wireless networks with latency issues. In contrast, CoAP (Constrained Application Protocol) utilizes a request/response architecture, while LoRaWAN specializes in long-range, low-power transmissions of small data packets.	This study recommends developing real-time monitoring systems to track machinery performance metrics like production rates, energy usage, and storage conditions, highlighting how ML-IoT integration can drive more efficient, secure, and sustainable industrial operations under the Industry 4.0 framework.
[42]	- Thingspeak IoT platform	The system enables real-time water level tracking with fast data transmission (≤10-second lag time) for real-time monitoring.	Future research should focus on minimizing data processing and transmission delays to enable faster flood alert dissemination, which is crucial for effective emergency response.

[45]	- LoRaWAN technology - Things Network in Packetview	The FMS utilizes LoRaWAN transmission with solar charging capability, sending data to The Things Network for subsequent visualization in PacketView.	To further develop this innovative barometric flood monitoring system (FMS), subsequent research should incorporate testing across multiple elbow configurations while optimizing the system for urban flood management applications. These enhancements will maintain the solution's alignment with dynamic disaster response demands.
[46]	- Global System for Mobile Communication (GSM) module	This technology automatically generates SMS alerts to notify users of impending flood conditions.	These enhancements will extend the system's functionality to more effectively manage East Africa's distinctive flood risks.
[51]	- Blynk application	This article implements pop-up notifications to provide users with immediate flood alerts and real-time data displays.	The findings suggest implementing sophisticated data analytics and evaluating new functional components to substantially improve system performance.
[52]	- LoRaWAN - TagoIO and ThingSpeak IoT platforms - The Flood Alert system includes sound alarms, LED blinking, SMS messages, and phone calls	This study employs LoRaWAN for energy-efficient, long-range data transmission, while TagoIO and ThingSpeak platforms enable robust data analysis and visualization. The system delivers real-time flood alerts through multiple channels, including audible alarms, visual indicators, SMS, and automated calls, ensuring rapid community notification of flood risks.	The authors recommend integrating machine learning algorithms into the system to improve flood prediction accuracy and reliability, suggesting that current analytical capabilities require enhancement.

IV. CONCLUSION AND RECOMMENDATION

This systematic literature review identifies key components of effective IoT-based flood monitoring systems. Ultrasonic sensors, water level detectors, rain gauges, flow sensors, and temperature/humidity sensors emerge as the most reliable for real-time flood detection. For prediction, machine learning algorithms, particularly Random Forest (RF), K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP), Decision Trees (DT), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN) demonstrate strong performance, with RF achieving the highest accuracy. Data transmission relies on robust protocols like LoRaWAN, Zigbee, MQTT, and GSM, while platforms such as ThingSpeak, TagoIO, Grafana, and Blynk enable efficient data visualization and analysis. These findings underscore the potential of integrated IoT solutions for flood monitoring while highlighting persistent implementation challenges.

In order to improve flood detection capabilities, research should emphasize two key areas: 1) enhancing water level sensor precision using next-generation technologies and specialized calibration methods [42]; 2) strengthening predictive model performance under diverse environmental conditions by integrating multi-source data such as satellite imagery, GIS layers, and meteorological datasets. By combining these complementary approaches, flood monitoring systems will become significantly more accurate and reliable.

Flood prediction models should be expanded to support disaster logistics by optimizing routes for delivering essential goods during emergencies. These models can also be adapted to detect leaks in water infrastructure [16]. Furthermore, it is important to pursue three interconnected AI advancements for flood prediction: First, research should focus on hybrid and ensemble algorithms, which are superior to traditional multilayer perceptron in creating more accurate forecasts tailored to specific scenarios [2,38]. Second, using Explainable AI (XAI) methodologies to make model predictions more understandable by emergency managers and policymakers, enabling better disaster response decisions [28]. Finally, ensuring timely warnings even with complex models by optimizing Edge AI implementations in geographically dispersed flood monitoring networks to maintain prediction accuracy while minimizing latency [15]. Together, these technical improvements would improve flood forecasting accuracy, transparency, and responsiveness.

Three essential technical upgrades are required to build a comprehensive flood warning system. First, real-time prediction systems with continuous data processing capabilities would enable faster and more accurate alerts [31]. Second, MQTT protocols should be implemented to optimize communication between field devices and central servers, ensuring rapid response to changing flood conditions [32]. Third, intuitive web interfaces supported by robust database solutions like MySQL would facilitate immediate analysis and long-term data access for various stakeholders [8,32]. Together, these improvements would significantly enhance the system's reliability, usability, and response speed for more effective flood risk management.

Future researchers should prioritize collaborating with government agencies to utilize their comprehensive data infrastructure, including meteorological records, historical flood records, and monitoring networks, to improve model accuracy and facilitate seamless integration with disaster management policies [49]. Effective collaboration ensures flood prediction systems meet real-world operational requirements by leveraging authoritative datasets. Such partnerships also bridge the crucial gap between technical development and practical implementation, enhancing the systems' effectiveness.

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