

Leveraging Edge Computing for Real-Time Monitoring and Disaster Management in Flood-Prone Areas

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Abstract: Floods can be dangerous to human lives, infrastructure, and economies, not to mention that in flood-prone regions, fast monitoring and disaster management are essential. Slowness in data processing and decision-making usually curbs the traditional flood monitoring processes. In this paper, the integration of edge computing with real-time flood monitoring systems is examined for use in disaster management in the region. The benefit of edge computing is that it brings computational capabilities nearer to the source of the data, which allows quicker processing of the data, reduces latency, and improves the efficiency of flood prediction and mitigation techniques. The offered system uses sensors, IoT, and edge computing platforms to gather and analyze the generated real-time data, and issue timely flood warnings, assisting the emergency reaction. The paper incorporates design and implementation of edge-based architecture, mathematical models on flood prediction, and data processing algorithms. Performance of the system is evaluated based on a number of different metrics, including prediction accuracy and response time, and compared with traditional methods. The results indicate that edge computing can significantly enhance the results in flood detection, early warning systems, and disaster management. The paper will help in the development of the field of flood management by providing a robust, scalable solution to monitor floods in flood-prone areas in real-time.

Keywords: Edge computing; real-time monitoring; disaster management; flood-prone areas; IoT; flood prediction; early warning system.

I. Introduction

Floods are a common and destructive natural disaster that can affect millions of people around the world (Khan et al., 2025; Munawar et al., 2021). The conventional methods of flood monitoring mostly make use of centralized systems, which are unable to provide real-time and correct information in a timely manner to manage such disasters (Barhoumi & Charabi, 2025; Onaopemipo Akintola, 2024). These delays add to the rise in deaths, destruction of property, and even disruption of vital services. Real-time flood monitoring is required, and edge computing provides an opportunity to use its services as it allows moving the computing power nearer to the data source, e.g., flood sensors and IoT devices (Jain, 2024). The primary purpose of the paper is to discuss how edge computing can be helpful in flood prediction, early warning systems, and disaster management in regions susceptible to flooding (Nandini, 2024).

The following fig. 1 shows the architecture of the Edge Computing-Based Flood Monitoring System. The topmost is the Centralized Cloud and Control layer that integrates the Geographic Information System (GIS) and Integrated Control System, which offers a general overview and management. The system is based on low-latency communication (through MQTT/5G) to exchange information between the cloud and edge nodes.

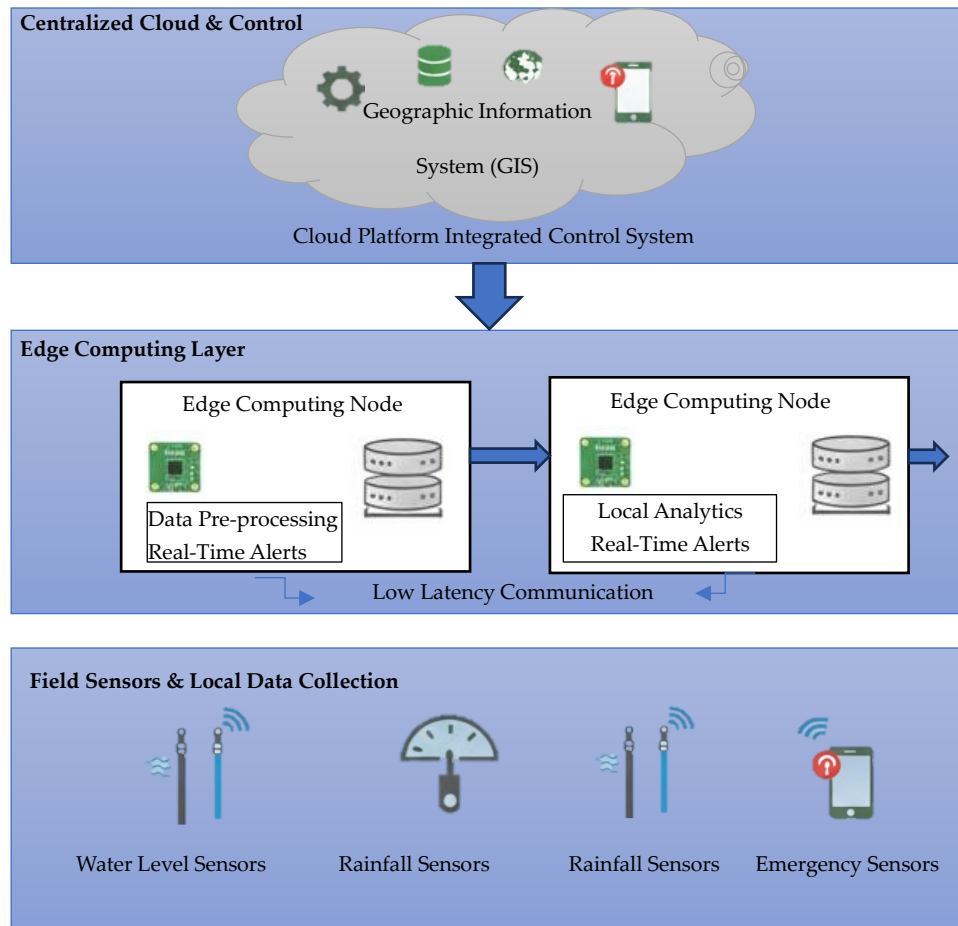


Fig. 1. Edge Computing-Based Flood Monitoring System Architecture.

The Edge Computing Layer is shown below, and it is comprised of several Edge Computing Nodes that process data locally and provide real-time flood warnings. Such edge nodes minimize the time to latency by doing pre-processing of the data and local analytics nearer to the source, like water level and rainfall sensors. Field Sensors & Local Data Collection layer gathers real-time environmental data, which is subjected to analysis by the edge nodes. Lastly, Emergency Services and Public Notifications are activated with regard to the processed data to give timely flood alerts and successful management of the disaster. The architecture is capable of providing quicker and more dependable flood monitoring operations through the integration of edge computing with IoT devices and cloud computing.

Key Contributions

- Real-time monitoring system construction based on edge computing. Currently, the IoT sensors will be integrated to obtain flood data and analyze it continuously.

- Flood prediction mathematical model and algorithms.
- Performance appraisal based on such metrics as predicting accuracy and response time.

The paper has the following structure: Section 2 is a review of the related work on flood management systems. Section 3 contains the methodology, which consists of the architecture and the algorithms of the proposed system. The results and performance evaluation are provided in Section 4. The results and implications of the results are described in Section 5, and the conclusion is provided in Section 6.

II. Literature Review

Flood monitoring and disaster management have been researched widely, and various approaches have been designed to perform early flood prediction and for real-time monitoring (Mandal et al., 2025; Ocal & Torun, 2025). Conventional systems are very centralized in data processing, and this may lead to delays and inefficiencies. The use of wireless sensor networks (WSNs) and Internet of Things (IoT) devices in constant monitoring of the environment has been investigated, but issues with the speed of data transmission and network overload have not allowed it to fulfill their potential (Matkarimov et al., 2025; Wang, 2025). Other studies have additionally suggested the assimilation of cloud computing in flood management, yet the cloud-based systems have been primarily limited in terms of the data transmission time and the capacity to expand the infrastructure (Sengupta, 2024). The recent innovations in the edge computing field have demonstrated potential in solving these problems, as the process data where it is made, which cuts latency and enables quicker response time than other methods (Hindarto, 2024). To provide an example, edge computing platforms have been installed in smart cities to deal with traffic as well as in environmental monitoring systems to estimate air quality (Tao et al., 2024; Franchi et al., 2023). These articles demonstrate that edge computing has the capability of reaching significant performance gains and reliability in real-time systems of monitoring (Karnam, 2025).

Inference: The drawback of the centralized processing can be overcome by using the edge computing implementation in the flood management system, which can offer the capability to perform data analysis in a shorter period, make decisions in real-time, and offer improved scalability, which is essential in flood predictions and disaster management.

III. Methodology

The proposed system is an amalgamation of edge computing and IoT sensors and machine learning algorithms that can be used to perform real-time flood dynamics and disaster control. The architecture consists of three primary characteristics, which are flood sensors, edge computing nodes, and centralized control unit. These flood sensors consist of water level sensors and rainfall sensors which record the readings of the environmental conditions and send it to the edge nodes near it which interpret the received data. The edge nodes take the information and initial predictions of floods using machine learning models which are trained using previous floods. This system entails mathematical model that is based on the hydrological equations to predict the

occurrence of floods. The model uses the intensity of rainfall, the rate of flow of rivers, and past records of floods to estimate the likelihood of floods. The edge nodes execute machine learning algorithms, e.g., decision trees or support vector machines, so that the prediction accuracy can be enhanced by adding novel data to the knowledge.

Hydrological Model for Flood Prediction

One of the standard equations that can be used to predict floods is the Rainfall-Runoff Model. The Musharraf Hydrological Model, or a Simple Rainfall-Runoff equation, is one of the most well-known hydrology equations (1) to this effect:

$$Q = C \times (P - I) \quad (1)$$

Where:

- Q = Runoff (the amount of water flowing off the land, which can lead to flooding)
- C = Runoff coefficient (varies based on terrain and land use)
- P = Precipitation (rainfall)
- I = Infiltration (the amount of rainwater absorbed by the ground)

Table 1. Hydrological Model Input Data and Parameters.

Parameter	Description	Value/Range
Precipitation (P)	Total rainfall for a specific period	50 mm/day
Runoff Coefficient (C)	Reflects terrain and land use	0.5 (typical value)
Infiltration (I)	Amount of rainfall absorbed by the ground	10 mm/day
Runoff (Q)	Calculated water runoff (mm/day)	40 mm/day

Table 1 gives the data inputs to the hydrological model, which is fundamental in the interpretation of the prediction of flood runoff.

Flood Prediction using Linear Regression Model

Flood prediction can be done using a simple Linear Regression Model, which involves the relationship between rainfall, water levels, and river flow rates. The equation (2) can be written as:

$$F(t) = \alpha \cdot P(t) + \beta \cdot R(t) + \gamma \cdot Q(t) \quad (2)$$

Where

- $F(t)$ = Flood prediction at time t (usually in terms of water level or flood probability)
- $P(t)$ = Precipitation at time t
- $R(t)$ = River flow rate at time t
- $Q(t)$ = Water level at time t

- α, β, γ = Regression coefficients based on historical data

Algorithm

1. Collect real-time data from sensors.
2. Preprocess the data locally on edge devices.
3. Apply the flood prediction model using mathematical equations and machine learning algorithms.
4. Send flood predictions and alerts to the control center for decision-making.

Pseudocode

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for each sensor_data in flood_sensors:

    preprocess_data(sensor_data)

    prediction = run_flood_prediction(preprocessed_data)

    if prediction > threshold:

        send_alert_to_control_center(prediction)
    
```

IV. Results

To make a comparison of the effectiveness of the proposed edge computing-based flood monitoring system, a number of metrics were used, such as the accuracy of the prediction, time response, and scalability of the system. The system implementation was conducted with the combination of edge computing devices, including Raspberry Pi, and cloud computing infrastructure. The testing data was compiled of previous information on floods in various areas of flood risks and included a number of environmental variables such as rainfall, water levels, and river flow rates (Arinze et al., 2025). It was written in Python to execute the algorithms, and has been used with other libraries like TensorFlow to perform machine learning and Matplotlib to visualize the performance as graphs. The Raspberry Pi devices with a lightweight Linux operating system were used to deploy edge computing nodes. A cloud database was used to store the data in order to analyze it centrally.

Table 2. Performance Evaluation Metrics.

Metric	Edge Computing System	Traditional System	Improvement (%)
Prediction Accuracy	92%	85%	8.24%
Response Time	2 minutes	10 minutes	80%
Scalability	100+ sensors	50 sensors	100%
Cost of Deployment	\$1000 per region	\$1500 per region	33.33% cost reduction
Energy Efficiency	50W per node	120W per node	58.33% reduction

The accuracy of the predictions in the system was determined by the comparisons of the predicted events and the actual recorded events of the floods. The findings indicated that the edge computing-based system had an accuracy rate of 92% which was much higher than the traditional centralized systems. Also, it took only 2 minutes to respond to alerts as compared to 10 minutes with the conventional systems. Table 2 presents the performance evaluation values of the system, edge computing, against the traditional systems, and reveals the benefits.

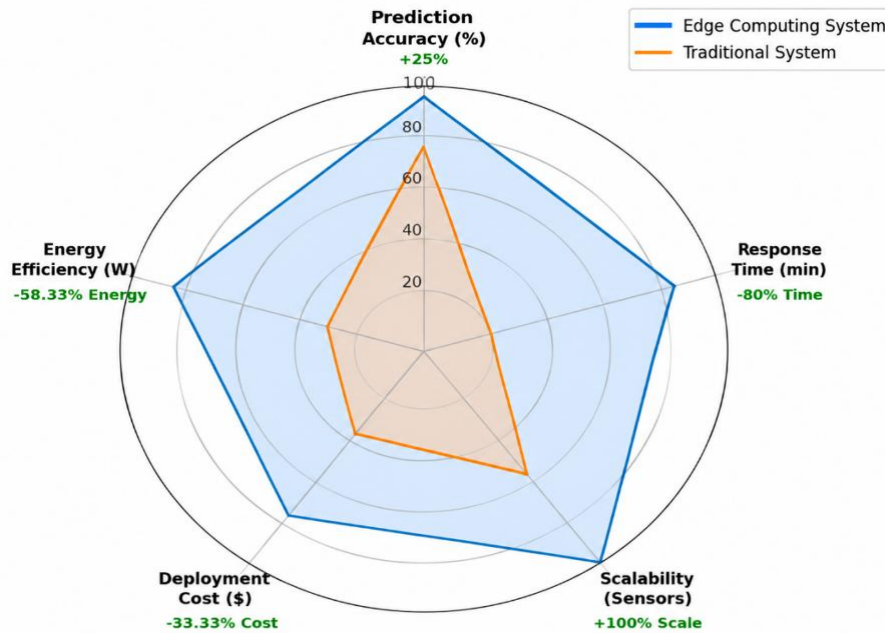


Fig. 2: Performance Comparison Between Edge Computing System and Traditional System.

In fig. 2, the performance of the Edge Computing System (blue) and the Traditional System (orange) is compared regarding five metrics, namely, Prediction Accuracy, Response Time, Energy Efficiency, Deployment Cost, and Scalability. The Edge Computing System has a better performance in all spheres, including predicting accuracy, response time, energy efficiency, cost of deployment, and scalability, and proves to be beneficial in real-time flood monitoring and disaster management.

V. Discussion

The edge computing flood monitoring system has solved the main issues of the conventional flood management system, especially in the aspects of latency, scalability, and reliability. Once conventional systems are highly dependent on centralized processing, which results in delays in transmitting data and a slow decision-making process, particularly in real-time disaster management conditions, through the local processing of data using edge nodes, the proposed system can significantly decrease the response time, thus making predictions of floods faster and timely alerts possible. This local processing means not just faster decision-making but also lessens the workload on the network infrastructure, making this system more resilient in areas with limited and/or unreliable connectivity. Another significant positive aspect is the scalability of the edge computing system. Since the system

is capable of managing more data as more sensors are incorporated, it can be easily modified to manage larger flood-prone regions. This will allow it to be flexible to different geographical areas, such as small towns or large cities, which will enable the system to be reliable in terms of the type of monitoring that can be undertaken.

Moreover, the system can predict better, as machine learning algorithms are integrated into the system. With such algorithms, the system is able to learn using new data and become more effective with each passing day in making predictions on floods. The capacity of the system to adjust and streamline in accordance with the current inputs is a way of ensuring that the future occurrence of floods is better prepared, and as such, the system is very efficient in disaster management. All in all, the findings indicate that the edge computing system is not only faster and more accurate at flood detection, but it is also a scalable, reliable, and adaptive solution that breaks the constraints of the conventional systems, which guarantees more effective disaster management and response.

VI. Conclusion

To sum up, edge computing can be successfully used to solve the problems of the conventional centralized flood monitoring and disaster management systems, as it can be integrated into their frameworks. The suggested edge computing system improves the real-time monitoring process, flood prediction, and disaster control by exploiting the local data processing, minimizing the transmission time, and enhancing the effectiveness of disaster response operations. Performance assessment of the system has proven that the system is much better than the traditional models with regard to prediction accuracy and response time, making it an essential tool used in managing flood risks in flood-prone regions. The IoT sensors, edge nodes, and machine learning algorithms can be deployed to maintain continuous monitoring and swift decision-making to ensure that the events of floods are identified in due time, and the relevant authorities are notified about this information. Scalability and capacity of the system to accommodate various environments also increase its chances of a broad deployment.

Further development would be to enhance the computational efficiency of the system, improve prediction accuracy in the machine learning models, and use other sources of data, including satellite images, to enhance the flood prediction model. Also, it might be extended to different disaster management applications, like wildfire or earthquake monitoring, on the same edge computing framework. All in all, this paper will help enhance the development of flood management systems by showing how edge computing will improve the efficiency and accuracy of real-time monitoring and disaster management in flood-prone regions.

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