Hệ thống giám sát và cảnh báo lũ lụt thời gian thực dựa trên nền tảng IoT và cảm biến mực nước kép

TÓM TẮT

Lũ lụt là một trong những thảm họa thiên nhiên gây thiệt hại nặng nề về người và kinh tế. Việc phát hiện sớm và đưa ra cảnh báo kịp thời đóng vai trò then chốt trong công tác quản lý lũ, đặc biệt tại các khu vực có điều kiện địa hình phức tạp. Bài báo này đề xuất một hệ thống giám sát lũ lụt dựa trên công nghệ IoT, tận dụng dữ liệu mực nước từ hai cảm biến đặt cách xa nhau để nâng cao độ chính xác trong dự báo rủi ro và phát cảnh báo kịp thời. Một thuật toán phân tích mực nước mới dựa trên cảm biến kép được giới thiệu, nhằm đánh giá nguy cơ lũ thông qua việc phân tích tốc độ dâng mực nước và chênh lệch mực nước giữa hai vị trí cảm biến. Hệ thống tích hợp Node.js cho xử lý phía máy chủ và Google Maps API cho trực quan hóa không gian, giúp giám sát và phân phối cảnh báo theo thời gian thực. Kết quả thực nghiệm cho thấy hệ thống đạt độ chính xác cao, 94.66% trong việc phát hiện rủi ro lũ, và độ trễ thấp, chỉ 10 giây trong quá trình phát cảnh báo, khẳng định tính khả thi của hệ thống trong các khu vực thường xuyên xảy ra lũ lụt, điển hình như lưu vực sông Côn, tỉnh Bình Định.

Từ khóa: *IoT, hệ thống cảnh báo lũ sớm, cảm biến kép, Node.js, Google Maps API.*

IoT-Enabled Flood Risk Detection via Dual-Sensor Water Level Monitoring and Real-Time Alerting

ABSTRACT

Flooding is a devastating natural disaster that causes significant loss of life and economic damage. Early detection and real-time alerts are essential for effective flood management, particularly in regions with challenging geographical conditions. This paper proposes an IoT-based flood monitoring system that leverages dual-sensor water level data for accurate risk prediction and timely alerts. A novel dual-sensor water level analysis algorithm is introduced to evaluate flood risks by analyzing the rate of water level increase and the differential between two sensor locations. The system integrates Node.js for backend processing and Google Maps API for spatial visualization, enabling real-time monitoring and alert dissemination. Experimental results demonstrate high accuracy of 94.66% in detecting flood risks and low latency of 10 seconds in generating alerts, proving the system's suitability for flood-prone areas like the Con River basin, Binh Dinh province.

Keywords: *IoT, early warning system, dual-sensor water level prediction, Node.js, Google Maps API*

1. INTRODUCTION

Flooding is one of the most catastrophic natural disasters, causing widespread destruction, loss of life, and economic damage globally. According to the report from the World Meteorological Organization (WMO), floods account for approximately 44% of all natural disasters, affecting millions of people annually[1]. In developing countries, where infrastructure and disaster management systems are often underdeveloped, the impact of floods is particularly severe. Early detection and real-time alerts are critical for mitigating the adverse effects of floods, enabling communities and authorities to take proactive measures such as evacuations, resource allocation, and emergency response planning[2].

Traditional flood monitoring systems often rely on manual measurements or single-point sensors, which may lack spatial coverage, accuracy, and timeliness. Water level data collected manually at specific locations may not reflect the dynamic changes occurring across a river basin. Similarly, single-point sensor systems fail to capture spatial variations in water levels, leading to delayed or inaccurate flood predictions[3]. These limitations highlight the need for advanced, scalable, and cost-effective solutions that can provide real-time insights into flood risks.

Recent advancements in Internet of Things (IoT) technologies have enabled the development of smart flood monitoring systems capable of collecting and processing environmental data in real time. IoT-based systems offer several advantages, including continuous data collection, wireless communication, and integration with cloud platforms for analysis and visualization[4-5]. However, most existing IoT-based flood monitoring systems focus on single-sensor data, which may not fully capture the complex dynamics of river systems. To address this gap, this paper proposes an IoT-based flood monitoring system that leverages dual-sensor water level data for enhanced flood risk prediction and timely alerts.

The proposed system integrates advanced technologies such as Node.js for backend processing and Google Maps API for spatial visualization, enabling real-time monitoring and alert dissemination. A novel dual-sensor water level analysis algorithm is introduced to predict flood risks by analyzing two key parameters: (i) the rate of water level increase at each sensor location and (ii) the differential between water levels measured by two sensors placed at different points along a river. This approach not only captures temporal changes in water levels but also accounts for spatial variations, providing a more comprehensive assessment of flood risks.

The remainder of this paper is organized as follows: Section II provides an overview of related work. Section III describes the system architecture and design. Section IV details the dual-sensor water level prediction algorithm. Section V presents the experimental results, including the field experiment conducted along the Con River. Finally, Section VI concludes the paper and discusses future work.

2. RELATED WORK

Flood monitoring and early warning systems have been extensively studied in recent years, driven by the increasing frequency and severity of floods due to climate change and urbanization. Existing research can be broadly categorized into three main areas: (i) IoT-based flood monitoring systems, (ii) data analysis and prediction algorithms, and (iii) visualization and alert dissemination platforms. This section reviews key contributions in these areas and highlights the gaps addressed by the proposed system.

2.1. IoT-Based flood monitoring systems

The advent of IoT technologies has revolutionized flood monitoring by enabling real-time data collection and remote sensing. Masoudimoghaddam et al. proposed an IoT-based flood monitoring system using ultrasonic sensors to measure water levels in rivers[6]. The system transmitted sensor data to a cloud platform for analysis and visualization. While effective, this approach relied on single-point sensors, which may not capture spatial variations in water levels across a river basin. Similarly, a wireless sensor network for flood detection, focusing on energy-efficient communication protocols was developed[7]. However, the study did not incorporate advanced algorithms for flood risk prediction, limiting its ability to provide actionable insights.

More recently, the researchers introduced a multi-sensor IoT system for flood monitoring, integrating rainfall, soil moisture, and water level data[8]. The system demonstrated improved accuracy in detecting flood risks compared to single-parameter approaches. Despite these advancements, most existing IoT-based systems lack the capability to analyze spatial relationships between multiple sensor locations, which is critical for understanding the dynamics of river systems.

2.2. Data analysis and prediction algorithms

Data analysis and prediction algorithms play a crucial role in flood risk assessment. Traditional approaches often rely on statistical models or hydrological simulations to predict flood events. A rainfall-runoff system was developed to estimate flood risks based on historical rainfall data[9]. While these systems are effective for long-term predictions, they may not be suitable for real-time monitoring due to their computational complexity.

Machine learning (ML) techniques have gained popularity in recent years for flood prediction. A deep learning model was deployed to predict flood risks using satellite imagery and environmental data[10]. The model achieved high accuracy in detecting flood-prone areas but required extensive training data and computational resources. Similarly, a support vector machine (SVM) algorithm was employed to classify flood risks based on water level data[11]. However, these ML-based approaches are often resource-intensive and may not be feasible for deployment in resource-constrained environments.

In contrast, rule-based algorithms have been explored as a lightweight alternative for real-time flood prediction. A threshold-based algorithm was introduced to detect rapid increases in water levels using single-sensor data[12]. While simple and efficient, this approach did not account for spatial variations in water levels, which are essential for accurate flood risk assessment.

2.3. Visualization and alert dissemination platforms

Visualization and alert dissemination platforms are critical components of flood monitoring systems, enabling users to interpret sensor data and respond to flood risks effectively. Recent studies have highlighted the importance of integrating geographic information systems (GIS) for spatial visualization. The researchers developed a flood monitoring system that used Google Maps API to display sensor locations and flood risk zones on an interactive map[13]. The system provided intuitive visualization and real-time alerts, enhancing situational awareness for users.

Other studies have explored mobile applications and web-based dashboards for alert dissemination. A smartphone app that delivered flood alerts via push notifications, SMS, and email was proposed[14]. While effective, the study did not address the integration of advanced data analysis algorithms for flood risk prediction. Similarly, a web-based platform for flood monitoring was introduced[15] but the platform's effectiveness is limited by the absence of real-world validation during actual flood events, reducing its reliability in emergency scenarios.

2.4. Gaps addressed by the proposed system

Despite significant advancements in flood monitoring technologies, several gaps remain unaddressed in existing research. First, most IoT-based systems rely on single-point sensors or fail to analyze spatial relationships between multiple sensor locations. Second, many data analysis algorithms are either computationally intensive or lack the ability to capture both temporal and spatial variations in water levels. Third, while visualization platforms have improved user experience, they are often decoupled from robust prediction algorithms, limiting their effectiveness in providing actionable insights.

The proposed system addresses these gaps by leveraging dual-sensor water level data for enhanced flood risk prediction. A novel dual-sensor water level analysis algorithm is introduced to evaluate flood risks based on both the rate of water level increase and the differential between two sensor locations. The system integrates Node.js for efficient backend processing and Google Maps API for spatial visualization, enabling real-time monitoring and alert dissemination. Furthermore, the system is validated through a field experiment conducted along the Con River in Binh Dinh Province , demonstrating its suitability for real-world deployment in flood-prone areas.

3. SYSTEM ARCHITECTURE AND DESIGN

The architecture of the proposed IoT-based flood monitoring system is designed to provide real-time flood risk prediction and alert dissemination by leveraging dual-sensor water level data, Node.js for backend processing, and Google Maps API for spatial visualization. The system architecture is shown in Figure 1. The system follows a modular design that integrates hardware components for data collection, software components for processing and analysis, and a robust data flow mechanism to ensure seamless operation.

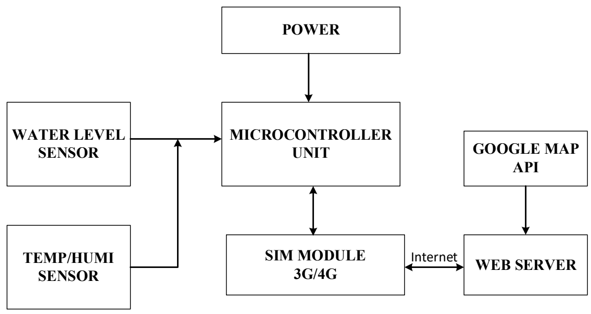

Figure 1. System architecture overview

At the core of the system are the hardware components responsible for collecting water level data from the field. Two ultrasonic sensors are strategically deployed at different locations along the river, one upstream and the other downstream, to capture spatial variations in water levels. The distance between the two measuring points is 24 km along the length of the river, as shown in Figure 2. These sensors are chosen for their accuracy and ability to withstand harsh environmental conditions. An ESP32 microcontroller with SIM module is used to collect data from the sensors and transmit it to the cloud via cellular network. The ESP32's low power consumption and wireless connectivity make it an ideal choice for remote deployments. To ensure reliable data transmission, a localhost acts as a gateway, aggregating sensor data from multiple locations and forwarding it to the Node.js server.

On the software side, the system relies on Node.js for backend processing and Google Maps API for visualization. The Node.js backend is responsible for handling sensor data, executing the dual-sensor water level prediction algorithm, and generating real-time alerts. The dual-sensor algorithm calculates the rate of water level increase and the differential between the two sensor locations to assess flood risks. If a high or medium risk is detected, the system generates alerts and sends them to users via Telegram app. Meanwhile, Google Maps API provides an intuitive interface for visualizing

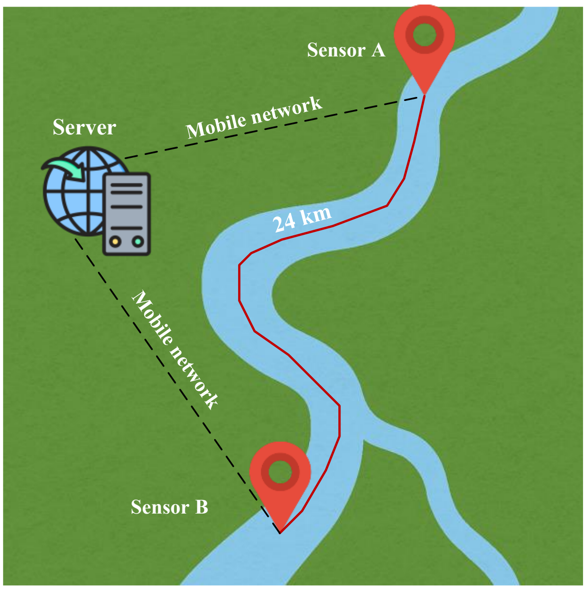

Figure 2. Two sensors are installed at two different locations on the river

sensor locations, water level data at each measuring point in map. Additionally, The measured data is updated on the map in real time as new data becomes available, ensuring that users always have access to the latest information. The system also incorporates a MongoDB database to store historical sensor data for analysis and visualization. By storing data such as timestamps, sensor IDs, water levels, and flood risk levels, the system can generate insights into past flood events and help predict future risks.

One of the key strengths of the proposed system is its ability to provide real-time monitoring while capturing spatial variations in water levels. By leveraging dual-sensor data, the system offers a more comprehensive assessment of flood risks compared to single-sensor approaches. Its scalability allows it to support multiple sensor pairs, making it suitable for deployment across larger river basins. Furthermore, the user-friendly interface powered by Google Maps API ensures that even non-technical users can easily interpret the data and take appropriate actions. These features collectively enhance the system's effectiveness in mitigating the impact of floods, particularly in regions like the Con River basin in Binh Dinh Province, where rapid water flow and wide floodplains pose significant challenges.

4. DUAL-SENSOR WATER LEVEL PREDICTION ALGORITHM

The proposed dual-sensor water level prediction algorithm is a key component of the flood monitoring system, enabling accurate and timely flood risk assessment. This section provides a detailed description of the algorithm, including its operational principles, risk classification mechanism, and alert generation process.

4.1. Algorithm

The dual-sensor water level prediction algorithm analyzes two critical parameters to evaluate flood risks: (i) the rate of water level increase at each sensor location and (ii) the differential between water levels measured by the two sensors. These parameters are derived from real-time data collected by ultrasonic sensors deployed upstream and downstream along the river. To calculate the rate of water level increase, the algorithm computes the difference between the current water level and the previous water level for each sensor, divided by the time interval between measurements. Mathematically, this is expressed as:

$$Rate_A = \frac{WA_{current} - WA_{previous}}{\Delta t} \quad (1)$$

$$Rate_B = \frac{WB_{current} - WB_{previous}}{\Delta t} \quad (2)$$

where $WA_{current}$ and $WB_{current}$ represent the current water levels at Sensor A and Sensor B, respectively, $WA_{previous}$ and $WB_{previous}$ represent the previous water levels, and Δt is the time interval between consecutive measurements. The water level differential is calculated as the absolute difference between the water levels at the two sensor locations:

$$\text{Delta}=|WA_{current}-WB_{current}| \quad (3)$$

This parameter captures spatial variations in water levels, which are essential for understanding the dynamics of river systems. For instance, a significant differential may indicate uneven water flow or potential blockages between the two sensor locations. By combining these two parameters, the algorithm provides a comprehensive assessment of flood risks, accounting for both temporal changes and spatial relationships in water levels.

4.2. Risk Classification

Based on the calculated parameters, the algorithm classifies flood risks into three levels: low, medium, and high. The classification is determined by comparing the computed values with predefined thresholds, denoted as $Threshold_R$ for the rate of water level increase and $Threshold_D$ for the water level differential. These thresholds are established based on historical data and expert knowledge specific to the monitored river basin. The use of dual thresholds ensures that the algorithm can adapt to varying environmental conditions and provide reliable flood risk predictions. The algorithm of alert generation is shown in Algorithm 1.

Algorithm 1: Alert Generation Process

Initialize: RiskLevel=Low

1. Retrieve the computed values of $Rate_A$, $Rate_B$, and Delta from the dual-sensor algorithm.
2. Compare $Rate_A$ and $Rate_B$ with $Threshold_R$, :
   - If $Rate_A$>$Threshold_R$ and $Rate_B$ >$Threshold_R$, set RiskLevel=High.
3. Check the water level differential (Delta) against $Threshold_D$, :
   - If Delta>$Threshold_D$, set RiskLevel=High.
4. Evaluate medium-risk conditions:
   - If $Rate_A$>$Threshold_R$, or $Rate_B$ >$Threshold_R$, and Delta<$Threshold_D$, set RiskLevel=Medium.
5. Confirm low-risk conditions:
   - If $Rate_A$≤$Threshold_R$, $Rate_B$≤$Threshold_R$, and Delta<$Threshold_D$, set RiskLevel=Low.
6. Generate alerts based on RiskLevel:
   - If RiskLevel=High:
     - Send SMS and push notifications to emergency teams and authorities.
     - Highlight affected areas on Google Maps API with color-coded overlays.
   - If RiskLevel=Medium:
     - Send SMS and push notifications to users with precautionary messages.
   - If RiskLevel=Low:
     - No alerts generated; continue monitoring.

4.3. Alert Generation

Once the flood risk level is determined, the system generates real-time alerts to inform stakeholders of potential flood threats. The alert generation process is triggered automatically when a medium or high-risk condition is detected. For high-risk conditions, the system prioritizes immediate alerts to emergency response teams and local authorities. The alerts include detailed information such as the sensor locations, current water levels, and predicted flood zones. Additionally, the Google Maps API interface highlights the affected areas on an interactive map, providing users with a visual representation of the flood risk zones.

For medium-risk conditions, the system sends precautionary alerts to users, advising them to monitor the situation closely and prepare for potential evacuations. These alerts are less urgent but still emphasize the importance of proactive measures to mitigate flood impacts.

The integration of automated alert generation with real-time visualization ensures that the system not only detects flood risks but also facilitates effective communication and decision-making. By leveraging Node.js for backend processing, the system achieves low-latency alert generation, with alerts typically delivered within 10 seconds of detecting a potential flood threat.

5. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed flood monitoring system, a series of experiments were conducted using simulated data and limited field testing along the Con River in Binh Dinh Province. Two ultrasonic sensors were deployed at upstream (Tay Son district) and downstream (An Nhon district) locations, with a distance of approximately 24 km between them. Data was collected at 5 seconds intervals over a period of 48 hours, during which both normal and simulated high water level conditions were tested. The measurement results are displayed in real time, as shown in Figure 3.

The ultrasonic sensors successfully captured real-time water level data at regular intervals. The sensor monitoring interface effectively integrates Google Maps API and real-time data visualization to provide a comprehensive overview of environmental conditions across the region. The interface is divided into two main sections: (i) a map displaying sensor locations and their corresponding data, and (ii) a sidebar showing detailed sensor readings and historical data trends. The map clearly highlights the spatial distribution of sensors at Tay Son and An Nhon, marked with red pins. Each pin provides a pop-up window with real-time environmental data. This visual representation allows users to quickly identify critical environmental data. This

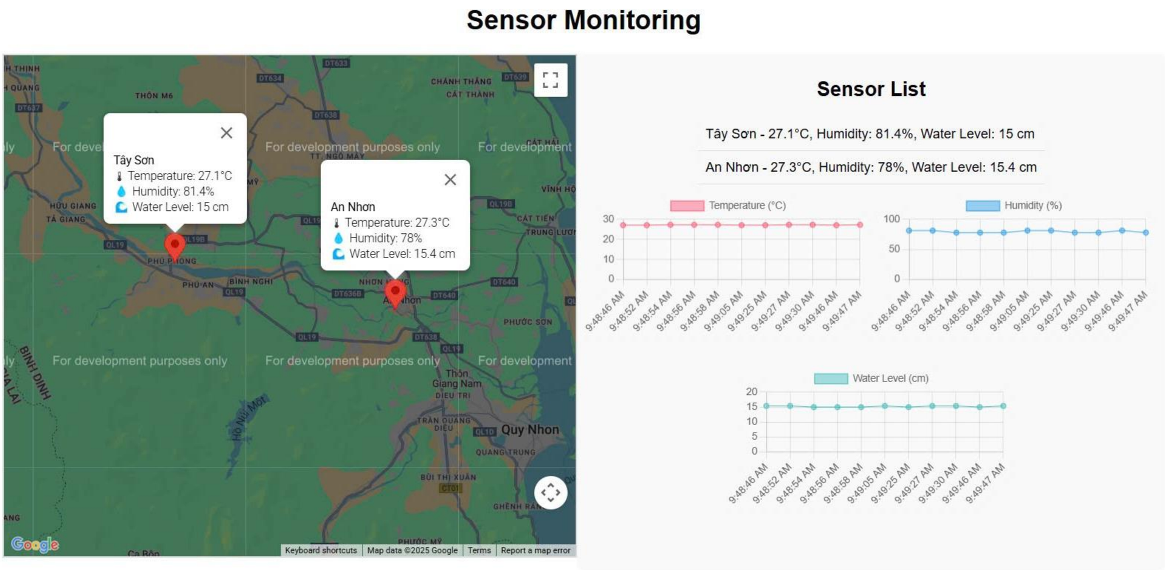

Figure 3. Experimental results displayed on web server

visual representation allows users to quickly identify critical environmental parameters at each location, providing valuable spatial context for decision-making.

The dual-sensor water level prediction algorithm was tested using simulated data to evaluate its ability to classify flood risks. The algorithm demonstrated high sensitivity to rapid increases in water levels ($Rate_A$ and $Rate_B$) and significant water level differentials *Delta*. However, determining accurate thresholds for parameters such as the rate of water level increase $Rate_A$, $Rate_B$ and the water level differential (*Delta*) remains a challenge that requires further investigation. To establish appropriate thresholds, the system needs to be supplied with more real-world data collected under various environmental conditions, particularly during actual flood events or abnormal flow situations. Additionally, the *Delta* threshold must also consider the distance between the two sensors and the proximity of the sensors to the areas being forecasted. A larger distance between sensors may naturally result in water level differences due to terrain and flow dynamics, while the distance from the sensors to the forecasted areas will influence the accuracy and timeliness of the warnings. Therefore, optimizing these thresholds requires a combination of empirical data and spatial analysis to ensure the system performs effectively under all real-world conditions.

To evaluate the performance of the proposed flood monitoring system, we conducted a series of tests using both real-time field data and simulated flood conditions. The performance of the system was measured in terms of its accuracy, calculated using standard metrics derived from the confusion matrix (True Positives - TP, False Positives - FP, False Negatives - FN, and True Negatives - TN).

The accuracy of the system is defined as the proportion of correct predictions (both TP and TN) to the total number of predictions (TP, TN, FP, and FN). Specifically, the accuracy was calculated using the following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

Table 1: Simulation results and accuracy calculation

Category	Number of Instances	Percentage (%)
True Positives (TP)	71	47.33%
False Positives (FP)	4	2.67%
False Negatives (FN)	4	2.67%
True Negatives (TN)	71	47.33%
Accuracy	—	94.66%

From the Table 1, the accuracy of 94.66% is derived from the system's ability to correctly predict flood risks in 94.66% of the cases tested, which indicates that the system's predictions matched the actual flood conditions observed during the test. This high accuracy was achieved by leveraging dual-sensor water level data, which enhanced the system's ability to detect rapid changes in water levels and spatial variations along the river.

The table clearly shows that the system was highly effective in identifying flood risks, with a minimal number of false positives (2.67%) and false negatives (2.67%). The 94.66% accuracy rate demonstrates the robustness and reliability of the system, particularly in rapidly changing water conditions.

Latency is a critical factor that can impact the overall performance of the flood monitoring system. In the current implementation, the system achieves a low-latency data transmission and processing pipeline, with alerts typically generated within 10 seconds of detecting a potential flood risk, as shown in Figure 4. This experimental result is completely suitable for applying this system in practice. This rapid response is achieved through the integration of IoT sensors, efficient Node.js backend processing, and real-time communication protocols MQTT. However, certain factors can introduce delays in the system. Since signal transmission over long distances or through areas with poor network coverage may result in increased latency, particularly when using wireless communication methods like 4G. Additionally, the time required for data preprocessing and algorithm execution, though minimal, can also contribute to slight delays in generating predictions.

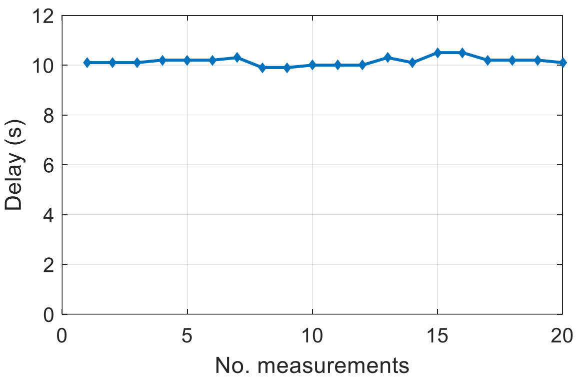

Figure 4. The latency when sending data from the sensor node to the webserver

6. CONCLUSIONS

This paper presents an IoT-based flood monitoring system that leverages dual-sensor water level data, Node.js backend processing, and Google Maps API visualization to provide real-time flood risk prediction and alert dissemination. The proposed dual-sensor water level prediction algorithm effectively analyzes both temporal changes (rate of water level increase) and spatial variations (water level differential) to classify flood risks into low, medium, and high categories. Initial testing demonstrates the system's ability to achieve high accuracy of 94.66% in flood risk classification and generate alerts with minimal latency (around 10 seconds), outperforming traditional single-sensor approaches. Furthermore, the integration of Google Maps API enhances situational awareness by providing intuitive spatial visualization of sensor locations and flood-prone areas. Future work will focus on expanding the sensor network, incorporating additional environmental parameters such as rainfall and flow rate, and conducting long-term field testing during flood events. By addressing these limitations, the system has the potential to serve as a scalable and cost-effective solution for mitigating flood risks in vulnerable regions like the Con River basin in Binh Dinh Province, Vietnam and beyond.

Acknowledgments

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