Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 3, July 2026
DOI : https://doi.org/10.33395/sinkron.v10i3.16612
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Monitoring of Irrigation Channel Discharge Based on IoT and LoRaWAN Communication with Long Short-Term Memory (LSTM) Predictive Analysis

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Submitted : Jun 29, 2026 | **Accepted** : July 27, 2026 | **Published** : July 30, 2026

Abstract: This study presents the design and implementation of an Internet of Things (IoT)-based irrigation canal monitoring system that integrates Long Range Wide Area Network (LoRaWAN) communication with a Long Short-Term Memory (LSTM) prediction model. The system is designed to provide real-time monitoring and prediction of water discharge in irrigation canals to support efficient water resource management on agricultural land. The proposed system consists of two IoT sensor nodes, each equipped with a YF-B5 flow sensor, an HC-SR04 ultrasonic sensor, and a DS18B20 temperature sensor, all connected to an ESP32 microcontroller. The collected data are transmitted via the LoRaWAN protocol and stored in Firebase Realtime Database, where they are visualized through an Android application. The predictive component employs an LSTM algorithm to forecast future water discharge based on historical time-series data. Experimental results indicate that the LSTM model achieved a Mean Absolute Error (MAE) of 13.1640 and a Root Mean Squared Error (RMSE) of 23.0630, demonstrating high accuracy and stability in predicting water discharge fluctuations. The integration of IoT, LoRaWAN, and LSTM-based prediction enables real-time monitoring and predictive analysis for smart irrigation management.

Keywords: IoT, LoRaWAN, LSTM, irrigation monitoring, predictive analysis, smart agriculture

INTRODUCTION

Rice is the primary staple food for most of the population in Asia, including Indonesia. The high level of rice consumption continues to drive demand for increased rice production. However, this growing demand has not been accompanied by an expansion of the harvested area. According to Indonesia's Central Statistics Agency (BPS), the harvested area in 2023 reached 10.20 million hectares, yielding approximately 30.90 million tons of rice. This represents a 2.45% decline in harvested area compared with 2022 (BPS, 2023). In addition to the declining harvested area, agricultural productivity in Indonesia is strongly influenced by water availability, particularly rainfall (Suwandi et al., 2025). Therefore, effective irrigation management is essential for maintaining agricultural productivity. To maximize the productivity of available agricultural land, various strategies are needed to increase crop yields and reduce the gap between food demand and supply. One strategy to improve agricultural yields is optimizing irrigation systems, which is one of the five key agricultural practices "*panca usaha tani*". The success of this strategy depends on the condition of the irrigation infrastructure and the availability of sufficient water, as efficient irrigation has been shown to significantly improve agricultural productivity (Astutik & Suhardi, 2021).

Recent developments in Internet of Things (IoT) technology provide the potential to address these issues. Advances in IoT connectivity, sensor technology, and wireless communication enable automated and real-time monitoring of irrigation systems. IoT technology has been widely applied in agriculture to monitor environmental variables such as soil moisture, temperature, and field conditions (Ali & Asaduzzaman, 2024; S. et al., 2025; Saraswathi et al., 2025). However, studies on real-time monitoring and prediction of water discharge in agricultural

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irrigation canals remain relatively limited. The application of LSTM is based on several studies that have proven to help solve prediction problems in various irrigation cases (Nitya et al., 2025; Sibarani et al., 2025). The system is also integrated with Firebase Realtime Database to enable real-time monitoring through an Android application. The integration of Firebase provides secure cloud-based data storage and enables real-time remote monitoring and data access (Kumar et al., 2023; Mustaffa & Rizal, 2024; Savale et al., 2024). Although IoT-based irrigation monitoring systems have been extensively investigated, most existing studies primarily focus on real-time monitoring of environmental variables such as soil moisture, water level, and temperature without providing predictive capabilities for future irrigation conditions. Consequently, irrigation managers remain dependent on reactive decision-making based solely on current observations. Conversely, studies employing LSTM have mainly addressed rainfall prediction, irrigation scheduling, or environmental forecasting using offline datasets rather than integrating predictive intelligence into a real-time IoT monitoring platform. Furthermore, only a limited number of studies combine long-range wireless communication, cloud-based monitoring, and deep learning prediction within a single irrigation management framework suitable for large agricultural areas. Therefore, this research proposes an integrated irrigation monitoring system that combines IoT sensing devices, LoRaWAN communication, Firebase cloud services, and an LSTM prediction model. Unlike previous studies, the proposed system not only performs real-time monitoring of irrigation discharge but also predicts future discharge conditions using historical sensor data, enabling proactive water management for smart irrigation applications.

LITERATURE REVIEW

Several previous studies have explored the application of IoT-based monitoring systems. One previous study proposed a prototype of an automated dam monitoring system capable of remotely monitoring water conditions and controlling floodgates. This system was developed using a NodeMCU ESP32 microcontroller as the central control unit and implemented the WhatsApp API for remote monitoring (Dahira et al., 2024). Similar research was also conducted by Aprianti et al. (2025) on automatic water level measurement with an accuracy of nearly 97%. Another study developed a mobile application integrated with Arduino and ESP8266 based IoT devices for rice field monitoring. The proposed system monitored soil moisture, irrigation water levels, and pump water levels while providing automatic pest control through high-frequency sound emitted by speakers. The application enables farmers to monitor their rice fields remotely at any time, thereby reducing transportation costs associated with field inspections. The main advantage of this application is the use of the Firebase database, which ensures that data on soil moisture, irrigation water levels, and pest control are transmitted and updated in real time by sending data from the IoT device to the mobile application (Syahaddan & Waluyo, 2023).

Meanwhile, research on LSTM has shown that the LSTM method is quite effective in predictive case studies. A study by Li et al. (2020) introduced an IoT-based air quality monitoring system and LSTM model aimed at monitoring, analyzing, and predicting air quality in real time at five locations on campus using temperature, humidity, and dust (PM2.5 and PM10) sensors. Sensor data were transmitted through an NB-IoT communication module and processed in a cloud platform using the MQTT protocol. The LSTM model was used to predict air quality over a 24-hour period. Correlation analysis indicated that PM2.5 and PM10 were strongly correlated with each other but showed weak correlations with temperature and humidity. In addition, Ciptaningtyas et al. (2024) developed an IoT- and LSTM-based system for automated irrigation and fertilization to improve shallot cultivation using soil moisture, temperature, and humidity data. The results showed that the irrigation classification system achieved an accuracy of 83%, while the LSTM model produced a low prediction error, demonstrating its effectiveness in monitoring environmental conditions and supporting automated irrigation and fertilization decision.Based on the reviewed literature, no previous study has integrated IoT-based irrigation monitoring, LoRaWAN communication, Firebase cloud services, and LSTM-based discharge prediction into a unified platform. Therefore, the novelty of this research lies in the development of an end-to-end smart irrigation monitoring system capable of (1) acquiring real-time irrigation discharge data through distributed IoT nodes, (2) transmitting data over long distances using LoRaWAN, (3) storing and visualizing information in Firebase-based Android applications, and (4) forecasting future water discharge using an LSTM deep learning model. This integration enables both real-time monitoring and predictive decision support for irrigation management.

METHOD

This section describes the research methodology applied in the development of the IoT-based irrigation monitoring system integrated with LoRaWAN communication and LSTM-based predictive analysis. The methodology was designed following a structured engineering research approach to ensure reliability in system design, implementation, and testing. The entire process was conducted at the Operating Systems Laboratory of Politeknik Negeri Malang, Kediri campus, with field testing performed at the Gunting Weir irrigation channel in Kediri Regency, Indonesia.

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Research Location and Setup

The research was carried out in two primary environments: (1) the laboratory for hardware prototyping and software integration, and (2) the irrigation field for real-time deployment as shown in Figure 1 where distance between node 1 and node 2 is approximately 50 meters.

Fig. 1 Deplyoment of IoT Device Node 1 and Node 2

The laboratory phase focused on building and configuring the IoT nodes, developing Android applications, and establishing server communication via Firebase. The field phase involved testing data transmission through LoRaWAN and validating sensor readings against manual measurements.

System Development Framework

The system was developed using the Waterfall Model, as it provides a clear and linear flow suitable for engineering system design. This model includes five main phases: requirements analysis, design, implementation, testing, and maintenance. Each stage ensures that every component of the system-hardware, software, and communication—is validated before progressing to the next stage.

Hardware Design

The IoT hardware was designed to monitor key irrigation parameters such as water flow rate, water level, and temperature. The schematic design includes an ESP32 microcontroller, YF-B5 flow sensor, HC-SR04 ultrasonic sensor, and DS18B20 temperature sensor. A power supply module, waterproof casing, and LoRa communication module were integrated to ensure long-range wireless data transmission. The sensor nodes transmit data periodically to a central receiver node that uploads the measurements to the Firebase cloud for processing. The schematic of the IoT circuit is shown in Fig. 2.

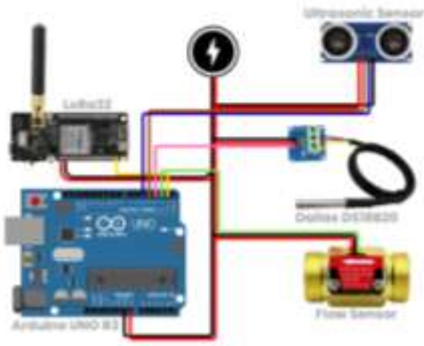

Fig. 2 The schematic of the IoT circuit

*name of corresponding author

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Software Architecture and Communication Flow

The software architecture consists of three main layers: the IoT sensing layer, communication layer, and application layer. At the sensing layer, microcontroller-based firmware reads and preprocesses sensor data. The communication layer handles data transmission using the LoRaWAN protocol, enabling low-power, long-distance communication between the remote sensors and the central server. At the application layer, the Android-based monitoring app retrieves and visualizes real-time data from the Firebase Realtime Database. This architecture ensures modularity and scalability for future system expansion.

E. Testing and Evaluation Procedures

System testing was conducted to verify functionality and reliability. Hardware testing included sensor calibration, power stability, and LoRa communication range measurement. Software testing covered user interface performance, real-time data synchronization, and prediction accuracy of the LSTM model used in the backend. The evaluation process focused on measuring sensor precision, data transmission reliability, and system response time. In-field testing was performed for one week under varying irrigation conditions to validate the robustness of the deployed nodes.

Overall, the methodology ensures a comprehensive workflow from design to deployment, covering all aspects of IoT system engineering. The combination of LoRaWAN-based communication and deep learning analysis establishes a reliable foundation for the predictive irrigation monitoring system.

RESULT

IoT Device

The device consisted of interconnected hardware and software components controlled by an ESP32 microcontroller. The first node acted as the transmitter, reading data from the sensors and sending it to the receiver node through LoRaWAN. The receiver node then processed and forwarded the information to the cloud database. The sensor readings were automatically updated in real-time, enabling continuous monitoring of irrigation flow conditions.

Fig. 3 IoT Device Implementation

Android Application for Irrigation Monitoring

The Android application named 'Irrigation Monitoring' was developed to provide real-time visualization and interaction with sensor data. The interface consisted of three main tabs: Average, Node 1, and Node 2, each displaying data graphs for water flow, level, and temperature over time. The data was dynamically fetched using Firebase Realtime Database and visualized with Kotlin Flow, ensuring real-time synchronization between field devices and the mobile dashboard.

*name of corresponding author

e-ISSN : 2541-2019
p-ISSN : 2541-044X

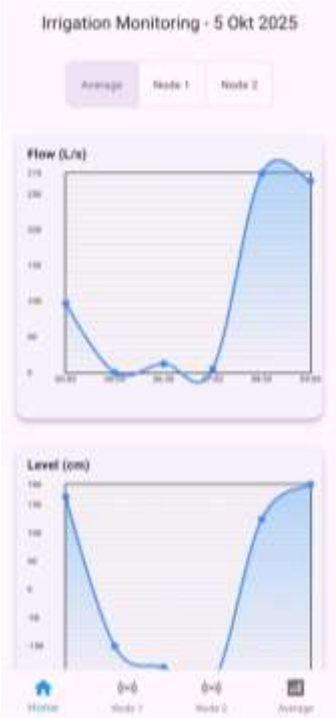
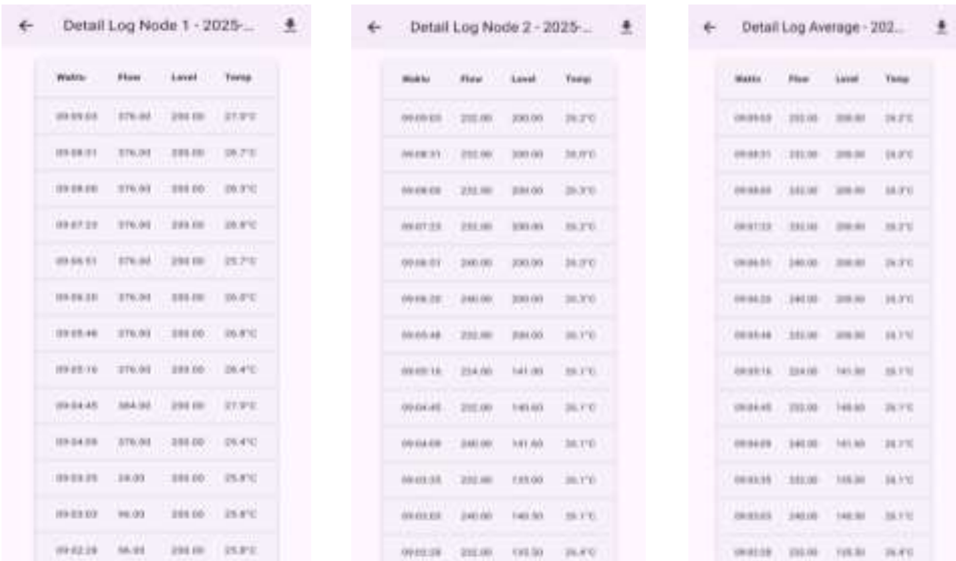


Fig. 4 Home Screen of the Android application

Fig. 4 illustrates the Home Screen of the application where users can monitor the real-time data stream. Each graph shows variations in flow rate and water level along with the corresponding temperature values. The user can also switch between tabs to view individual sensor node performance or aggregated averages. Figure 5(a) presents the dashboard displaying the average values collected from both sensor nodes. The graphs visualize real-time water discharge, water level, and water temperature simultaneously, enabling users to observe overall irrigation conditions. Figure 5(b) shows the detailed monitoring interface for Node 1, where individual measurements of flow rate, water level, and temperature are continuously updated from the upstream monitoring point. Figure 5(c) illustrates the monitoring interface for Node 2, representing measurements collected from the downstream node. The comparison between Node 1 and Node 2 enables operators to evaluate discharge consistency along the irrigation channel and identify possible water losses or anomalies.



a) detail log node 1 b) detail log node 2 c) detail log node 3

Fig. 5 The Android application detailed log view

e-ISSN : 2541-2019
p-ISSN : 2541-044X

The application included a detailed log view allowing users to export data in CSV format for further analysis. The data logs were sorted chronologically and displayed flow, level, and temperature readings collected from both sensor nodes. This feature enhances data traceability and supports post-field validation of IoT device performance. The integration between IoT devices, LoRa communication, and the Android monitoring platform was successfully implemented. Data transmission through LoRa proved to be stable and efficient over the irrigation field, achieving consistent connectivity between nodes. The Firebase-based backend ensured low-latency synchronization, allowing real-time updates to be reflected on the Android dashboard without manual refresh. In field testing, the sensors accurately captured variations in water discharge and level under changing irrigation flow conditions.

Fig. 6 Implementation of IoT Device

The results of the water flow sensor readings are presented in Figure 5, where the measured water discharge values range between 200 and 500 liters per second, while the corresponding water level varies between 20 and 40 cm. These data were obtained from Node 1, which functioned as the server, and Node 2, which acted as the client communicating through the LoRaWAN protocol. The consistent transmission and synchronization between both nodes demonstrate the reliability of the LoRaWAN-based communication system in supporting real-time data acquisition in irrigation monitoring applications.

Overall, the developed system effectively combined IoT sensing, wireless communication, and mobile visualization for comprehensive water monitoring. This integration supports predictive analysis when connected with the LSTM model in the backend, forming a foundation for smart irrigation systems that optimize water distribution based on forecasted discharge patterns.

A. *Model Training Performance*

The LSTM model was trained using 361 processed data points derived from two sensor nodes (node1 and node2) that measure real-time water flow. During training, the Mean Squared Error (MSE) loss function and Adam optimizer were used to optimize the learning process. The model was trained for 90 epochs, showing a significant reduction in loss value from 0.1067 in the first epoch to 0.0035 by the 20th epoch. This consistent decline in loss demonstrates that the LSTM network effectively learned the temporal dynamics of the water flow dataset.

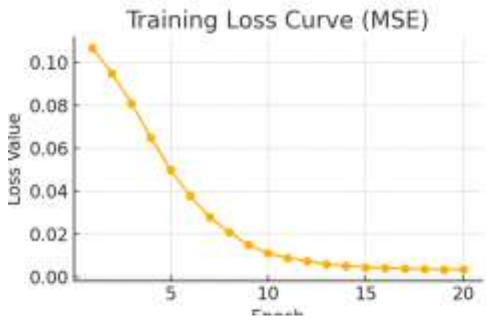


Fig. 7 Training loss curve showing the model's convergence during the learning process

Prediction and Visualization

After the training phase, the LSTM model was tested to predict water discharge using a sequence of 20 prior time steps to estimate the next one. The prediction results were visualized against actual sensor data to assess

*name of corresponding author

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model alignment with real-world observations. Figure 2 illustrates the comparison between the actual and predicted discharge levels, indicating that the model successfully captured the general flow trends, with only minor deviations due to sensor noise.

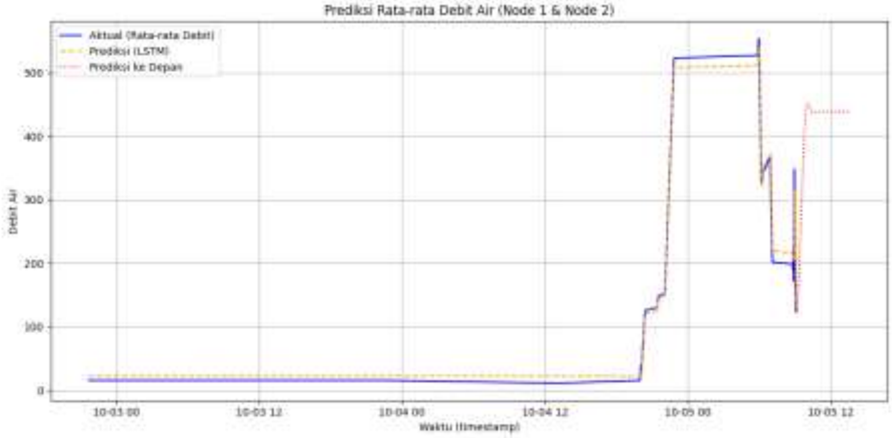

Fig. 8 Comparison between actual and predicted average water discharge from IoT sensors

Model Evaluation Metrics

The evaluation process was conducted using two primary performance metrics to assess the accuracy of the LSTM model in predicting water discharge values:

1. Mean Absolute Error (MAE)

The MAE measures the average absolute difference between the actual discharge values and the predicted values. It quantifies how close the model's predictions are to the observed data, where lower values indicate higher prediction accuracy. The MAE is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

2. Root Mean Squared Error (RMSE)

The RMSE measures the magnitude of deviation between the predicted values and the actual observed values. It provides an indication of how much error is typically present in the model's predictions, where smaller RMSE values signify better model performance and lower prediction variance. The RMSE is mathematically expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

To quantitatively evaluate the model's predictive accuracy, two main statistical indicators were used: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The LSTM model achieved an MAE of 13.1640 and an RMSE of 23.0630, as shown in figure 9 indicating that the average prediction deviation from actual discharge values was relatively small. These metrics confirm that the model demonstrates strong generalization ability in learning both seasonal and dynamic water flow variations.

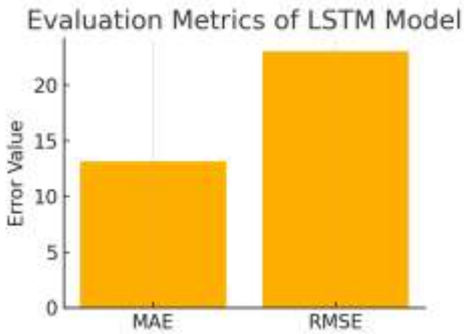

Fig. 9 Model evaluation results showing MAE and RMSE performance indicators

*name of corresponding author

DISCUSSIONS

The experimental results demonstrate that the LSTM model is capable of effectively identifying temporal correlations in water discharge data. The low MAE and RMSE values indicate that the model can adapt to real-time sensor variability while maintaining high predictive stability. The low prediction error indicates that the LSTM architecture successfully captured temporal dependencies within irrigation discharge data. Because irrigation flow changes gradually over time rather than randomly, LSTM memory cells are able to retain historical information and improve forecasting accuracy. Compared with Li et al. (2020), who employed LSTM for air-quality prediction, the proposed system demonstrates that LSTM is equally effective for irrigation discharge forecasting. Likewise, unlike Ciptaningtyas et al. (2024), whose work focused on irrigation control based on environmental parameters, the proposed study predicts water discharge directly from real-time IoT measurements collected in irrigation canals. The integration of LoRaWAN communication enables reliable long-distance data transmission suitable for large irrigation areas where Wi-Fi coverage is unavailable. Moreover, combining cloud-based monitoring with predictive analytics allows irrigation operators to anticipate discharge fluctuations before they occur, thereby supporting proactive water allocation decisions. Although the proposed system demonstrates promising performance, the evaluation was conducted using data collected from two sensor nodes over a relatively short observation period. Future studies should involve more monitoring locations and seasonal datasets to improve model generalization.

CONCLUSION

The development of an IoT-based irrigation monitoring system integrated with LoRaWAN communication and LSTM predictive analysis has been successfully implemented and validated through laboratory and field experiments. The results show that the designed hardware and software components function reliably in real-time monitoring and data transmission. The LoRaWAN protocol provides stable long-range connectivity between sensor nodes, while the Android-based application offers an accessible and responsive monitoring interface. The LSTM predictive model demonstrated strong capability in capturing temporal variations in water discharge data, producing accurate estimates with low MAE and RMSE values with MAE of 13.1640 and RMSE of 23.0630. Overall, this system can serve as an effective tool for optimizing irrigation water management and supporting decision-making in agricultural operations. Future research may focus on integrating additional environmental parameters, optimizing power consumption, and extending the system to multi-node networks for large-scale deployment in agricultural regions.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Center for Research and Community Service (P3M) of Politeknik Negeri Malang (Polinema) for providing financial support and research facilities for this study.

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