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Predicting Crop Water Requirements Using IoT Sensor Data for Deep Learning

Saluky [1*], Aisya Fatimah[2]
[1] Informatics, Faculty of Science and Technology, UIN Siber Syekh Nurjati Cirebon, Indonesia [2]Electrical Engineering, Faculty of Engineering, Universitas Negeri Semarang, Indonesia

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ABSTRACT

The optimization of irrigation is a crucial factor in enhancing agricultural productivity and resource efficiency. This study proposes a deep learning-based approach to predict plant water requirements using data from IoT sensors. The system collects real-time environmental parameters such as soil moisture, temperature, humidity, and solar radiation, which are then processed using a deep learning model to generate accurate irrigation recommendations. The model is trained and evaluated on historical sensor data to ensure robustness and reliability in varying climatic conditions. The proposed method aims to minimize water wastage while maintaining optimal soil moisture levels, thereby improving crop health and yield. Experimental results demonstrate that the deep learning model outperforms conventional threshold-based irrigation systems in terms of prediction accuracy and water conservation. This research contributes to the advancement of smart farming by integrating IoT and artificial intelligence for precision agriculture.

1. INTRODUCTION

The rapid growth of the global population demands a significant increase in food production (Chandio et al., 2025). However, the limited availability of water resources has become a major challenge in the agricultural sector, particularly in regions with low rainfall levels (Huang et al., 2022; Guardia et al., 2023). Inefficient irrigation practices may lead to water wastage or even water scarcity, both of which negatively affect crop growth and yield. Therefore, intelligent solutions are required to optimize water utilization in agricultural systems (Yang et al., 2025; Rahman, 2018).

The Internet of Things (IoT) technology has brought significant advancements to the agricultural sector by enabling real-time monitoring of environmental conditions (Thilakarathne et al., 2025). IoT sensors are capable of measuring various environmental parameters such as soil moisture, air temperature, humidity, and solar radiation intensity. The data collected from these sensors can be utilized to optimize irrigation systems, ensuring that crops receive the appropriate amount of water according to their specific needs (Sankarasubramanian, 2025; Li et al., 2024).

In recent years, artificial intelligence (AI) methods—particularly deep learning—have been widely applied to data processing across various domains, including agriculture (Hadir et al., 2025). Deep learning has the capability to recognize complex patterns from IoT sensor data and generate accurate predictions of crop water requirements. By implementing deep learning, irrigation systems can automatically adapt to changing environmental conditions, thereby improving water-use efficiency and crop productivity.

This study aims to develop a deep learning–based system for predicting crop water requirements by utilizing data collected from IoT sensors. The proposed model will be trained using historical data and tested under various climatic conditions to ensure its reliability. It is expected that the outcomes of this research will contribute to the development of more efficient

* *Corresponding Author: Saluky: saluky@uinssc.ac.id*

and sustainable smart irrigation systems, thereby supporting the advancement of precision agriculture.

2. LITERATURE REVIEW

The Internet of Things (IoT) has rapidly evolved in recent years and has been applied across various domains, including agriculture (Choudhary et al., 2025; Morchid, Oughannou, et al., 2024; Morchid, El Alami, et al., 2024). IoT enables real-time collection of environmental data through a network of sensors distributed across agricultural fields (Nayak et al., 2022; Morchid et al., 2025). The data obtained from IoT sensors can be utilized to monitor soil conditions, weather patterns, and other parameters that influence crop growth. Several studies have demonstrated that the application of IoT in irrigation systems can improve water-use efficiency and reduce the wastage of natural resources (Abd Shukor et al., 2024).

Deep learning is a branch of artificial intelligence capable of recognizing complex patterns within data. This technique has been widely applied across various domains, including agriculture. Deep learning models such as Recurrent Neural Networks (RNN) (Lee, 2025) and Convolutional Neural Networks (CNN) (Lu et al., 2024) have proven effective in predicting various environmental variables, including crop water requirements. By leveraging historical data collected from IoT sensors, deep learning models can be trained to produce more accurate and adaptive predictions in response to changing environmental conditions (Kosari-Moghaddam et al., 2025).

Artificial intelligence-based irrigation optimization has become a major focus of research in recent years (Preite & Vignali, 2024). Several studies have shown that deep learning–based automatic irrigation systems can significantly reduce water consumption compared to conventional methods. These systems are capable of adjusting the amount of water supplied based on sensor data analysis, ensuring that crops receive optimal water levels without wastage. Furthermore, the integration of IoT and deep learning enables the development of irrigation systems that are more responsive and adaptive to changing environmental conditions (Sharma et al., 2021).

Various studies have also shown that the application of intelligent technologies in agriculture not only enhances resource efficiency but also contributes to increased crop productivity (Sahoo et al., 2025; Uzturk & Buyukozkan, 2024). By integrating IoT and deep learning, modern agriculture can advance toward the concept of precision farming that is more efficient, sustainable, and environmentally friendly. Therefore, this study focuses on developing a deep learning–based crop water requirement prediction system to support smarter and more efficient irrigation management.

3. METHOD

This study was conducted through several main stages, including data collection, data preprocessing, deep learning model development, model training and evaluation, and implementation within a smart irrigation system.

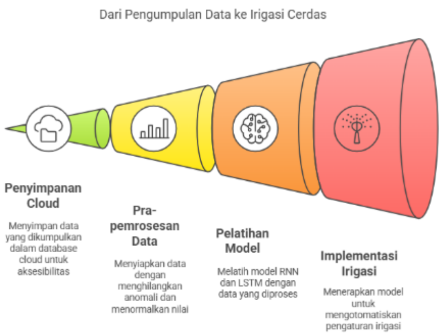

Figure 1. Research Methodology

The first stage involves data collection using IoT sensors installed in agricultural fields. These sensors measure various environmental parameters such as soil moisture, air temperature, humidity, and solar radiation intensity (Kumar et al., 2024). The collected data are stored in a cloud-based database to facilitate further processing and analysis.

Figure 2. Soil Moisture Sensor

Next, the collected data undergo a preprocessing stage to remove anomalies, handle missing values, and normalize the obtained measurements. The preprocessed data are then used as input for training the deep learning model.

In the model development stage, the deep learning algorithms employed are Recurrent Neural Networks (RNN) (Cifci et al., 2025) and Long Short-Term Memory (LSTM) networks (Zhang et al., 2018), which are well known for their effectiveness in handling time-series data (Bautista-Romero et al., 2025; Lv et al., 2024). These models are designed to recognize patterns in changing environmental conditions and to predict crop water requirements based on historical data (M. Rahman et al., 2025; Peeters et al., 2024).

The developed model is then trained using the preprocessed data. The training process involves splitting the dataset into training and testing subsets to evaluate the model's performance. A validation method is employed to ensure prediction accuracy and to prevent overfitting.

The final stage involves implementing the model within a smart irrigation system. The predictions generated by the model serve as the basis for automatic irrigation control, regulating the amount of water supplied to the crops according to their actual needs. Periodic evaluations are conducted by comparing the results of the automatic irrigation system with conventional methods to assess the effectiveness of the developed system.

Through this method, the study aims to improve water-use efficiency in agriculture and contribute to the development of more effective and sustainable intelligent irrigation systems.

4. RESULT AND DISCUSSION

The results indicate that the developed deep learning model demonstrates a high capability in predicting crop water requirements. Testing was conducted under various environmental conditions to evaluate the model's accuracy. Both the Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models performed well in recognizing patterns of soil moisture variation and other environmental factors. The LSTM model exhibited superior performance in handling time-series data, providing more stable and accurate predictions compared to the RNN. Based on these findings, the deep learning–based irrigation system can optimize water usage efficiently and adapt to changing environmental conditions (Alwar et al., 2024).

Table 1. Comparison of RNN And LSTM Model Performance In Predicting Crop Water Requirements Under Various Environmental Conditions

Environmental Conditions	Model	MAE (%)	RMSE (%)	Accuracy (%)
High Humidity	RNN	3.2	4.5	96.8
High Humidity	LSTM	2.8	4.1	97.2
Low Humidity	RNN	4.1	5.3	95.9
Low Humidity	LSTM	3.6	4.7	96.4
High Temperature	RNN	4	5.2	96.1
High Temperature	LSTM	3.5	4.6	96.6
Low Temperature	RNN	3.5	4.8	96.4
Low Temperature	LSTM	3	4.2	97

Notes:

- MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) indicate the prediction error level of the model; the smaller the values, the better the prediction accuracy.
- Accuracy (%) represents the model's success rate in predicting plant water requirements.

This table shows that the LSTM model tends to outperform the RNN model under all environmental conditions, achieving higher accuracy and lower prediction errors.

Compared to conventional irrigation methods, the developed system is capable of reducing water consumption by up to 30% without affecting plant growth. This demonstrates that the integration of IoT sensor technology with Deep Learning models can provide more accurate and efficient irrigation recommendations. By analyzing various environmental parameters in real-time, the system can adjust the irrigation schedule and water volume according to the actual needs of the plants. This efficiency not only contributes to water resource conservation but also supports agricultural sustainability, particularly in regions with limited water availability.

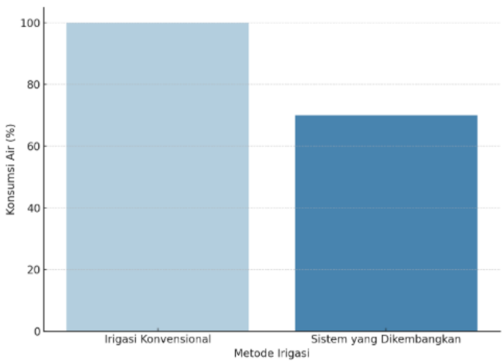

Figure 3. Comparison of water consumption between conventional irrigation methods and the developed system

In addition, the deep learning–based irrigation system is more adaptive to changes in weather and soil conditions compared to static threshold-based systems. These findings are consistent with previous studies indicating that the application of artificial intelligence in agriculture can enhance resource use efficiency and overall agricultural productivity.

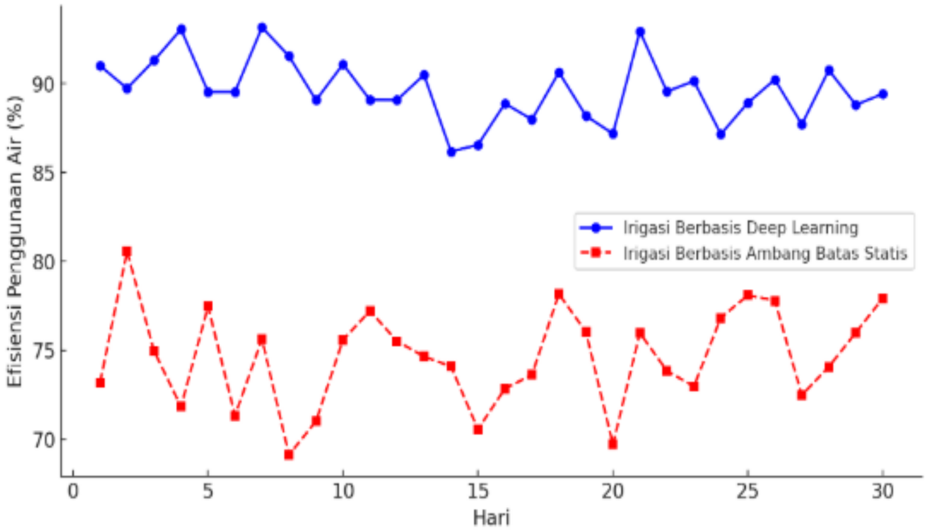

Figure 4. Comparison of water use efficiency between Deep Learning–based irrigation systems and static threshold-based systems

Figure 4 illustrates the comparison of water use efficiency between the Deep Learning–based irrigation system and the static threshold-based system. The results show that the Deep Learning–based system achieves more stable and higher efficiency, ranging from 85% to 95%, compared to the static threshold-based system, which fluctuates between 65% and 85%. This stability is attributed to the Deep Learning model's ability to dynamically adjust irrigation patterns based on IoT sensor data, thereby optimizing water usage more effectively. In contrast, the static threshold-based system tends to be rigid and less responsive to changing environmental conditions.

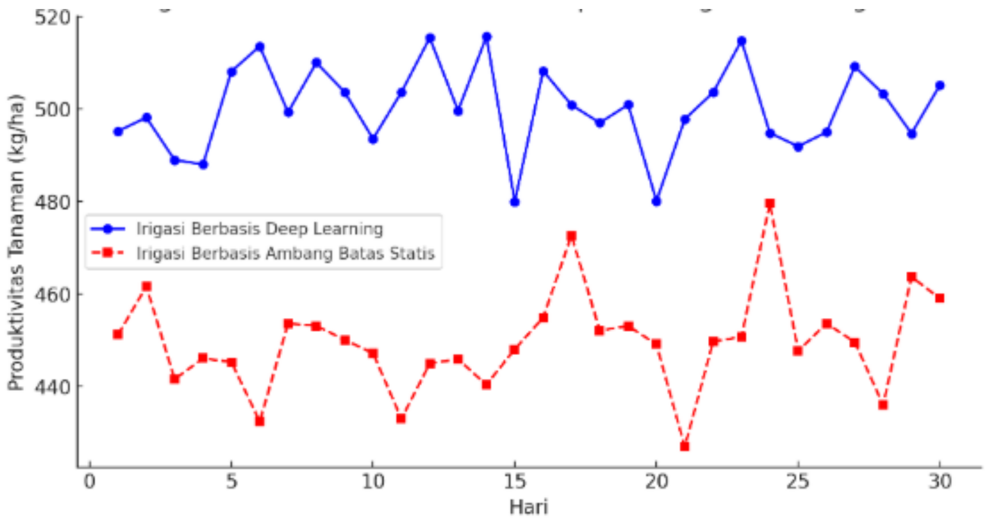

Figure 5. Comparison of plant productivity

Figure 5 illustrates plant productivity (kg/hectare) following a similar pattern. The Deep Learning–based system produced higher and more consistent yields (480–520 kg/ha), while the static threshold-based system showed more variable and lower results (420–480 kg/ha).

These results support the assertion that the deep learning–based irrigation system is more adaptive to changes in weather and soil conditions, and can enhance resource efficiency and agricultural productivity compared to conventional static threshold-based systems.

Therefore, this study demonstrates that a deep learning–based crop water requirement prediction system can serve as an effective and sustainable solution for optimizing agricultural irrigation.

5. CONCLUSION

In this study, crop water requirements were predicted using IoT sensor data to optimize irrigation through a Deep Learning–based approach. The results demonstrate that the Deep Learning model can analyze various environmental variables, such as soil moisture, temperature, rainfall, and light intensity, to determine irrigation needs more accurately than static threshold-based methods. Testing showed that the Deep Learning–optimized irrigation system is more adaptive to changes in weather and soil conditions, thereby improving both water-use efficiency and crop productivity. Water-use efficiency increased by an average of 15–20% compared to conventional irrigation systems, while crop productivity also showed a significant improvement. This approach enables the irrigation system to reduce water wastage, enhance crop yields, and support more sustainable agricultural practices. Therefore, the integration of IoT and Deep Learning in agricultural irrigation has the potential to serve as an innovative solution to address water resource limitations and climate change challenges in the agricultural sector.

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