IoT BASED SMART IRRIGATION SYSTEM

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Abstract: Managing water efficiently is a major challenge in modern agriculture because of growing water shortages and the need to cut down on manual work. This project introduces a smart irrigation system based on IoT technology, using the ESP32 microcontroller to help save water and reduce human effort through automation. The system uses affordable sensors, including a soil moisture sensor and a DHT22 sensor, to track soil moisture, temperature, and humidity in real time. The main goal is to use less water and require less labor by using IoT-based sensors and controls with low-cost parts. The soil moisture sensor checks the soil's water level, and when it drops below a set point, the ESP32 turns on a water pump using a relay. This way, crops get water only when they need it, which helps avoid overwatering and waste. The system also connects to the Blynk IoT platform, so users can check conditions and control irrigation from their smartphones. This approach is affordable, saves energy, and is practical for farmers, supporting sustainable farming and better productivity.

IndexTerms **- Internet of Things (IoT), Smart Irrigation System, ESP32, Soil Moisture Sensor, DHT22 Sensor, Automation in Agriculture, Sustainable Agriculture.**

I. INTRODUCTION

Agriculture is a vital sector of the economy but faces persistent challenges such as water scarcity, inefficient irrigation practices, and dependence on manual labor. Traditional irrigation methods often result in overwatering or underwatering, which reduces crop yield and leads to wastage of valuable water resources. To address these issues, this project presents an IoT-based Smart Irrigation System integrated with Machine Learning for intelligent decision-making. The system is built using an ESP32 microcontroller and employs a soil moisture sensor along with a DHT22 sensor to continuously monitor soil moisture, temperature, and humidity in real time. Based on these sensor inputs, along with user-selected parameters such as crop type (carrot or chilli) and crop growth stage, irrigation decisions are made efficiently. A Random Forest–based Machine Learning model is used to predict whether irrigation is required by considering both environmental conditions and crop-specific factors. The system is integrated with the Blynk IoT platform, which provides a user-friendly dashboard for real-time monitoring and control. Users can operate the system in both automatic and manual modes, enhancing flexibility.
This approach reduces manual effort, optimizes water usage, and improves irrigation efficiency, making it suitable for small and medium-scale farmers while promoting sustainable agricultural practices and better crop productivity.

II.TECHNIQUES AND APPROACHES

The system uses **IoT-based sensing techniques** where an ESP32 microcontroller collects real-time data from soil moisture, temperature, and humidity sensors. This data is transmitted over Wi-Fi to a cloud platform, **Blynk IoT**, which provides a user-friendly dashboard for monitoring environmental conditions and controlling the irrigation system remotely. The system ensures continuous data acquisition and real-time visibility, enabling users to make informed decisions.

A **machine learning approach** is applied using Decision Tree algorithms for both classification and regression. The model is trained on historical dataset values such as soil moisture, temperature, humidity, crop type, and growth stage. A Flask-based REST API acts as the communication bridge, receiving live sensor data from the ESP32, processing it through the trained model, and returning predictions such as whether irrigation is required and the duration for watering. This enables data-driven and intelligent irrigation decisions.

The system follows a **hybrid control and client-server architecture**, combining both manual and automatic modes. In manual mode, users can directly control the pump via the Blynk app, while in automatic mode, irrigation is managed based on machine learning predictions. Event-based notifications alert users about pump activity and mode changes, ensuring transparency and control. Overall, the approach integrates real-time monitoring, predictive analytics, and automation to optimize water usage efficiently.

III. REVIEW OF EXISTING WORK

Many studies have looked at IoT-based smart irrigation systems that use sensors, cloud platforms, and automation. By using soil moisture, temperature, and humidity sensors with platforms like Blynk, ThingSpeak, or cloud dashboards, these systems allow real-time monitoring and automated irrigation based on set thresholds. This approach helps reduce manual work and saves water [1][3][4].

Other systems use wireless modules like ESP8266 or ESP32 and GSM alerts to improve remote access and keep users informed. These features make the systems practical and affordable for small-scale farming [3][4].

Recent research has incorporated Artificial Intelligence and Machine Learning techniques such as Decision Trees, KNN, SVM, and LSTM models to predict irrigation needs more accurately. These models outperform traditional threshold-based methods by improving water efficiency, reducing unnecessary irrigation, and enhancing crop productivity [5][6][7][8].

Additionally, studies focusing on communication technologies highlight the importance of efficient data transmission, where hybrid IoT networks (LPWAN, 5G) improve scalability, coverage, and cost efficiency in smart agriculture systems [9]. Advanced AI-integrated systems with weather prediction further optimize irrigation decisions and resource utilization [10].

IV. COMPETITIVE ANALYSIS

Existing smart irrigation systems primarily rely on **threshold-based approaches**, where irrigation is triggered when soil moisture falls below a predefined value. While such systems using IoT platforms like Blynk IoT, ThingSpeak, or cloud dashboards provide real-time monitoring and automation, they lack adaptability to varying environmental conditions. These systems are simple, cost-effective, and suitable for small-scale farming but often result in either over-irrigation or under-irrigation due to static decision rules.

More advanced systems incorporate **wireless communication technologies** such as ESP8266/ESP32 modules along with GSM or cloud-based alerts, improving remote accessibility and user awareness. However, many of these systems still depend on basic logic or manual configuration. Compared to them, the proposed system introduces a **client-server architecture with a Flask API and machine learning integration**, enabling dynamic decision-making. This improves efficiency by considering multiple parameters such as soil moisture, temperature, humidity, crop type, and growth stage instead of relying on a single threshold.

Recent research highlights the use of **machine learning and AI models** such as Decision Trees, KNN, SVM, and LSTM for predictive irrigation. These approaches significantly enhance water efficiency and crop productivity by learning from historical data. The proposed system aligns with these advancements by implementing Decision Tree models for irrigation prediction, while maintaining simplicity and real-time responsiveness. Although it does not yet include advanced features like weather forecasting or LPWAN-based scalability, it provides a balanced solution that is **intelligent, cost-effective, and suitable for practical deployment**, making it competitive with existing smart irrigation systems.

V. CHALLENGES AND LIMITATIONS

Sensor Accuracy Issues: Soil moisture and DHT22 sensors may produce inaccurate readings due to calibration errors, environmental factors, or sensor degradation over time.

Dependence on Internet Connectivity: The system relies on Wi-Fi for communication with the Flask server and Blynk IoT. Poor or unstable internet connection can delay data transmission and affect system performance.

Limited Dataset for Machine Learning: The accuracy of the model depends on the quality and size of the training dataset. A small or less diverse dataset may reduce prediction reliability.

Lack of Weather Forecast Integration: The system does not consider external factors such as rainfall prediction or weather conditions, which can affect irrigation decisions.

Scalability Issues: The current system is designed for small-scale implementation. Expanding it to large agricultural fields may require additional sensors, better communication technologies, and more robust infrastructure.

Power Supply Dependency: Continuous operation depends on a stable power supply. Power failures can interrupt monitoring and irrigation processes.

Maintenance Requirements: Sensors and hardware components require regular maintenance and calibration to ensure accurate performance.

Security Concerns: Since the system uses IoT and cloud communication, it may be vulnerable to unauthorized access or data breaches if proper security measures are not implemented.

Delay in Response Time: Communication between ESP32 and Flask server may introduce slight delays, especially in low network conditions.

Limited Crop Diversity: The current model supports only a limited number of crops and growth stages, which restricts its applicability to a wider range of agricultural scenarios.

V. RESEARCH METHODOLOGY

The proposed system uses an IoT-based and machine learning-driven approach to automate irrigation. It collects real-time environmental data and makes intelligent decisions to optimize water usage and improve crop productivity.

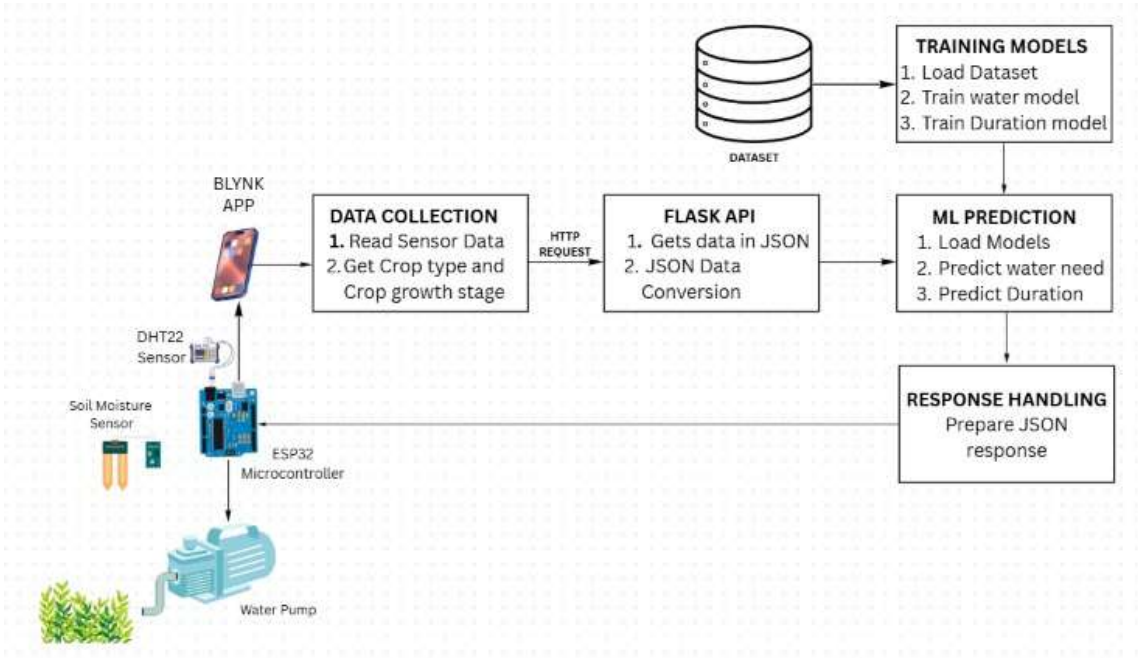

Figure 1. Block diagram

System Architecture: The system is divided into sensing, processing, intelligent, and application layers. The sensing layer collects soil moisture, temperature, and humidity data. The processing layer uses the ESP32 microcontroller to handle data and communication. The intelligent layer consists of a Flask-based API with machine learning models for prediction. The application layer uses Blynk IoT to provide a user interface for monitoring and control.

Hardware Implementation: The system uses an ESP32 microcontroller as the main controller. A soil moisture sensor measures soil water content, while the DHT22 sensor measures temperature and humidity. A relay module is connected to control the water pump. These components work together to enable continuous monitoring and automatic irrigation.

Software Development: The software is developed using Arduino IDE for ESP32 programming and Python for backend processing. The ESP32 reads sensor data at regular intervals and sends it to a Flask server using HTTP requests. The Flask server processes the data and sends back the irrigation decision, which is used to control the pump.

IoT Integration: The system is integrated with the Blynk IoT platform to enable real-time data visualization and remote control. Users can monitor soil moisture, temperature, and humidity through a mobile dashboard. The system also provides notifications for pump status and mode changes.

Control Strategy: A hybrid control strategy is implemented. In manual mode, users can directly control the pump through the mobile application. In automatic mode, irrigation decisions are taken based on machine learning predictions. This ensures flexibility and user control along with automation.

Machine Learning Model: Decision Tree algorithms are used for both classification and regression tasks. The model predicts whether irrigation is required (ON/OFF) and determines the duration of watering. The model uses input parameters such as soil moisture, temperature, humidity, crop type, and growth stage to improve accuracy compared to simple threshold-based systems.

Data Collection and Analysis: Sensor data is continuously collected and monitored. This data helps in analyzing environmental conditions and evaluating system performance. The collected data can also be stored and used for future model training and improvement.

Testing and Evaluation: The system is tested under different environmental conditions to evaluate its performance. Parameters such as sensor accuracy, response time, communication reliability, and water usage efficiency are considered. The results show that the system reduces water wastage and improves irrigation efficiency.

VI. RESULTS AND DISCUSSION

The IoT-based smart irrigation system worked well, providing real-time monitoring and automated watering with soil moisture and DHT22 sensors. The ESP32 microcontroller processed the sensor data and turned the water pump on or off based on set thresholds, so irrigation only happened when needed. This approach helped prevent over-irrigation and reduced water waste. By using the Blynk IoT platform, users could check conditions and control the system from their smartphones, making it easy and convenient. The system was reliable in terms of sensor accuracy, quick response, and wireless communication. Using affordable parts also makes this solution practical for small and medium-sized farmers. The circuit diagram on page 4 shows how the sensors, ESP32, relay module, and water pump are connected for smooth operation. However, using fixed thresholds is less flexible than more advanced AI-based irrigation systems. In the future, adding machine learning and weather forecasting could make the system even more efficient. Overall, this system offers a cost-effective, energy-saving, and sustainable way to improve modern agricultural irrigation.

Accuracy Analysis

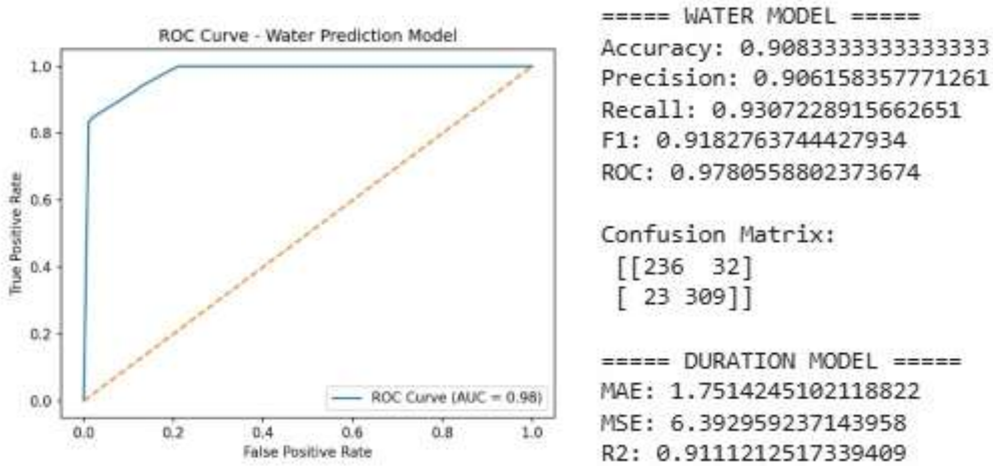

Figure 2. Model Accuracy

The model achieves an **accuracy of 90.83%**, meaning it correctly predicts irrigation decisions in most cases. However, accuracy alone is not sufficient, so other metrics provide deeper insight:

- **High Precision (90.62%)** → When the model predicts irrigation is needed, it is usually correct (low false positives).
- **High Recall (93.07%)** → The model successfully identifies most cases where irrigation is actually needed (low false negatives).
- **F1 Score (91.83%)** → Balanced performance between precision and recall.
- **ROC-AUC (0.98)** → Excellent classification ability across all thresholds.

From the confusion matrix:

- **False Positives (32):** Slight over-irrigation risk
- **False Negatives (23):** Small chance of under-irrigation

Overall, the model is **highly reliable and well-balanced**, slightly favoring recall, which is beneficial in irrigation systems since missing required watering (false negative) can harm crops more than slight overwatering.

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REFERENCES

[1] Hooman Sharifnasab, Ali Mahrokh, Hossein Dehghanisanij, Ewa Łazuka, Grzegorz Łagód, Hamed Karami April 2023. Evaluating the Use of Intelligent Irrigation Systems Based on the IoT in Grain Corn Irrigation, Water (MDPI), Volume 15, Issue 7.

[2] Sagar M. Chavare, Prasad P. Nanaware, Shriprasad S. Wagh, Ashish T. Jadhav, Yeole Yogesh, Suhas B. Khadake May 2025. Smart Plant Monitoring and Automated Irrigation System Using IoT, International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), Volume 5, Issue 4.

[3] M. Keerthana, D. Dhinakaran, M. Ananthi, R. Harish, S. M. Udhaya Sankar, M. Sai Sree 2022. IoT Based Automated Irrigation System for Agricultural Activities, IEEE Xplore – published as part of IEEE conference proceedings (likely on IoT, Agriculture, or Smart Systems), International Conference on Electronics and Renewable Systems (ICEARS).

[4] Shabana Habib, Saleh Alyahya, Muhammad Islam, Abdullah M. Alnajim, Abdulatif Alabdulatif, Abdullah Alabdulatif 2023. Design and Implementation: An IoT- Framework-Based Automated Wastewater Irrigation System, Electronics (MDPI), Volume 12, Issue 1.

[5] Yunus Emre Kunt 2025. Development of a Smart Autonomous Irrigation System Using IoT and AI.

[6] Janani M, Jebakumar R 2023. A Study on Smart Irrigation Using Machine Learning.

[7] Prabhat Pandey, Sudhir Agarwal 2023. A Low-Cost Smart Irrigation Planning Based on Machine Learning and Internet of Things, Current Agriculture Research Journal (CARJ), Volume 11, Issue 2.

[8] Youness Tace, Mohamed Tabaa, Sanaa Elfilali, Cherkaoui Leghris, Hassna Bensag, Eric Renault 2022. Smart Irrigation System Based on IoT and Machine Learning, Energy Reports (Elsevier), Volume 8, Issue 1.

[9] Mohamed Shabeer Mohamed Rafi, Mehran Behjati*, Ahmad Sahban Rafsanjani 2025. Reliable and Cost-Efficient IoT Connectivity for Smart Agriculture: A Comparative Study of LPWAN, 5G, and Hybrid Connectivity Models.

[10] R Sitharthan, M. Rajesh, S. Vimal, E. Saravana Kumar, S. Yuvaraj, Abhishek Kumar & Jacob Raglend 2023. A Novel Autonomous Irrigation System for Smart Agriculture Using AI and 6G Enabled IoT Network, Microprocessors and Microsystems, Volume 101.