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Abstract:

Water scarcity and inefficient irrigation remain critical challenges in modern agriculture. Traditional irrigation practices rely on manual estimation, leading to over-watering or under-watering and significant resource wastage. This paper presents a Smart Irrigation Recommendation System that addresses these challenges through a software-only, sensor-free approach. The proposed system integrates a Random Forest Regression model with the FAO-56 Penman-Monteith evapotranspiration formula to compute precise water requirements based on user-provided inputs—crop type, soil type, and plot area—combined with real-time weather data from the Open Weather Map API. Geolocation is automatically detected via the browser GPS API, ensuring location-specific recommendations. The system suppresses irrigation when rain is detected and splits high-volume schedules into morning and evening slots to reduce evaporation loss. Implemented as a lightweight Streamlit web application, it is accessible on smartphones and laptops without hardware sensors. Unit, integration, and system testing confirm consistent accuracy across all test scenarios.

Keywords — **Smart Irrigation, Machine Learning, Random Forest, Penman-Monteith, Water Optimization, Precision Agriculture, Evapotranspiration**.

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I. INTRODUCTION

Water is among the most critical resources for agricultural productivity, and its efficient management is increasingly challenging under climate variability and growing global demand [1]. Conventional irrigation methods depend on farmer intuition, resulting in excessive water application, nutrient runoff, and reduced crop health. Modern IoT-based irrigation systems utilize hardware components such as soil moisture sensors and microcontrollers to automate irrigation. However, high equipment costs, maintenance requirements, and technical barriers limit their adoption among smallholder farmers and home gardeners [2].

This paper proposes the Smart Irrigation Recommendation System—a software-based predictive solution that eliminates the need for physical hardware. The system requires only simple user inputs: crop type, soil type, plot area, and last watering interval—alongside automatically fetched GPS coordinates and live weather data—to generate precise irrigation recommendations. By combining a trained Machine Learning model with the FAO-56 Penman-Monteith equation, the system computes exact water volumes and optimal watering schedules [3].

II. LITERATURE SURVEY

Several studies have investigated ML-based approaches to irrigation management. Dong et al. [4] developed a large-scale evapotranspiration estimation framework using deep learning across diverse climate datasets. While achieving high accuracy, it required substantial computational resources and limited regional adaptability.

Dong et al. [5] proposed a soil moisture estimation framework combining multi-sensor data fusion with Auto ML. Although effective, high setup costs and calibration challenges limited deployment. Shiri et al. [6] applied soft computing models to simulate wetting front patterns in drip irrigation, requiring soil-dependent tuning.

Alibabaei et al. [8] applied Deep Reinforcement Learning for irrigation optimization, achieving promising water savings but requiring extensive training data. Filgueiras et al. [9] combined regression-based ET estimation with satellite imagery, though cloud cover reduced accuracy. A common gap is that sophisticated models require sensors, large datasets, or high user expertise. Table I summarises these prior works.

TABLE I.
LITERATURE SURVEY SUMMARY

Ref.	Approach	Limitation
[4]	DL-based ET	High compute
[5]	Multi-sensor+ Auto ML	High cost
[6]	Soft computing drip	Soil-specific
[7]	ML hourly ET	Station dep.
[8]	Deep RL irrigation	Large dataset
[9]	Regression+ satellite	Cloud cover

PROBLEM STATEMENT

To design and develop a smart irrigation system using machine learning that accurately predicts the amount of water supply required and the optimal time slots for irrigation delivery—without requiring physical sensors, specialized hardware, or domain expertise from the end user.

OBJECTIVES

- (i) Develop a software-only irrigation system that predicts when and how much to irrigate using Machine Learning.
- (ii) Integrate crop type, soil type, and real-time weather data to generate accurate, data-driven irrigation recommendations.
- (iii) Reduce water wastage through intelligent, optimized scheduling that adapts dynamically to local weather conditions.
- (iv) Provide an intuitive web interface accessible on smart phones and laptops without requiring technical expertise.

III. METHODOLOGY

The system automates irrigation requirement calculation by integrating real-time weather data with Machine Learning and evapotranspiration models. Fig. 1 presents the complete methodology flowchart.

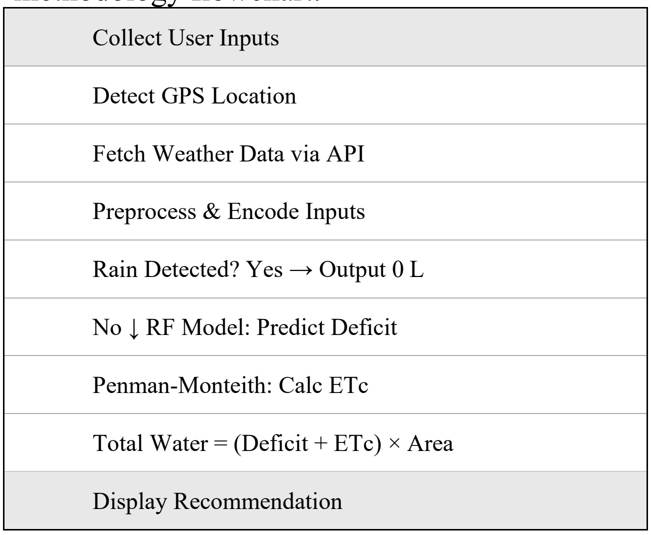


Fig. 1. Proposed Methodology Flowchart

A. Data Collection

User inputs are gathered through the web interface: crop type (e.g., Tomato, Rose), soil type (e.g., Sandy, Clay, Loamy), plot area in square metres, and last watered date. The system automatically retrieves GPS coordinates via the browser Geolocation API. Real-time temperature

(°C), relative humidity (%), and rainfall status are fetched from the Open WeatherMap API.

B. Data Preprocessing

Raw inputs are cleaned to handle invalid entries. Categorical variables (crop name, soil type) are mapped to numerical identifiers matching the training dataset schema. Continuous features are standardized, and JSON Weather API responses are parsed to extract meteorological fields.

C. ML Model and ETc Calculation

The core intelligence employs a hybrid approach: a trained Random Forest Regressor predicts the soil moisture deficit based on encoded inputs, while the FAO-56 Penman-Monteith formula computes crop evapotranspiration (ETc). The total irrigation volume is:

Total Water (L) = (Deficit + ETc) × Area

D. Dynamic Recommendation Logic

If the Weather API reports active rainfall, output is overridden to zero litres with a rain alert. Results below 0.5 L are rounded to zero. For high-volume requirements (>20 L), the schedule is split into morning and evening sessions to minimize evaporation loss.

VI. SYSTEM ARCHITECTURE

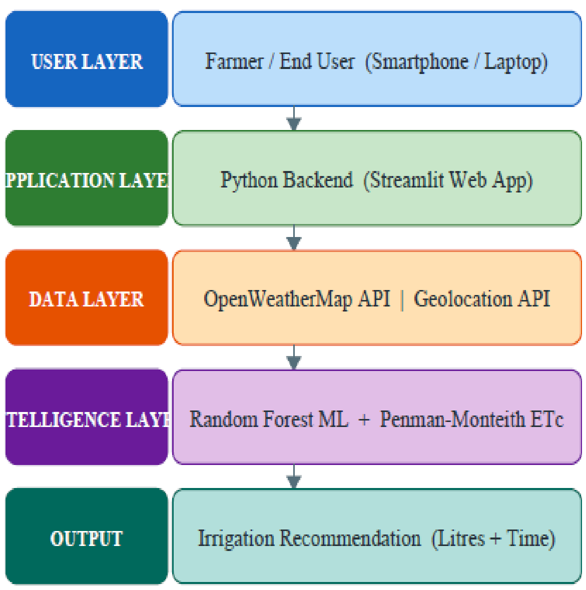


Fig. 2. System Architecture (4-Layer Model)

VII. SYSTEM DESIGN

A. Use Case Diagram

Fig. 3 shows the use case diagram illustrating interactions between the farmer and the system's core functionalities.

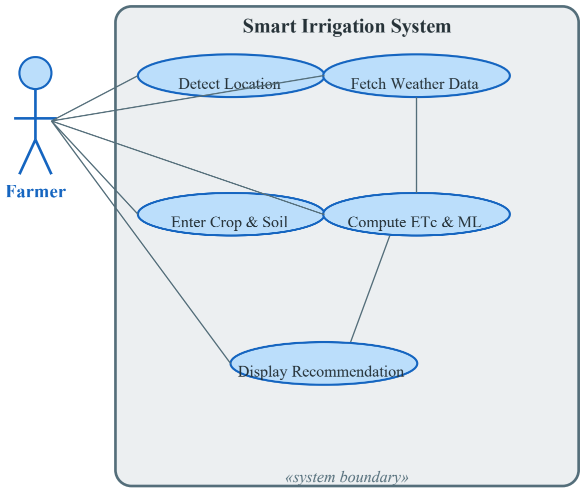


Fig. 3. Use Case Diagram

B. Activity Diagram

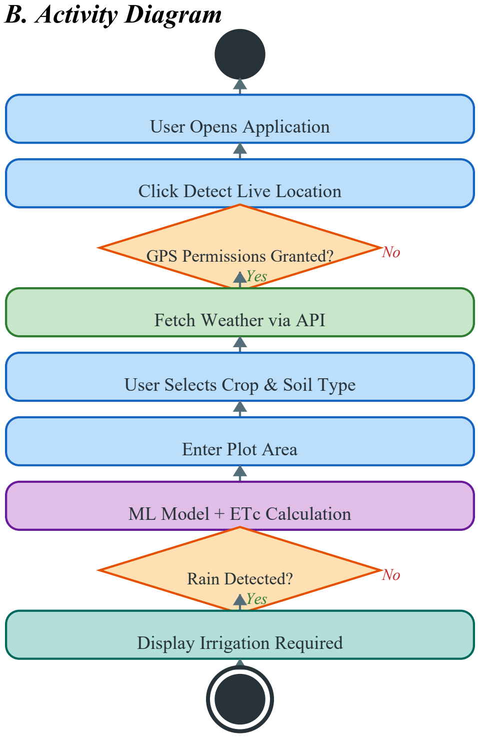
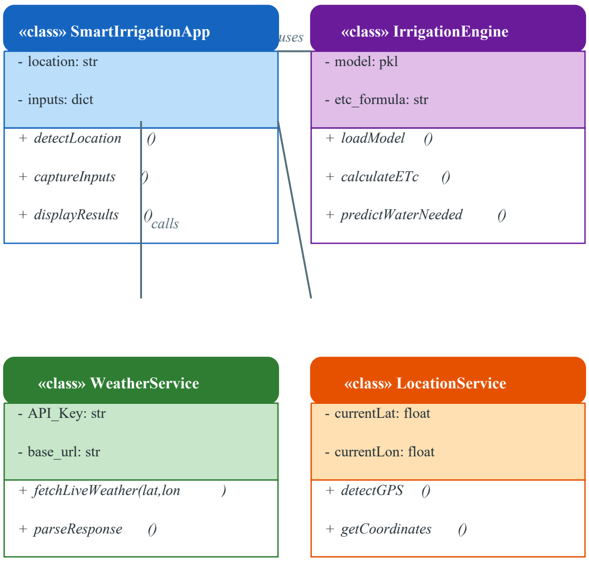


Fig. 4. Activity Diagram

B. Class Diagram

Fig. 5 presents the structural design of the system, defining the four main classes: Smart Irrigation App, Irrigation Engine, Weather Service, and Location Service, along with their attributes, methods, and associations.



IX. Testing and Evaluation

D. Sequence Diagram

Fig. 6 shows the message sequence between the user, application, weather API, and ML engine during a prediction cycle.

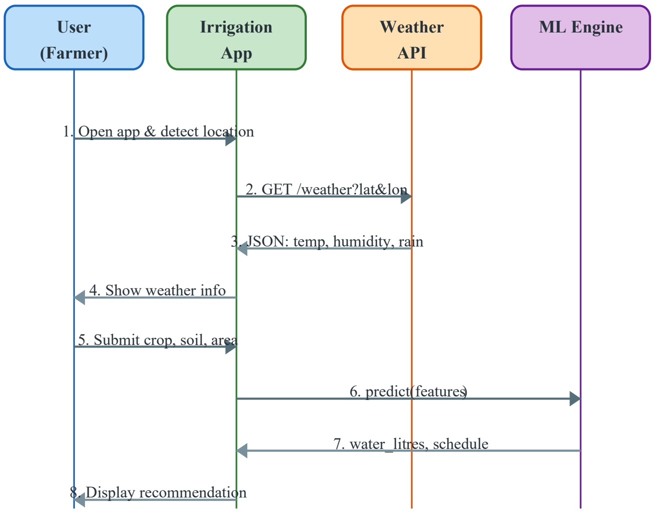


Fig. 6. Sequence Diagram

VIII. Implementation

A. Technology Stack

The system is implemented in Python. Streamlit provides the responsive web interface. Scikit-learn is used for the Random Forest Regression model. The Open Weather Map REST API supplies weather data in JSON format. The trained model is serialized via pickle (irrigation_model.pkl).

B. Stepwise Execution Flow

Step 1: App loads irrigation_model.pkl and initializes dashboard.
Step 2: User triggers GPS detection; lat / lon are captured.
Step 3: Coordinates query Open Weather Map for temperature, humidity, and rainfall.
Step 4: User selects crop type and soil type, enters plot area.

Step 5: Inputs are encoded; ML model predicts moisture deficit; Penman-Monteith computes ETc; final litres calculated.
Step 6: UI renders alert card with exact litres and morning/evening split schedule.

TABLE II.
UNIT TEST RESULTS

A. UNIT TESTING

Table II summarises the unit test results for individual modules.

ID	Description	Status
UT-01	Web app loads	PASS
UT-02	Location detection	PASS
UT-03	Weather API fetch	PASS
UT-04	Input validation (−ve area)	PASS
UT-05	model loading	PASS
UT-06	Irrigation calculation	PASS
UT-07	Rain logic override	PASS
UT-08	Crop encoding	PASS

B. Integration and System Testing

All seven integration test scenarios passed, validating seamless interaction between UI, Geolocation API, Weather API, preprocessing engine, ML model, and recommendation display. End-to-end system testing across seven scenarios including full irrigation cycle, rain alert handling, invalid data, network failure, and browser/mobile compatibility—achieved PASS status for all cases.

X. RESULTS

The deployed Streamlit application correctly detects location, accepts user inputs, and displays irrigation recommendations within 2–3 seconds. The ML model achieves an R^2 accuracy of 97.69%, confirming strong predictive reliability. When rain is detected, the system correctly overrides the model output to recommend zero litres. Table III presents a performance comparison with related approaches.

Fig. 7 and Fig. 8 show screenshots of the deployed Streamlit application. The system correctly detects location, accepts user inputs, and displays irrigation recommendations within 2–3 seconds.

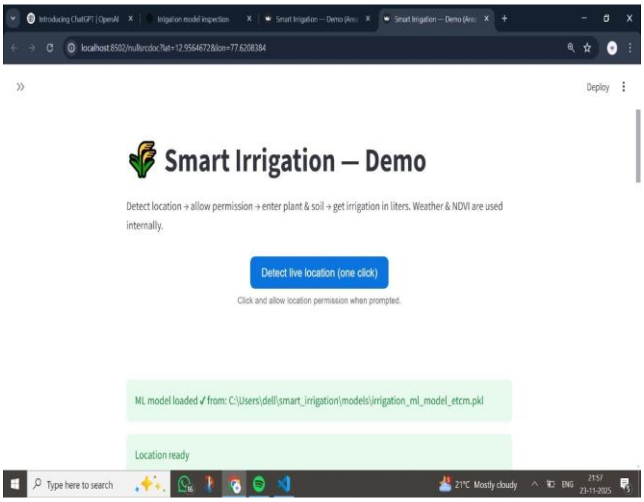


Fig. 7. Application Interface – Location Detection & Model Load

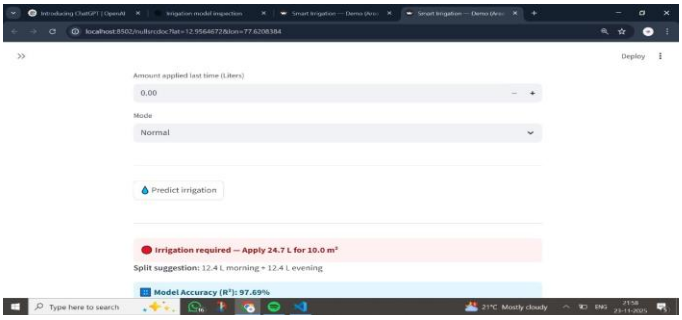


TABLE III.
PERFORMANCE COMPARISON

Criteria	IoT Sensor	DL-based [4]	Proposed
Hardware	Required	Required	None
Live Weather	Partial	No	Yes
Setup Cost	High	High	Zero
Response	>10s	>5s	2–3s
Rain Override	Manual	No	Auto
Mobile	Limited	No	Yes
R^2 Accuracy	N/A	~90%	97.69%

XI. Advantages and Limitations

A. Advantages

- **Cost-Effective and Sensor-Free:** The software-only approach eliminates hardware acquisition and maintenance costs, making the system accessible to smallholder farmers.
- **Precise Water Optimization:** The hybrid ML +Penman-Monteith approach computes exact irrigation volumes, preventing both over-watering and under-watering.
- **Real-Time Weather Adaptation:** Dynamic integration with a live weather API ensures recommendations reflect current conditions, with automatic rain override.
- **Scalability:** Cloud-based API architecture allows extension to new crop varieties, soil types, and geographic regions without hardware changes.
- **Accessibility:** The Streamlit interface is fully responsive on both smartphones and laptops, requiring no technical expertise.

B. Limitations

- **Internet Dependency:** Stable connectivity is required for weather data retrieval, which may be unavailable in remote agricultural areas.
- **API-Dependent Accuracy:** Accuracy depends on the proximity of the nearest weather station, introducing variance for isolated field locations.

- **Manual Input Reliance:** Incorrect user-provided data can propagate to inaccurate irrigation recommendations.
- **API Rate Limits:** The free-tier Open Weather Map API has usage limits requiring paid subscriptions for high-concurrency deployment.

XII. Conclusion and Future Work

This paper presented the Smart Irrigation Recommendation System, a sensor-free, software-only solution that leverages Machine Learning and the FAO-56 Penman-Monteith evapotranspiration model to deliver precise, real-time irrigation guidance. By abstracting complex agronomic computations behind a simple web interface, the system democratizes precision irrigation technology for farmers, gardeners, and water resource managers without hardware investment or domain expertise.

The integration of the Random Forest algorithm (R^2: 97.69%) with weather-adaptive decision logic ensures water-efficient recommendations that dynamically respond to real-world conditions. End-to-end testing confirmed the system's reliability, accuracy, and cross-platform accessibility.

Future work will extend the system in three directions: **(1)** hardware integration with IoT microcontrollers (Arduino/Node MCU) and relay modules for fully automated pump control; **(2)** a CNN-based plant disease detection module allowing farmers to photograph crop leaves for real-time diagnosis; and **(3)** multilingual NLP support for regional languages (Kannada, Hindi, Telugu) to expand accessibility among rural farming communities.

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