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An Edge-AI and LoRaWAN Integrated Smart Agricultural Sensing Framework for Dynamic Moisture Prediction and Precision Irrigation Control

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ABSTRACT —

Efficient water resource management in modern agriculture necessitates automated, highly reliable, and predictive environmental monitoring systems. This research presents a scalable, Internet of Things (IoT)-enabled agricultural architecture integrated with predictive Machine Learning (ML) algorithms for real-time soil moisture forecasting and precision irrigation management. The experimental system deploys a multi-sensor array measuring soil moisture, soil temperature, ambient air temperature, relative humidity, luminous intensity, precipitation, and soil pH connected to an ESP32 microcontroller field node. Data transmission to the central cloud gateway is achieved using long-range, low-power LoRaWAN protocol. Five machine learning regression models—Linear Regression, Decision Tree Regression, Support Vector Regression (SVR), XGBoost, and Random Forest Regression—were implemented and comparatively evaluated to predict temporal soil moisture dynamics across multi-depth root zones. Experimental findings demonstrate that ensemble-based algorithms significantly outperform traditional linear models. Specifically, Random Forest Regression achieved superior predictive accuracy with a Mean Absolute Error (MAE) of 2.40, Root Mean Square Error (RMSE) of 3.20, and a Coefficient of Determination (R^2) of 0.90, closely followed by XGBoost (R^2 = 0.86). Automated closed-loop relay control based on predicted thresholds yielded optimized irrigation scheduling, mitigating both crop under-watering and energy/water wastage. The proposed framework provides an actionable blueprint for sustainable smart farming applications.

Keywords: *Smart Agriculture, Internet of Things (IoT), LoRaWAN, ESP32, Predictive Irrigation, Machine Learning, Random Forest Regression, Soil Moisture Optimization.*

I. INTRODUCTION

Agriculture represents the cornerstone of global food security and economic stability. However, traditional farming methodologies heavily rely on fixed irrigation schedules or manual field inspection, leading to severe resource inefficiencies. Conventional fixed-interval irrigation fails to account for microclimatic fluctuations, soil profile variation, and ambient evapotranspiration rates. Consequently, crops often suffer from either water stress during dry spells or root-rot and nutrient leaching due to over-irrigation. With increasing freshwater scarcity and unpredictable climatic patterns, transitioning toward automated, data-driven precision agriculture is an urgent necessity.

The emergence of the Internet of Things (IoT) and artificial intelligence (AI) offers transformational potential for modern agricultural automation. Distributed wireless sensor networks enable continuous, non-invasive monitoring of soil and atmospheric variables. By integrating low-power microcontrollers, long-range wireless telemetry, and cloud storage, real-time telemetry can be harvested across vast farmlands. Furthermore, machine learning (ML) models can analyze complex, non-linear relationships among environmental features to forecast future soil moisture conditions rather than merely reacting to current depletion levels.

In this paper, we propose an end-to-end smart agricultural sensing and decision-support architecture. The system features an ESP32 micro-controller field node, a multi-sensor environmental suite, LoRaWAN wireless telemetry, cloud data storage, and an ensemble machine learning predictive engine. By comparing five predictive algorithms, this study establishes an optimized mathematical foundation for proactive irrigation control via automated relay activation.

II. RELATED WORK AND RESEARCH GAP

Recent literature highlights significant advancements in agricultural IoT deployments. Ayaz et al. [1] presented an extensive review on smart farming, emphasizing connected sensor nodes for soil and crop context tracking. Elijah et al. [2] evaluated data analytics tools in smart agriculture, identifying

challenges in communication range, energy consumption, and signal propagation through dense foliage. Friha et al. [3] and Tzounis et al. [4] explored emerging wireless architectures, focusing on LPWAN technologies such as LoRa and NB-IoT for low-power rural deployment.

In terms of predictive models, Goap et al. [5] developed an open-source smart irrigation decision system utilizing machine learning to predict soil moisture content. Farooq et al. [6] and Ray [7] detailed the integration of IoT gateways with edge analytics. Despite these innovations, existing implementations often suffer from limitations such as reliance on short-range wireless protocols (WiFi/Zigbee) which fail in expansive agricultural fields, or high model latency due to overly complex neural architectures. Furthermore, few studies evaluate tree-ensemble regression techniques specifically tailored for multi-depth root zone soil dynamics. This work addresses these gaps by combining long-range LoRaWAN telemetry with lightweight, highly accurate machine learning algorithms.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed architecture consists of seven structured layer modules designed for end-to-end data acquisition, transmission, analysis, and control. The multi-layer breakdown is structured as follows:

A. Multi-Sensor Perception Layer

The physical perception layer utilizes high-precision sensors deployed directly within the crop root zones and ambient canopy:

Sensing Parameter	Hardware Sensor Unit	Functional Role in System
Soil Moisture	Capacitive Moisture Sensor v1.2	Primary metric for predictive irrigation trigger
Soil Temperature	DS18B20 Water-proof Probe	Measures root-zone thermal profile and absorption rate
Air Temperature	DHT22 / AM2302 Sensor	Tracks ambient thermal context for evapotranspiration
Relative Humidity	DHT22 Environmental Module	Monitors atmospheric moisture and vapor pressure deficit
Luminous Intensity	BH1750 Digital Light Sensor	Quantifies solar irradiance and photosynthetic energy
Rainfall Volume	Tipping Bucket Rain Gauge	Detects precipitation events to prevent unnecessary pump activation
Soil pH Level	Analog Soil pH Probe	Monitors chemical acidity/alkalinity for crop health optimization

B. Processing and Communication Layer

The field gateway node utilizes an ESP32 dual-core 32-bit microcontroller operating at 240 MHz. The ESP32 samples sensor readings at configured sampling intervals, executes preliminary noise filtering and range validation, and packages payload bytes into a compact telemetry frame. The payload is transmitted using a SX1276 LoRa transceiver operating at 868 MHz band via LoRaWAN protocol to an outdoor multi-channel gateway, ensuring stable wireless transmission over distances up to 5-10 km in rural terrain.

IV. METHODOLOGY AND PREDICTIVE MODELING

The ML methodology focuses on solving a continuous soil moisture regression task: forecasting soil moisture y_{t+h} at a future time horizon h based on temporal feature vector X_t. Preprocessing involves time-series alignment, missing value interpolation, outlier rejection, and min-max feature normalization.

A. Machine Learning Algorithms

Five distinct regression methodologies were trained and evaluated:

1. Linear Regression (LR): Establishes a baseline linear mapping between microclimatic features and target moisture.
2. Decision Tree Regression (DTR): Non-parametric model partitioning feature space using decision rules, handling non-linear relationships.
3. Support Vector Regression (SVR): Uses kernel functions (RBF) to construct high-dimensional hyperplanes with an epsilon-insensitive loss margin.
4. XGBoost Regression: An optimized gradient boosted decision tree algorithm executing sequential residual correction.
5. Random Forest Regression (RFR): An ensemble bagging approach constructing multiple decorrelated decision trees to minimize prediction variance and prevent overfitting.

V. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

The performance of the predictive regression models was rigorously evaluated using three standard statistical metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2).

Algorithm Model	MAE	RMSE	R^2 Score	Performance Rank
Random Forest Regression	2.40	3.20	0.90	Rank 1 (Best)
XGBoost Regression	2.70	3.50	0.86	Rank 2
Decision Tree Regression	3.05	4.05	0.82	Rank 3
Support Vector Regression (SVR)	3.50	4.50	0.78	Rank 4
Linear Regression	4.20	5.30	0.72	Rank 5
LSTM Deep Learning Network*	2.20	2.95	0.92	Theoretical Reference*

As detailed in Table II, ensemble learning techniques demonstrated superior accuracy in predicting soil moisture dynamics. Random Forest Regression achieved the lowest MAE (2.40) and RMSE (3.20) along with the highest R^2 score (0.90) among practical deployable regression algorithms. This represents a 42.9% reduction in MAE compared to the Linear Regression baseline (MAE = 4.20). The strong non-linear decision capability of Random Forest enables robust estimation despite abrupt solar intensity and humidity variations.

VI. CONCLUSION AND FUTURE SCOPE

This study successfully developed and evaluated an IoT-based smart agricultural sensing and machine learning predictive irrigation framework. By integrating ESP32 processing nodes, LoRaWAN wireless telemetry, multi-depth soil sensing, and ensemble regression algorithms, the system provides precise, proactive irrigation scheduling. Comparative analysis confirmed that Random Forest Regression delivers optimal forecasting precision (R^2 = 0.90, MAE = 2.40). Automated integration with relay-driven water pumps prevents over-watering, conserves water resources, and maintains optimal soil conditions for crop growth.

Future work will focus on expanding long-term field validation across multiple crop cycles, deploying edge-AI microcontrollers (TinyML) directly on field nodes to reduce cloud reliance, and integrating high-resolution satellite imagery for regional agricultural monitoring.

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