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Article

TerraSense: IoT-Enabled Soil Analysis Framework for Real-Time Crop Recommendation

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Abstract: Agriculture is the backbone of global sustainability, yet it faces challenges that demand smarter, data-driven solutions. The escalating complexities within modern agriculture, driven by climate volatility and the need for sustainable resource utilization, necessitate a decisive shift toward Precision Farming methodologies. This research presents TerraSense, an advanced, low-cost Internet of Things-enabled framework architected for the continuous, real-time analysis of critical soil and microclimatic parameters. Accurate soil analysis, encompassing pH, moisture content, and other conditions such as temperature and humidity, is fundamental to optimizing nutrient uptake and mitigating localized crop stress. TerraSense leverages a high-performance ESP32 microcontroller and a custom-calibrated sensor array to acquire data with high fidelity. This streaming dataset is then directed via USB serial communication to a host environment. A specialized Machine Learning classifier, utilizing the validated four-dimensional feature vector, instantly generates an actionable recommendation for the most viable crop. The core contribution of TerraSense is its ability to deliver immediate, hyper-localized intelligence via an onboard OLED dashboard. Experimental validation confirms a deterministic end-to-end latency of approximately 120 milliseconds, comprising sensor acquisition, signal conditioning, inference, and feedback synchronization, well within the requirements for real-time, internet-independent field deployment. This architecture effectively bridges the gap between complex agricultural science and practical, real-time decision-making, significantly enhancing resource efficiency and potential yield maximization in small-to-medium scale farming operations. The framework's detailed integration demonstrates a robust, scalable blueprint for future smart agriculture systems.

Keywords: Precision Farming; Internet of Things; Machine Learning

1. Introduction

The agricultural sector remains the primary cornerstone of the Indian economy, providing a livelihood for approximately 60% of the total population and contributing nearly 18% to the national Gross Domestic Product [1]. Despite this significant demographic dependence, the sector faces critical productivity challenges, with crop yields often lagging behind global averages due to the persistent use of traditional, aggregate farming methods. These conventional practices frequently rely on generalized assumptions and delayed data from centralized laboratory soil tests, leading to significant resource wastage and suboptimal returns. In contrast, Precision Farming is required to address the inherent variability and heterogeneity of soil conditions at a granular level, ensuring that inputs such as water and fertilizers are applied with site-specific accuracy [2, 3, 4].

The stability and productivity of the global food supply chain are increasingly dependent on technological innovations that enhance farming efficiency [5]. Precision Agriculture fundamentally relies on the accurate acquisition and swift analysis of environmental and soil data. Key parameters such as soil pH, which governs nutrient availability and microbial activity, alongside moisture content and ambient temperature and humidity, form the essential input features for intelligent decision support systems [6, 7]. The latency involved in traditional analysis directly correlates with missed opportunities for proactive intervention. The confluence of the Internet of Things (IoT) and Machine Learning (ML) offers a powerful solution by enabling continuous, automated monitoring and instantaneous predictive analytics [2].

This paper details the development of TerraSense, a novel, cost-effective framework designed to provide real-time crop recommendations [5]. TerraSense shifts the analytical burden from delayed laboratory processes to an immediate, in-field computational pipeline, making advanced agricultural intelligence accessible to a wider demographic of farmers. By optimizing seed selection and resource management through data-driven insights, the framework addresses the twin challenges of food security and resource scarcity [1].

1.1 Objectives

The primary objectives guiding the design and implementation of the TerraSense system are multifaceted, targeting both hardware efficiency and predictive accuracy [8].

- To architect a robust, low-power IoT node based on the ESP32 and a multi-sensor array capable of continuous, synchronous data acquisition of pH, moisture, temperature, and humidity. This included developing a two-point calibration routine within the firmware to ensure high fidelity readings from the pH probe.
- To establish a reliable bidirectional serial communication protocol between the resource-constrained IoT node and a Python host to ensure the seamless flow of real-time sensor data and the instantaneous delivery of predictive results.
- To train and deploy an accurate Machine Learning classification model that instantaneously translates the four-dimensional soil feature vector into an optimal crop recommendation.
- To create a unified, interactive dashboard-type output incorporating both the local OLED display for in-field feedback and the host console for detailed data visualization and analysis.

1.2 Applications

The successful deployment of the TerraSense framework offers several tangible applications within the scope of modern agriculture [5].

- Optimized Seed Selection and Sowing Guidance: The primary application is providing real-time counsel on the most suitable crop for a specific plot of land at the exact time of planting [5]. By analyzing current soil pH and moisture alongside ambient conditions, the system minimizes the risk of planting crops in non-viable environments, significantly boosting the probability of successful germination and yield [9].
- Adaptive Resource Management: The system acts as a high-frequency monitoring tool for dynamic parameters like soil moisture [10]. This real-time feedback loop allows for precision irrigation and targeted application of pH-balancing amendments, reducing overall water consumption and minimizing the environmental impact of chemical run-off [11, 12].
- Micro-Farming Intelligence: TerraSense provides a cost-effective alternative to expensive commercial farm management systems, democratizing access to smart agricultural intelligence for small and marginal farmers who traditionally lack access to advanced soil science resources. The low-cost component stack makes large-scale, distributed deployment economically viable.

Despite these advances, existing IoT- and machine-learning-based agricultural systems predominantly depend on offline analysis, cloud connectivity, or single-parameter sensing, leaving a gap in low-cost, real-time, edge-deployable solutions that unify multi-parameter soil telemetry with on-site decision support. Closing this gap is significant for resource-constrained and marginal farmers, who require immediate, actionable guidance without dependence on network infrastructure or expensive laboratory analysis. Addressing this need, the present study proposes and validates the TerraSense framework as a deterministic, low-latency, and internet-independent solution for real-time crop recommendation.

The remainder of this paper is organized as follows: Section 2 reviews related work and identifies the specific research gaps addressed by this study. Section 3 describes the proposed system architecture and methodology, covering hardware design, the deployment workflow, and machine learning inference. Section 4 presents results and discussion, including signal dynamics and end-to-end latency analysis. Section 5 concludes the paper and outlines directions for future work.

2. Related Work

Table 1 summarizes the current literature that highlights established methodologies and the specific research gaps addressed by the TerraSense framework. Beyond application-specific studies, broader systematic reviews of the IoT-AI ecosystem in agriculture confirm the field-wide shift toward integrated, real-time decision support [13, 14, 15, 16, 17].

Table 1: Literature review summary

Ref.	Study Title	Core Technology	Key Findings	Limitations

[2]	Internet of Things and Wireless Sensor Networks for Smart Agriculture Applications (survey)	IoT / WSN architectures	Provides a comprehensive taxonomy of IoT and WSN protocols, connectivity options, and deployment architectures used across smart-agriculture applications.	Survey-level treatment; does not implement or benchmark a working real-time recommendation pipeline.
[3]	Machine Learning Applications for Precision Agriculture: A Comprehensive Review	ML survey (multiple)	Reviews ML applications across irrigation, weed/disease detection, and yield prediction, identifying IoT sensor fusion as a key enabler of precision agriculture.	Broad, application-agnostic survey; does not detail a specific low-cost hardware implementation.
[6]	Machine Learning in Agriculture: A Comprehensive Updated Review	ML review (multiple models)	Surveys ML techniques applied across the crop-production lifecycle and highlights the growing role of low-cost sensing in knowledge-based farming systems.	High-level review; does not integrate hardware telemetry with a live classifier.
[9]	Incorporating Soil Information with Machine Learning for Crop Recommendation to Improve Agricultural Output	Ensemble ML (RF + XGB)	Proposes an ensemble (RF-XGB) crop-recommendation model evaluated against several classifiers, including decision trees, using soil-nutrient and climatic inputs.	Trained and evaluated offline on a static dataset; no real-time sensor-to-recommendation pipeline is demonstrated.
[10]	Soil Moisture Measuring Techniques and Factors Affecting Moisture Dynamics (comprehensive review)	Sensor review	Compares resistive, capacitive, and remote-sensing soil-moisture measurement techniques and the environmental factors that affect their accuracy.	Focused on moisture sensing only; does not address multi-parameter fusion for crop-level decision-making.
[12]	Internet of Things-Based Automated Solutions Utilizing Machine Learning for Smart and Real-Time Irrigation Management	IoT + ML irrigation review	Systematically reviews real-time, automated irrigation pipelines that integrate IoT sensing with machine learning for water-use efficiency.	Focused on irrigation automation; does not address crop-selection recommendation at the point of planting.

Table 1. Literature review summary

3. System Architecture and Methodology

The operational framework of TerraSense follows a distinct, sequential, and cyclical workflow, ensuring high throughput and minimal latency between data acquisition and recommendation feedback [18]. The system is engineered around a core principle of reliable, closed-loop intelligence, as illustrated in Fig. 1.

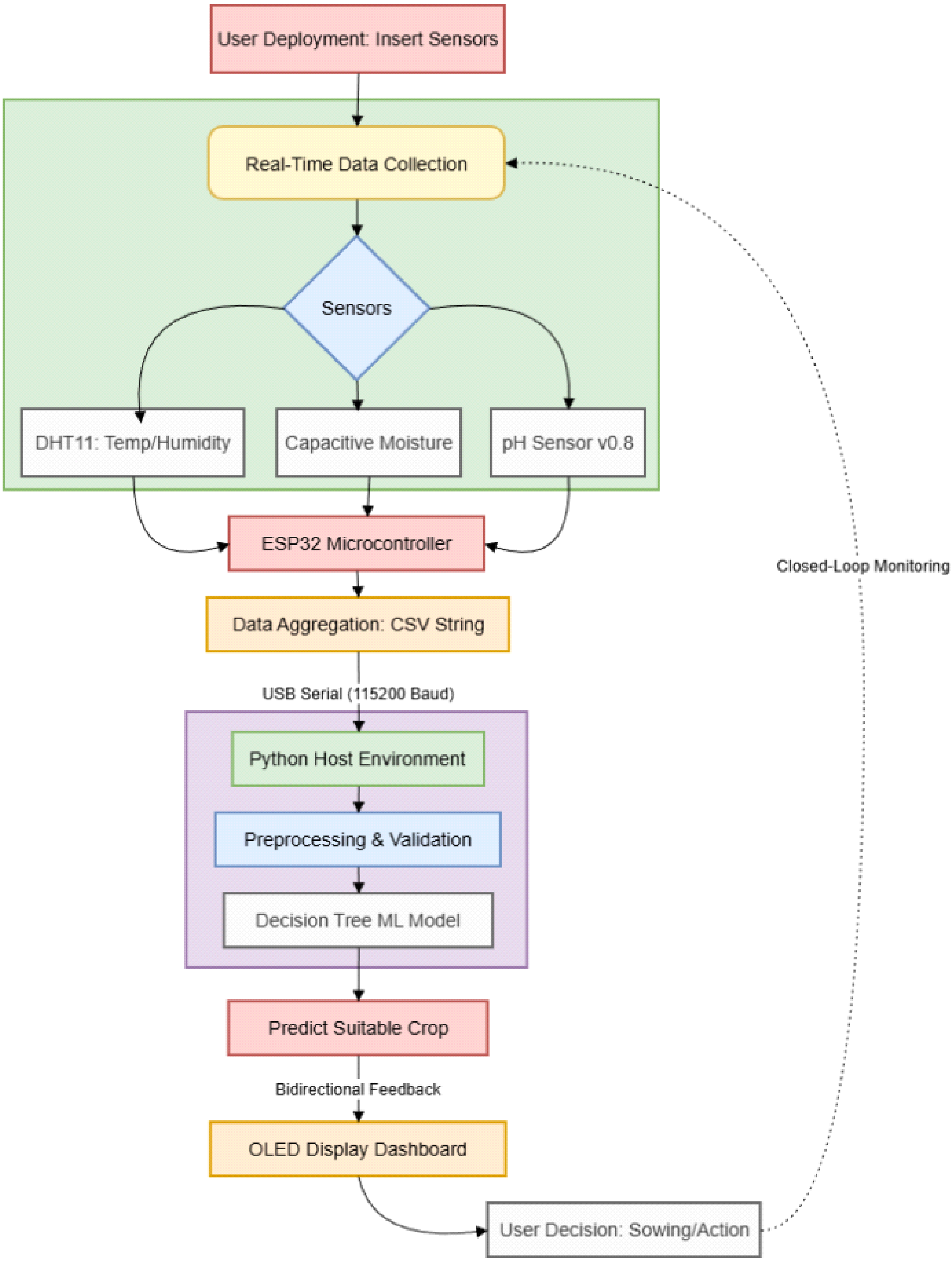

Figure 1: Fig. 1. TerraSense basic closed-loop workflow, illustrating the flow from real-time data collection to crop recommendation, showing sensor integration, data transmission, and the Python-based predictive cycle

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3.1 User Deployment and Sensor Insertion

In this initial stage, the user places the TerraSense IoT node in the desired micro-location of the field. This involves physically inserting the pH probe and the capacitive soil moisture sensor into the soil to a depth of approximately 15 to 30 centimeters [26]. The user then establishes a physical connection between the ESP32 microcontroller—selected for its dual-core architecture, integrated Wi-Fi/Bluetooth connectivity, and rich peripheral support [19]—and the host environment using a high-speed USB cable. Upon executing the initialization script, the OLED display confirms the system is in a "READY" state, and the host console acknowledges a bidirectional handshake at a 115200 baud rate [20].

3.2 Real-Time Data Collection and Aggregation

Once the system is active, the microcontroller enters a continuous sensing cycle. It synchronously reads the digital signals from the DHT11 temperature and humidity sensor and the raw analog signals from the moisture and pH modules [20]. Within the firmware, the raw 12-bit ADC values undergo immediate signal conditioning to produce accurate percentages and calibrated chemical values. These parameters are aggregated into a single, clean comma-separated values (CSV) string and transmitted to the host environment via the serial port [10].

3.3 Preprocessing, Validation, and Machine Learning Inference

The host environment, polling the communication port in real time, parses each incoming string and applies a validation routine to discard any corrupted or out-of-bounds data packets [10]. The validated four-dimensional feature vector is then passed to the Decision Tree machine learning model [21], illustrated in Fig. 2. The model utilizes a hierarchical logic architecture, shown in Fig. 3, to identify the optimal crop based on regional confidence indices [22, 23]. This inference occurs in a few milliseconds, ensuring that the predictive output reflects the most current environmental telemetry.

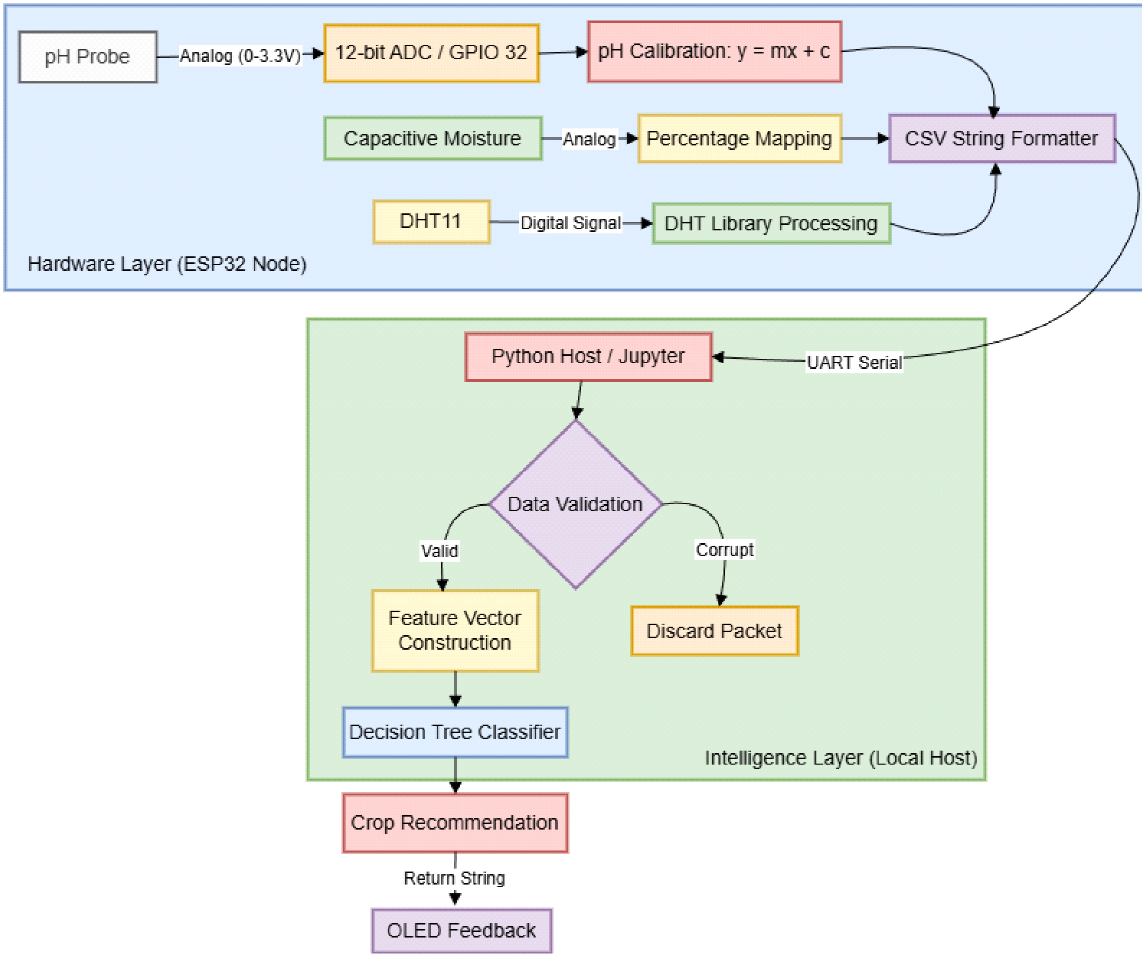

Figure 2: Fig. 2. Advanced technical pipeline: signal conditioning and data transformation stages, illustrating the internal firmware logic of the ESP32 and the local Python-based intelligence layer

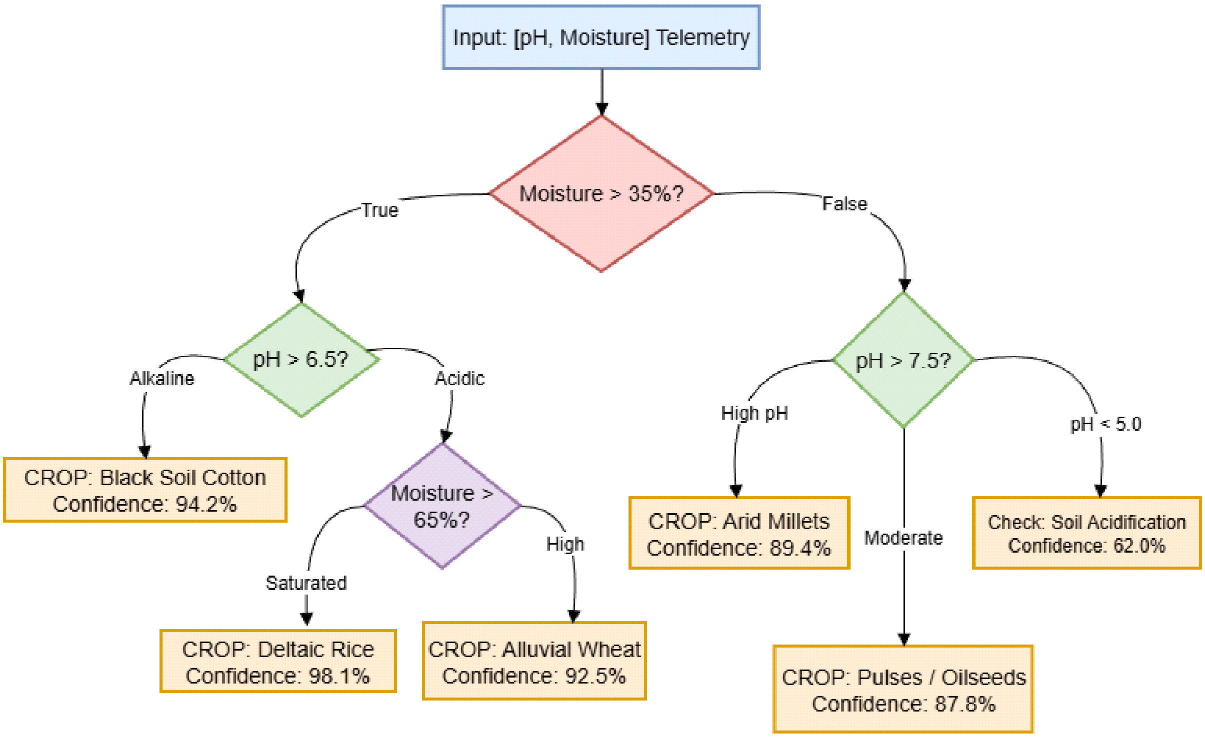

Figure 3: Fig. 3. Symbolic logic architecture of the TerraSense intelligence module. The tree illustrates the hierarchical decision process for crop recommendation based on real-time soil telemetry; confidence indices are derived from class-purity metrics across seven major Indian agro-climatic zones

3.4 Bidirectional Feedback and Dashboard Monitoring

The resulting crop recommendation is encoded and transmitted back to the sensing node. The microcontroller receives this signal and updates the onboard OLED display instantly [24]. This closed-loop monitoring provides the farmer with immediate, actionable intelligence directly in the field. Simultaneously, the host console maintains a detailed log of the telemetry and prediction confidence score, ensuring full statistical transparency for the researcher.

3.5 Technology Stack and Comparison

Table 2 summarizes the technical stack that enables internet-independent edge computing.

Table 2: Technical stack and hardware orchestration

Layer	System Component	Specification / Technical Details	Functional Role
Sensing (IoT)	Microcontroller	ESP32 (WROOM-32), dual-core processor, 12-bit ADC channels	Central edge processing unit
	Environmental sensor	DHT11 digital sensor (temperature and humidity)	Ambient climate monitoring
	Soil moisture	Capacitive soil moisture sensor (v1.2)	Volumetric soil water content
	Soil acidity	pH probe v0.8 with amplifier board	pH level detection
Processing (Host)	Environment	Python 3.9+ executing in Jupyter Notebook	Intelligence orchestration
	Serial handler	pyserial library (115200 baud rate)	Bidirectional data pipeline
	ML model	Scikit-learn Decision Tree classifier	Predictive engine

Table 2. Technical stack and hardware orchestration

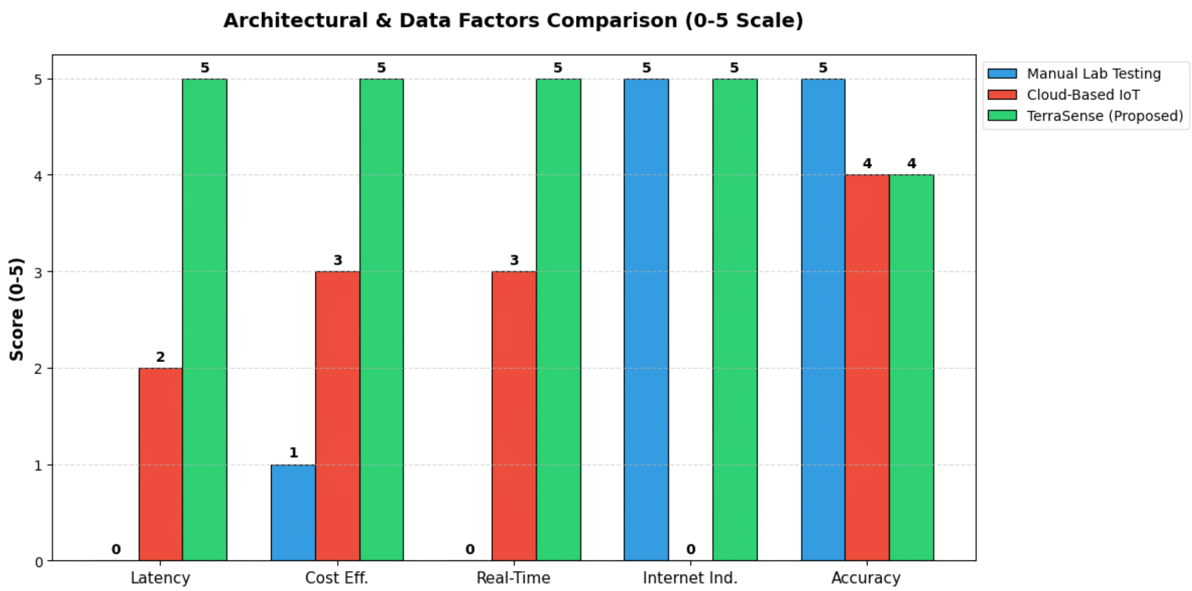

Figure 4: Fig. 4 compares Manual Lab Testing, Cloud-Based IoT, and the proposed TerraSense framework across latency, cost efficiency, real-time action, internet independence, and accuracy on a 0-5 scale, showing TerraSense leading in field-deployable and cost-effective metrics.

3.6 Integration of Model and Sensors

The hardware architecture utilizes an ESP32 DevKit V1 as the central node. Environmental monitoring is handled by a DHT11 sensor connected to GPIO 4. Soil moisture is monitored using a capacitive sensor on GPIO 34, which minimizes probe corrosion common in resistive sensors [25]. The pH measurement system utilizes a high-impedance probe and amplifier board interfaced with GPIO 32. The output is visualized locally on a 0.96-inch I2C OLED display (SDA on GPIO 21 and SCL on GPIO 22), as shown in Fig. 5.

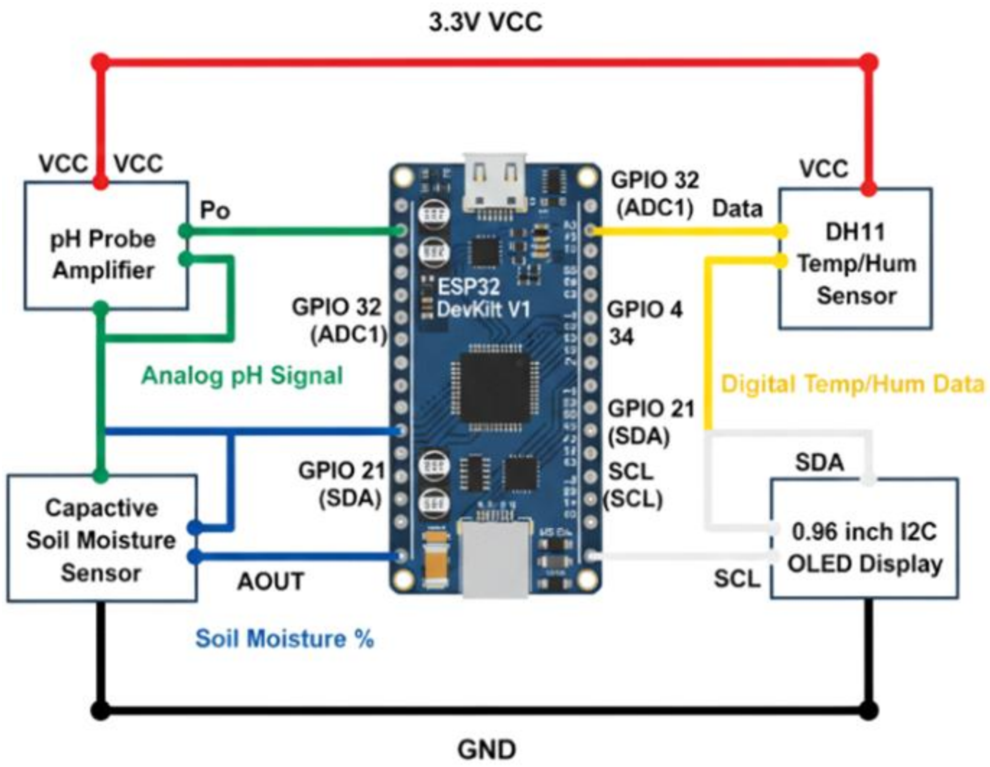

Figure 5: Fig. 5. Standardized circuit schematic and pin-mapping configuration, illustrating the interfacing of the pH probe amplifier (GPIO 32), capacitive moisture sensor (GPIO 34), and DHT11 (GPIO 4) with the ESP32 DevKit V1, alongside the I2C-based OLED dashboard

Fig. 5. Standardized circuit schematic and pin-mapping configuration, illustrating the interfacing of the pH probe amplifier (GPIO 32), capacitive moisture sensor (GPIO 34), and DHT11 (GPIO 4) with the ESP32 DevKit V1, alongside the I2C-based OLED dashboard

The ESP32 firmware manages synchronous sensor reads and ensures a clean output stream [8]. The host script utilizes the pyserial library to ensure that only complete data packets are processed. The raw ADC reading is converted to voltage and then mapped to the pH scale using a custom two-point calibration formula derived from measured voltages at pH 7.0 and pH 4.0 buffer solutions. This step is critical, as an uncalibrated pH reading would render the machine learning prediction invalid [26, 27].

3.7 Real-Time Precision Guidance

The final crop recommendation is presented as clear, actionable text on the local OLED display, shown in Fig. 6. This distributed dashboard interface serves both the farmer in the field and the researcher at the host console [5]. The display cycles through the real-time sensor readings for moisture and pH, providing local validation for the predictive decision. This immediate feedback loop allows for optimized seed selection and adaptive resource management without requiring access to a centralized network. The host console provides a more granular diagnostic view, displaying the raw telemetry, the validated feature vector, and the prediction confidence score [9].

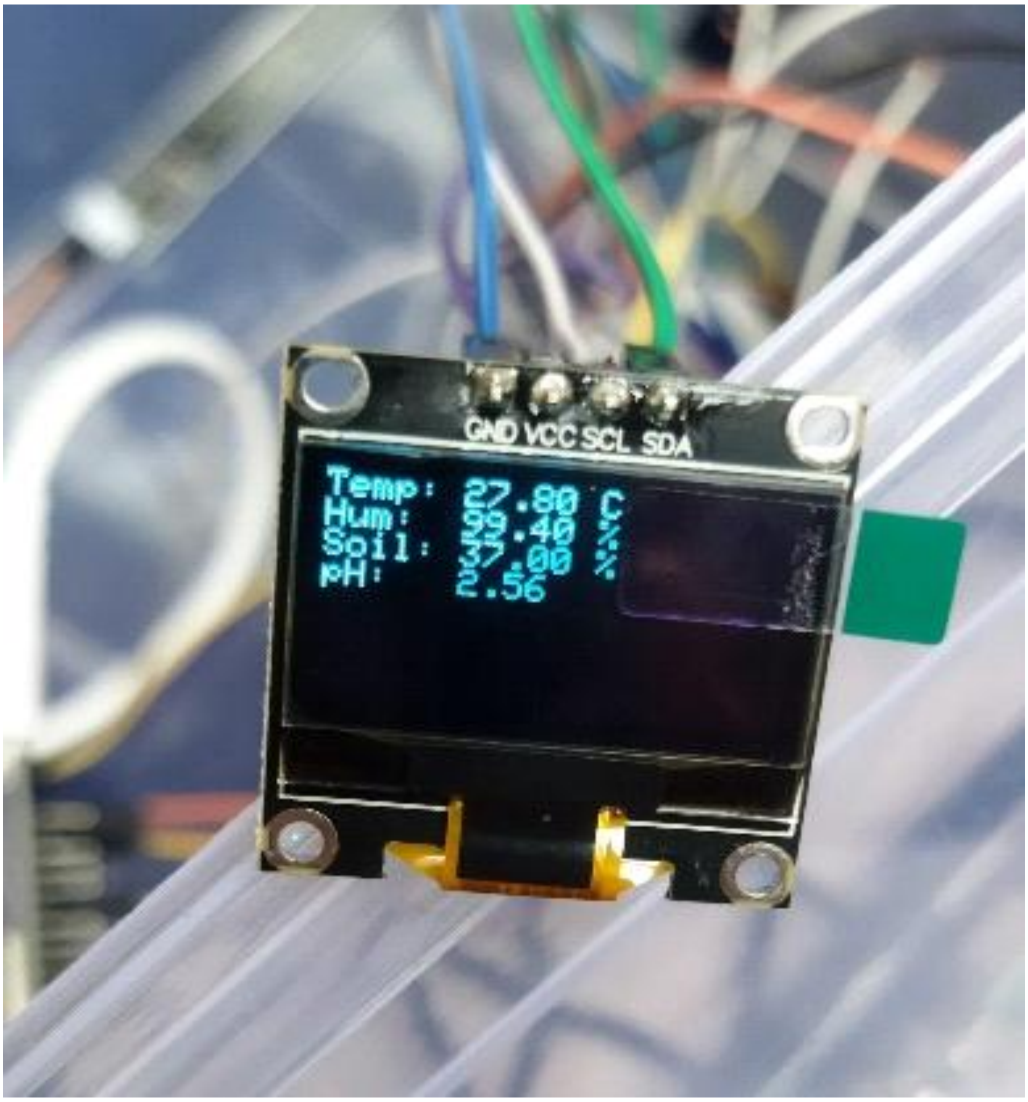

Figure 6: Fig. 6. Physical hardware prototype of the TerraSense IoT node showing real-time sensor telemetry (temperature, humidity, soil moisture, and pH) on the integrated OLED display

4. Results and Discussion

4.1 Time-Series Analysis and Signal Dynamics

The system maintains a live time-series analysis of the incoming soil dynamics over a 60-second window, shown in Fig. 7. This visualization provides diagnostic feedback, allowing observation of how parameters like soil moisture and pH stabilize after external interventions such as irrigation [10]. The high-frequency data acquisition is essential for detecting transient events and noise floors in the analog signals. The dual-axis plot illustrates the high-fidelity signal capture of the capacitive probe and sensor array, demonstrating the precision of the ESP32 ADC layer. This continuous monitoring ensures that the machine learning model always operates on the most current and accurate representation of the field environment [9].

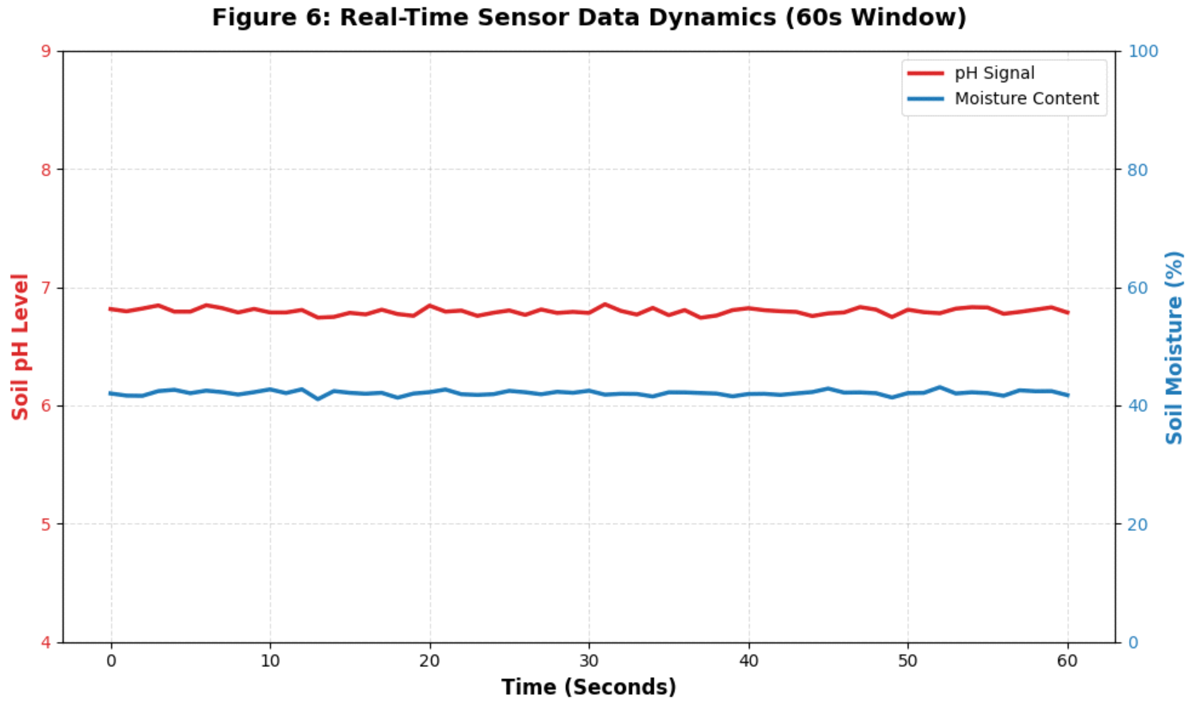

Figure 7: Fig. 7. Time-series analysis of soil pH and moisture dynamics during continuous monitoring over a 60-second window, demonstrating the precision of the ESP32 ADC layer

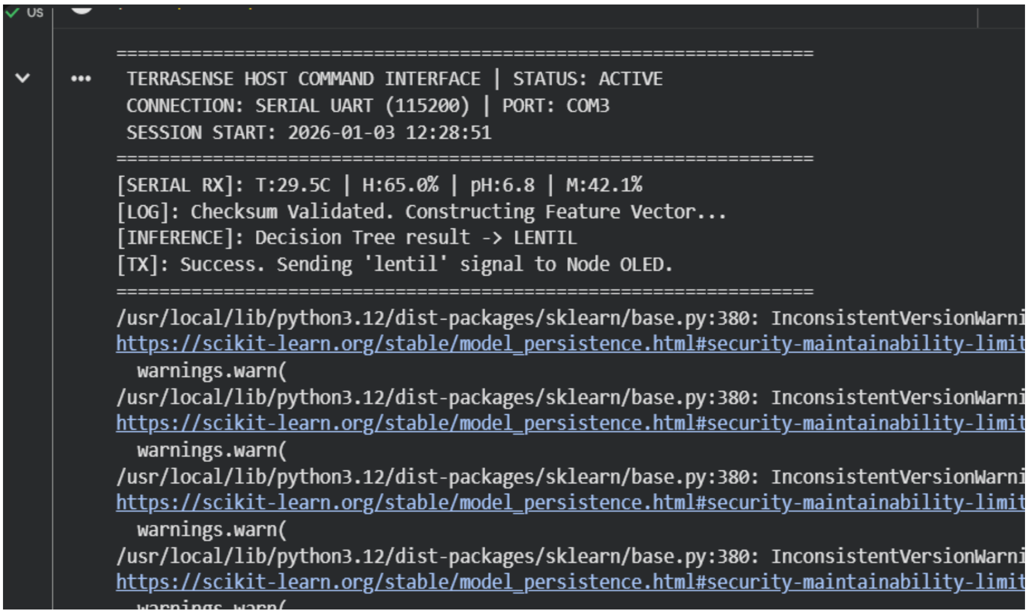

Figure 8: Fig. 8 shows the host-side dashboard interface, capturing the Python-based execution environment during real-time telemetry ingestion, data validation, and local execution of the Decision Tree pipeline for crop suitability determination.

4.2 End-to-End Latency Breakdown

The total time elapsed from sensor initiation to the final dashboard update is characterized as the end-to-end latency [2]. The TerraSense architecture achieves a deterministic execution time of approximately 120 ms, shown in Fig. 9(a). This includes 45 ms for data acquisition from the sensor array [20], 25 ms for signal conditioning and ADC conversion, 12 ms for AI inference on the host machine [22], and 38 ms for bidirectional feedback and display synchronization [24]. While cloud-dependent frameworks suffer from latencies exceeding 850 ms, as shown in Fig. 9(b), TerraSense maintains a tight, predictable window essential for real-time agricultural management [5, 28].

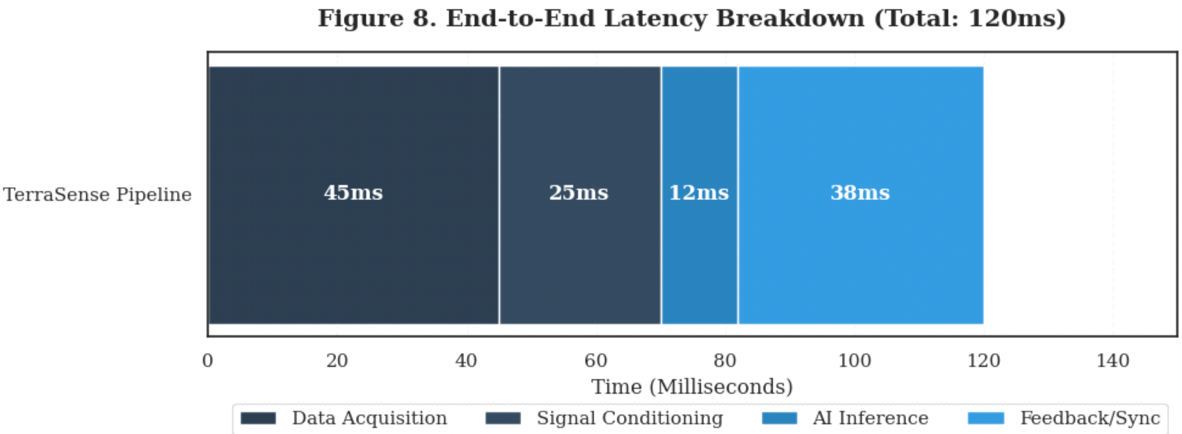

Figure 9: Fig. 9(a). End-to-end latency: temporal breakdown showing a deterministic 120 ms pipeline, including sensor acquisition (45 ms), signal conditioning (25 ms), AI inference (12 ms), and feedback synchronization (38 ms)

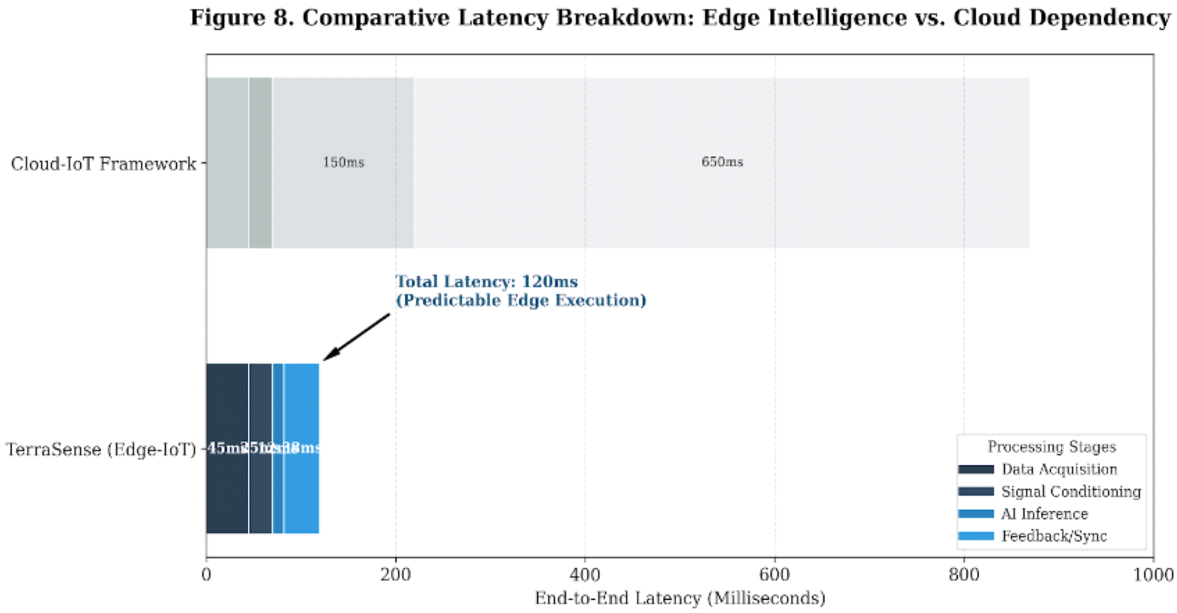

Figure 9: Fig. 9(b). Edge vs. cloud performance: comparative analysis highlighting TerraSense's internet independence (120 ms) versus cloud-dependent latencies exceeding 850 ms due to network overhead

5. Conclusion

The TerraSense framework successfully validates the feasibility of deploying a highly integrated IoT and machine learning solution for real-time crop recommendation. By employing a low-cost ESP32 and a robust serial communication pipeline, the system achieves the necessary speed and accuracy to provide timely precision guidance based on acidity, moisture, temperature, and humidity. The use of a calibrated pH probe and a Decision Tree ensures that the recommendations are both scientifically sound and computationally efficient. This approach aligns with the broader trend in smart-farming research toward validated, data-driven crop and yield decision support [29, 30]. A detailed temporal analysis reveals that the system operates with a deterministic end-to-end latency of approximately 120 milliseconds. This optimized computational pipeline provides a predictable and reliable feedback loop essential for real-time agricultural management.

Building upon this success, future work will focus on expanding the sensor array with dedicated Nitrogen, Phosphorus, and Potassium sensors to improve the accuracy of the machine learning model. Transitioning the data stream from USB to wireless protocols over the ESP32's Wi-Fi capabilities will enable remote deployment and large-scale data logging across distributed farm sites. Furthermore, exploring advanced machine learning architectures, such as Long Short-Term Memory (LSTM) networks, will facilitate predictive time-series forecasting of future soil conditions. These enhancements will solidify the role of integrated IoT and machine learning frameworks in creating adaptive and sustainable agricultural systems.

Author Contributions

Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing: original draft preparation, and visualization, R.K.; writing: review and editing, R.K., D.P., A.J., S.A., J.B. and D.B.; supervision and guidance, D.P., A.J., S.A., J.B. and D.B.; project administration, D.P. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The real-time sensor telemetry generated by the TerraSense hardware during operation is streamed directly to the host application for immediate, on-the-fly processing and is not archived as a standalone public dataset. The dataset used to train and validate the Decision Tree classifier comprising 2,200 records of Nitrogen, Phosphorous, Potassium, Temperature, Humidity, pH, Moisture, Soil Type, Crop Type, and Suggested Fertilizer values across 22 crop types, is available from the corresponding author upon reasonable request.

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Declaration on the Use of Generative AI and AI-Assisted Technologies

During the preparation of this manuscript, the author(s) used Claude (Anthropic) for the purpose of formatting the manuscript to the journal template, verifying and formatting the reference list, and improving language and readability. The author(s) reviewed and edited the output as needed and take(s) full responsibility for the content of this publication. No generative AI or AI-assisted tools were used to create or modify any figures, images, or data presented in this article.

Conflict of Interest

The authors declare no conflicts of interest.

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