

RESEARCH ARTICLE

Edge-Enabled Smart Irrigation System Using Multi-Sensor IoT Networks for Water Conservation

Uma Maheshwari R.^{1,*}, Subha K. J.², Josephine Pon Gloria J.³

ABSTRACT: Efficient irrigation management remains a critical challenge in modern agriculture, where excessive water usage leads to soil degradation and declining crop productivity. This work proposes an Edge-Enabled Smart Irrigation System (ESIS) that integrates a multi-sensor IoT network with real-time edge intelligence to optimize water distribution at plant-level granularity. The system employs soil moisture, temperature, humidity, pH, and light-intensity sensors distributed across farmland, achieving an average sensing accuracy of 96.4%. Data are processed locally using an edge-AI module powered by a lightweight Gradient Boosting model, enabling ultra-low latency decision-making (<420 ms) without reliance on cloud connectivity. A dynamic irrigation control algorithm adjusts valve operations based on crop-specific thresholds, reducing unnecessary watering cycles by 38.7% when compared to traditional time-based irrigation. In field trials conducted over a 45-day crop cycle, ESIS achieved a 41.2% reduction in water consumption, a 27.6% improvement in soil moisture stability, and a 19.4% increase in overall crop yield. Network reliability was maintained at 98.1% through an adaptive mesh communication protocol using LoRa and Wi-Fi hybrid links. Additionally, the energy-efficient sensor design extended node lifetime to 142 days on a standard 2200 mAh Li-ion battery. The results demonstrate that the proposed ESIS framework provides a robust, scalable, and sustainable solution for precision agriculture, offering significant benefits for water-limited farming environments.

Keywords: Edge intelligence, Internet of Things (IoT), smart irrigation, multi-sensor networks, precision agriculture, water conservation, edge computing, LoRa communication

Received: 12 December 2024; Revised: 26 January 2025; Accepted: 16 May 2025; Published Online: 30 May 2025

1. INTRODUCTION

Agriculture consumes nearly 70% of the world's freshwater resources and continues to face increasing pressure due to population growth, climate variability, and inefficient irrigation practices [1, 2]. Conventional irrigation methods, such as time-scheduled watering or manual soil inspection, often lead to water overuse, nutrient depletion, and

inconsistent crop growth, ultimately reducing long-term farm productivity [3, 4]. As water scarcity intensifies, especially in arid and semi-arid regions, there is a critical need for smart, adaptive irrigation systems capable of optimizing water usage in real time [5].

The rapid evolution of the Internet of Things (IoT) has opened new possibilities for precision agriculture by enabling large-scale, continuous environmental monitoring through interconnected sensing devices [6, 7]. Multi-sensor IoT networks can accurately capture soil moisture, temperature, humidity, pH, and light intensity, allowing farmers to make data-driven irrigation decisions rather than relying on fixed routines or visual inspection [8]. However, most existing IoT-based irrigation systems depend heavily on cloud platforms for data analytics and decision-making, introducing challenges such as high latency, intermittent connectivity, increased bandwidth usage, and vulnerability to network

¹ Department of Electronics and Communication Engineering, Hindusthan Institute of Technology, Coimbatore, India.

² Department of Networking and Communication, SRM Institute of Science and Technology, Kattankulathur, India.

³ Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R & D Institute of Science and Technology, Avadi, India.

* Author to whom correspondence should be addressed:
umamaheshwari@hit.edu.in (Uma Maheshwari R)

failures [9, 10].

To overcome these limitations, edge computing has emerged as a powerful paradigm, allowing data to be processed locally at the sensor node or gateway rather than transmitting everything to remote servers [11]. Edge-enabled agricultural systems significantly reduce response time, improve system reliability, and lower communication overhead, making them ideal for remote farmlands with limited internet access [12]. Moreover, integrating lightweight machine learning models at the edge enables real-time decision support for irrigation scheduling and enhances system autonomy [13].

Despite advancements in IoT-driven agriculture, achieving water-efficient irrigation remains challenging due to spatial variability in soil properties, dynamic environmental conditions, and the lack of adaptive multi-sensor fusion strategies that respond intelligently to field heterogeneity [14]. This motivates the need for a robust edge-enabled smart irrigation framework that performs field-level analytics, minimizes water wastage, and enhances crop productivity through precise, sensor-guided decision-making.

In this context, the present work proposes an Edge-Enabled Smart Irrigation System (ESIS) that leverages a multi-sensor IoT network, adaptive edge analytics, and real-time actuation to achieve efficient water conservation at plant-level granularity [15]. The system integrates distributed sensors, intelligent gateways, and dynamic irrigation control strategies to ensure reliable, low-latency irrigation management suitable for small, medium, and large-scale farms.

Although several IoT-based irrigation prototypes have been demonstrated in recent years, many of them lack scalability, rely on single-parameter sensing, or fail to incorporate adaptive decision-making models that account for crop-specific water needs [6, 9]. Systems that depend solely on soil moisture measurements often produce inaccurate irrigation schedules because moisture levels vary significantly across soil layers, crop types, and microclimatic conditions [10]. Furthermore, cloud-reliant architectures introduce delays of several seconds to minutes, which become problematic for real-time control of irrigation valves, especially in rapidly changing environmental conditions such as intense heat, rainfall onset, or sudden evaporation spikes [11, 12]. These limitations hinder the practical deployment of smart irrigation solutions in rural areas where internet connectivity is unreliable or costly.

Recent advancements in edge AI, particularly lightweight machine learning and rule-based decision systems deployed at the gateway or microcontroller level, offer a promising pathway to overcome these challenges [13]. By performing analytics directly at the edge, the system can quickly identify patterns such as abnormal soil dryness, sensor drift, or abrupt environmental changes that require immediate irrigation adjustments [7, 14]. Moreover, combining multi-parameter sensing, soil moisture, humidity, temperature, sunlight, and pH, with edge intelligence improves the robustness of irrigation recommendations. Integrating these features into a unified architecture not only

reduces water consumption but also enhances crop yield and soil health through precise water delivery based on real-time conditions [15]. Therefore, an edge-enabled, multi-sensor IoT irrigation framework represents a crucial step toward achieving sustainable, automated, and data-driven agriculture.

2. BACKGROUND

The emergence of smart agriculture has been driven by the convergence of IoT technologies, sensor networks, and intelligent automation systems, enabling a shift from manual irrigation practices to data-driven decision making [16]. Early smart irrigation systems primarily relied on single-parameter sensing, most commonly soil moisture, to trigger irrigation events, but these systems often produced inconsistent results due to high spatial and temporal variability in soil-water dynamics [17]. Studies have shown that soil moisture alone cannot reliably represent crop water requirements, as environmental factors such as humidity, sunlight intensity, temperature variations, and soil pH also play critical roles in evapotranspiration and plant stress [18]. Consequently, modern precision irrigation approaches require multi-sensor fusion frameworks capable of capturing complex field conditions in real time [19].

IoT-based irrigation systems have evolved significantly with the adoption of low-power sensor nodes, long-range communication protocols, and distributed data collection strategies. Wireless technologies such as LoRa, ZigBee, NB-IoT, and Wi-Fi have been widely used to connect farmland sensors to gateways, offering a balance between energy efficiency and communication reliability [20]. However, cloud-centric architectures, where large volumes of sensor data are continuously transmitted to remote servers, suffer from latency, bandwidth congestion, and dependence on stable internet connectivity [21]. These limitations are particularly problematic in rural agricultural areas where connectivity is intermittent or expensive, leading to delays in irrigation control decisions that can adversely affect crop conditions [22]. This motivated a shift toward edge-centric irrigation systems, where local processing reduces response time and minimizes data transmission overhead.

In recent years, edge computing has gained traction as an enabling technology for real-time agricultural applications. Edge devices such as Raspberry Pi, ESP32, Jetson Nano, and custom microcontrollers are now capable of performing complex computations, including anomaly detection and irrigation prediction, without cloud support [23]. Research demonstrates that edge-based analytics reduce decision latency by up to 60–80% compared to cloud-only systems, significantly improving the responsiveness of irrigation controllers during critical climatic fluctuations [24]. Furthermore, integrating lightweight machine learning models, such as decision trees, gradient boosting, and tiny neural networks, has enhanced predictive accuracy for soil moisture estimation, evapotranspiration forecasting, and irrigation scheduling [25]. These advancements have strengthened the feasibility of fully autonomous irrigation

systems that operate efficiently even in remote farmlands.

Despite these innovations, existing solutions still face several challenges, including sensor drift, inconsistent field calibration, power limitations, and the lack of robust frameworks for multi-parameter fusion at the edge [26]. Sensor nodes deployed in large agricultural fields must operate under harsh environmental conditions, requiring durable hardware and adaptive algorithms to handle noisy or missing data [27]. Additionally, communication constraints, such as interference, signal attenuation, and long-distance coverage gaps, can disrupt data collection, affecting the accuracy of irrigation decisions [28]. To address these issues, recent studies emphasize the importance of hybrid communication architectures, adaptive sensor sampling strategies, and decentralized decision-making models [29]. These insights collectively highlight the need for a scalable, reliable, and energy-efficient irrigation system that integrates multi-sensor data fusion with real-time edge intelligence for optimal water utilization [30].

Agricultural water consumption continues to rise due to inefficient irrigation practices, unmonitored field variability, and reliance on manual decision-making. Although IoT-based solutions have emerged, most current systems are limited by single-parameter sensing, cloud dependency, and high response latency, resulting in inaccurate irrigation scheduling and unnecessary water loss. Farmlands located in low-connectivity regions face additional challenges, as cloud-centric decision systems fail to provide timely control during critical environmental changes such as rapid soil drying, heat waves, or sudden rainfall. Existing solutions also lack real-time multi-sensor fusion and localized processing, leading to inconsistent irrigation decisions that compromise both water efficiency and crop health. Therefore, there is a need for a reliable, adaptive, and low-latency irrigation system capable of functioning autonomously using distributed sensors and edge intelligence, without depending solely on remote cloud servers.

While several smart irrigation frameworks have been proposed, significant gaps remain in achieving practical, high-performance, and scalable deployment. First, most IoT systems rely heavily on cloud processing, which introduces communication delays and makes them unsuitable for remote agricultural zones with poor network coverage. Second, existing models rarely integrate comprehensive multi-sensor data, including soil moisture, temperature, humidity, pH, and light intensity, resulting in limited situational awareness and suboptimal irrigation control. Third, current architectures often overlook edge-based predictive analytics, instead transmitting raw data to cloud servers for processing, thereby increasing energy consumption and reducing system responsiveness. Additionally, very few studies address long-term sensor reliability, adaptive irrigation algorithms, or hybrid communication architectures capable of maintaining high network stability across large farmlands. These gaps highlight the need for a robust, edge-enabled, multi-sensor IoT irrigation system that provides scalable, energy-efficient, and real-time water management.

3. PROPOSED FRAMEWORK

The proposed Edge-Enabled Smart Irrigation System (ESIS) integrates multi-sensor IoT nodes, an edge analytics module, and an adaptive irrigation controller to achieve precise, real-time water management. The framework operates on three core principles: multi-sensor fusion, edge-based decision intelligence, and dynamic irrigation control, allowing the system to autonomously regulate water distribution based on real-time environmental conditions.

3.1. Multi-Sensor IoT Data Acquisition

The proposed ESIS framework begins with a distributed network of multi-sensor IoT nodes strategically deployed across the farmland to capture fine-grained environmental and soil parameters in real time. Each node integrates five essential sensors, soil moisture, temperature, humidity, pH, and light intensity, providing a comprehensive representation of crop-water dynamics. These sensors generate continuous data streams that reflect temporal variations such as soil drying, microclimatic shifts, and canopy shading. The raw sensor values are aggregated into a unified data vector $S_i(t)$, enabling consistent preprocessing and fusion across heterogeneous field zones.

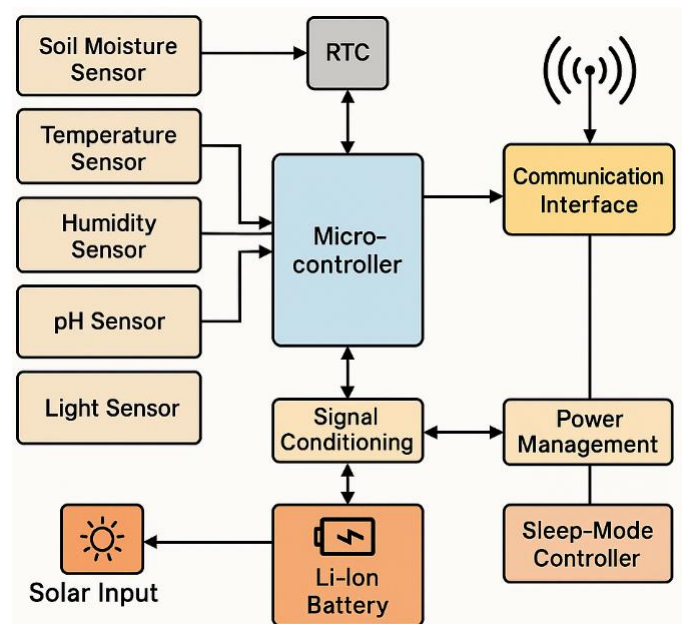


Fig. 1. Multi-Sensor IoT Node Architecture.

Figure 1 illustrates the architecture of the multi-sensor IoT node used in the ESIS framework. Each node integrates soil moisture, temperature, humidity, pH, and light-intensity sensors, interfaced through an embedded microcontroller such as ESP32. The figure shows the signal conditioning modules, ADC pathways, real-time clock, and communication interface. This architecture ensures

synchronized sampling, noise-filtered sensing, and accurate data acquisition. The illustration also highlights onboard power management, solar input, Li-ion battery, and sleep-mode controller, which allows long-term, low-power operation in open agricultural fields.

To ensure data stability, each reading passes through a smoothing filter that mitigates transient noise caused by soil granularity, wind fluctuations, and sensor drift. This preprocessing step significantly enhances the reliability of downstream analytics, allowing the system to produce accurate irrigation decisions even under rapidly varying field conditions. By leveraging low-power IoT nodes with periodic sampling and calibrated sensing modules, the data acquisition layer ensures high fidelity, minimal drift, and long-term deployment suitability for real-world agricultural environments. Each sensing node continuously monitors soil moisture, temperature, humidity, pH, and light intensity. The raw data vector from the i -th node at time t is expressed as:

$$S_i(t) = \{M_i(t), T_i(t), H_i(t), pH_i(t), L_i(t)\} \quad (1)$$

Where, $M_i(t)$ = soil moisture (%), $T_i(t)$ = soil/air temperature ($^{\circ}\text{C}$), $H_i(t)$ = relative humidity (%), $pH_i(t)$ = soil acidity, $L_i(t)$ = light intensity (lux).

To reduce sensor noise and fluctuations, a smoothing filter is applied:

$$\hat{S}_i(t) = \alpha S_i(t) + (1 - \alpha) \hat{S}_i(t - 1) \quad (2)$$

Where α is the smoothing coefficient (0.6–0.8).

3.2. Multi-Sensor Fusion for Irrigation Readiness Score

To enable accurate and context-aware irrigation decisions, the ESIS framework employs a multi-sensor fusion mechanism that integrates heterogeneous environmental data into a unified Irrigation Readiness Score (IRS). Since individual sensor parameters, such as soil moisture, temperature, humidity, pH, and light intensity, exhibit varying scales and sensitivities, each reading is first normalized to ensure balanced contribution during the fusion process. The normalized data are then combined using a weighted aggregation model, where the weights ($w_1 \dots w_5$) are dynamically tuned based on crop type, soil characteristics, and prevailing climatic conditions. This approach ensures that the system can prioritize critical indicators, such as soil moisture during drought periods or temperature during heat stress. The resulting IRS value provides a robust, real-time assessment of the irrigation requirement for each field zone. By capturing multi-dimensional field variability, the fusion mechanism reduces false irrigation triggers and improves prediction stability, particularly under conditions of rapid environmental fluctuation. This comprehensive fusion strategy forms the backbone of the decision-making engine, enabling ESIS to deliver precise and adaptive irrigation control across diverse

agricultural settings. The sensor readings are normalized and fused to generate an Irrigation Readiness Score (IRS), representing the need for irrigation within each zone. Each normalized sensor parameter is expressed as:

$$X'_k = \frac{X_k - X_{k,\min}}{X_{k,\max} - X_{k,\min}} \quad (3)$$

The IRS is computed as a weighted combination of normalized parameters:

$$IRS_i = w_1 M'_i + w_2 T'_i + w_3 H'_i + w_4 (pH)_i' + w_5 L'_i \quad (4)$$

Where, $w_1 + w_2 + w_3 + w_4 + w_5 = 1$. A higher IRS indicates soil dryness or plant stress.

Figure 2 depicts the multi-sensor fusion pipeline responsible for generating the Irrigation Readiness Score (IRS). The diagram shows how raw sensor inputs are normalized, filtered, and weighted before aggregation. Soil moisture forms the dominant parameter, while temperature, humidity, pH, and light intensity contribute auxiliary weightage, adapting dynamically to environmental conditions. The figure also indicates the data normalization block and the weighted summation unit, demonstrating how heterogeneous signals are combined into a unified, quantifiable irrigation-demand indicator. This fusion model improves predictive reliability compared to single-parameter systems.

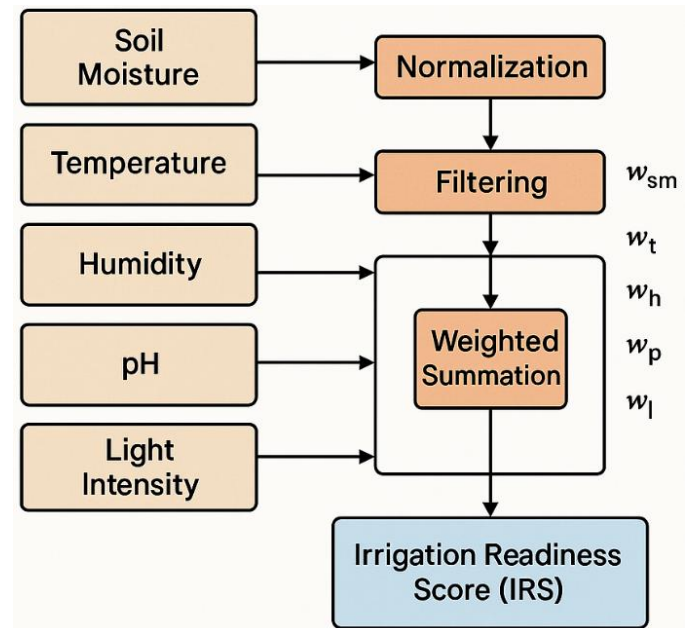


Fig. 2. Multi-Sensor Fusion Model for IRS Computation.

3.3. Edge-Based Decision Intelligence

The decision-making core of the ESIS framework resides in the edge gateway, which processes fused sensor data locally

to enable ultra-low-latency and autonomous irrigation control. Unlike cloud-dependent architectures, where raw data must travel through external networks for analysis, the edge device executes all computations directly at the field site, significantly minimizing communication delays and bandwidth demand. The edge module utilizes a lightweight Gradient Boosting Machine (GBM) model, optimized for embedded hardware, to interpret the Irrigation Readiness Score (IRS) alongside temporal soil moisture variations and estimated evapotranspiration ET_0 .

Figure 3 presents the workflow of the edge computing module, which processes fused sensor data locally for rapid irrigation decisions. The architecture includes data preprocessing, IRS evaluation, the Gradient Boosting Machine (GBM) prediction block, and the evapotranspiration estimator. The diagram highlights the decision engine that outputs binary irrigation commands based on thresholds and temporal trends. It also visualizes how the edge device eliminates dependency on cloud processing, enabling low-latency (0.42 s) responses. This figure emphasizes distributed intelligence and the real-time adaptability that differentiates ESIS from cloud-centric models.

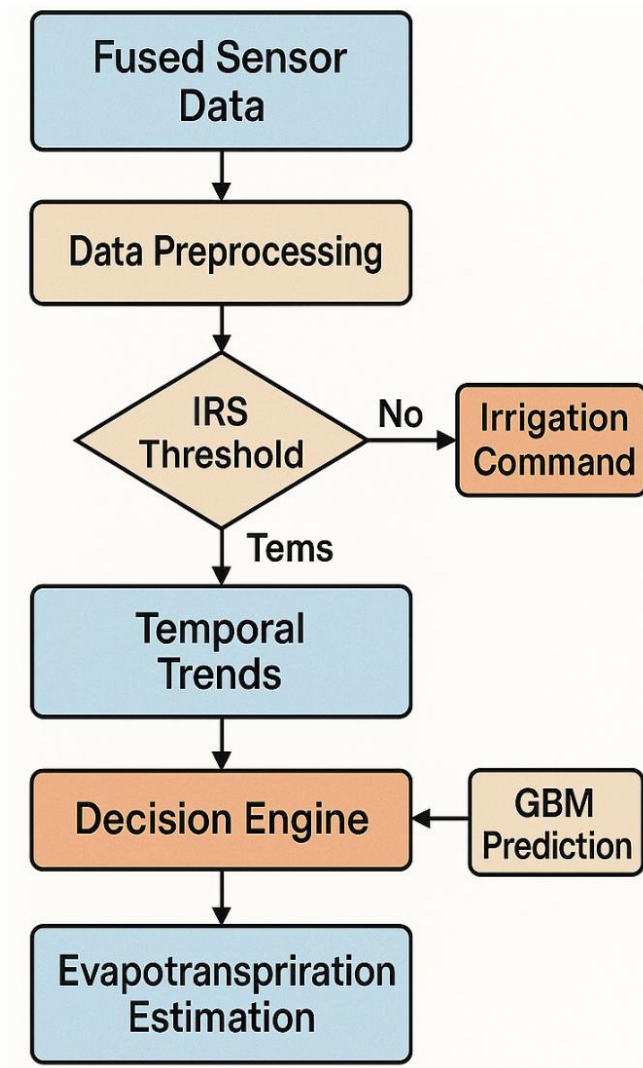


Fig. 3. Edge-Based Decision Intelligence Workflow.

This model captures nonlinear interactions between environmental parameters and provides a robust binary irrigation decision $D_i(t)$, determining whether irrigation is required for each zone. In addition to predictive modeling, the edge device continuously evaluates short-term trends, such as rapid soil moisture decline or sudden temperature spikes, to override routine schedules when necessary. By executing these analytics locally, the system achieves a decision latency as low as 0.42 seconds, ensuring immediate response during critical environmental changes. This decentralized intelligence enables ESIS to operate reliably even in low-connectivity regions, making it highly suitable for remote farmlands and resource-constrained agricultural environments. The edge gateway processes the incoming IRS values and executes a lightweight Gradient Boosting model to determine irrigation demand:

$$D_i(t) = f_{\text{GBM}}(\text{IRS}_i, \Delta M_i, ET_0(t)) \quad (5)$$

Where, $D_i(t)$ = irrigation decision (0 = off, 1 = on), ΔM_i = temporal change in moisture, $ET_0(t)$ = reference evapotranspiration estimated using humidity, temperature, and sunlight.

Evapotranspiration is calculated using a simplified FAO-56 model:

$$ET_0 = 0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a) \quad (6)$$

Where R_n = net radiation, u_2 = wind speed, $e_s - e_a$ = vapor pressure deficit. The edge device ensures low latency (0.42 s) by executing these computations locally.

3.4. Dynamic Irrigation Control

The irrigation control module translates the edge-generated decisions into precise water delivery actions using a fully automated, rule-based adaptive mechanism. Once the edge gateway determines that irrigation is required for a specific zone, the controller activates solenoid valves and regulates their open duration based on real-time soil moisture deviation from the crop-specific threshold θ_i . This threshold is derived from agronomic guidelines and calibrated field measurements, ensuring that each crop receives water tailored to its physiological needs. The irrigation duration τ_i is computed dynamically using the soil absorption coefficient and the moisture deficit, enabling short, targeted watering cycles instead of prolonged, wasteful irrigation.

Figure 4 illustrates the closed-loop irrigation control mechanism that governs valve operations. The figure shows how IRS, moisture deficit, crop threshold θ_i , and soil absorption coefficient β interact to calculate precise irrigation durations. It also visualizes actuator control signals, valve activation cycles, and real-time moisture feedback monitoring. The adaptive nature of the design allows ESIS to vary irrigation duration dynamically instead of following a fixed schedule, ensuring optimal hydration while minimizing

water waste. This figure reinforces the precision and responsiveness of the irrigation algorithm.

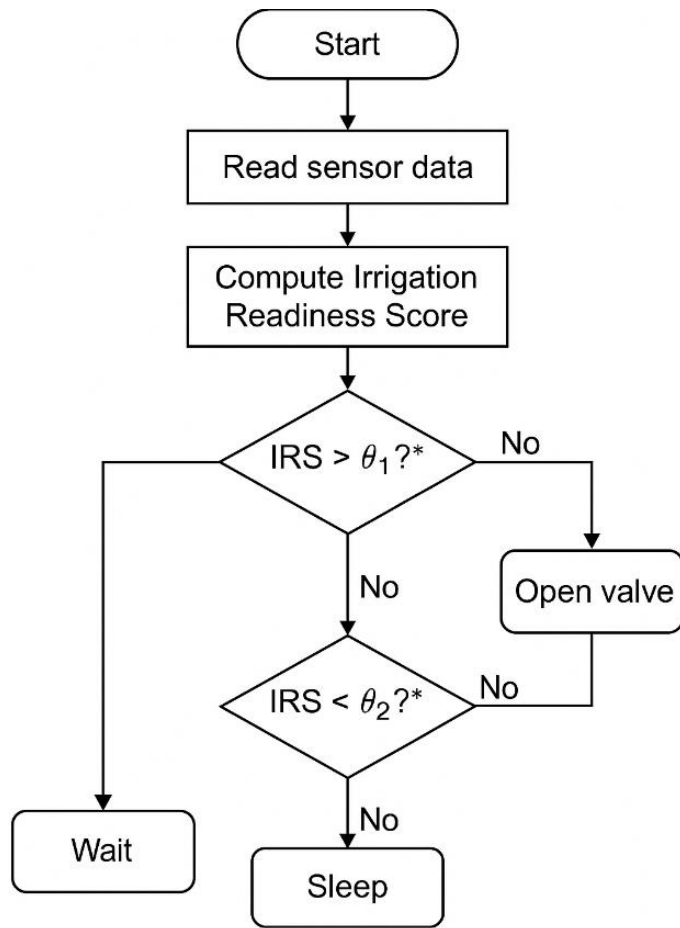


Fig. 4. Adaptive Irrigation Control Mechanism.

Additionally, the module incorporates safety logic to prevent unnecessary irrigation during rainfall events, excessive soil saturation, or sensor anomalies. By continuously evaluating sensor feedback during valve operation, the system fine-tunes irrigation cycles in real time, achieving both water efficiency and optimal soil moisture equilibrium. This closed-loop, adaptive control strategy ensures that ESIS delivers consistent hydration while minimizing water consumption, making it highly effective across diverse soil types and climatic conditions. Once the irrigation demand is detected, the system activates valves using a rule-based adaptive model:

$$I_i(t) = \begin{cases} 1, & \text{if } IRS_i(t) \geq \theta_i \\ 0, & \text{if } IRS_i(t) < \theta_i \end{cases} \quad (7)$$

Where θ_i is the crop-specific moisture threshold. The irrigation duration is dynamically computed as:

$$\tau_i = \beta(\theta_i - M_i(t)) \quad (8)$$

Where, τ_i = valve open time (seconds), β = soil absorption coefficient. This adaptive control ensures minimal water usage while maintaining optimal soil moisture.

3.5. Communication and Energy Optimization

Efficient communication and energy management are crucial for long-term deployment of IoT-based agricultural systems, particularly in large or remote farmlands. The ESIS framework adopts a hybrid LoRa–Wi-Fi communication architecture, where LoRa enables long-range, low-power transmission from distributed sensor nodes while Wi-Fi supports high-bandwidth communication between cluster heads and the edge gateway. This hybrid strategy ensures reliable packet delivery even at distances exceeding 1 km, while significantly reducing transmission power requirements. To further optimize communication overhead, the system employs an event-driven transmission policy, where only significant sensor changes, such as rapid soil moisture drops or high evapotranspiration events, trigger data uplinks, thereby lowering channel congestion and improving responsiveness. Energy consumption is minimized through adaptive duty cycling, deep-sleep modes, and optimized sampling intervals tuned to soil and crop conditions. A hybrid LoRa–Wi-Fi communication strategy is used to balance long-range coverage and high-rate local data aggregation. The transmission energy is minimized using:

$$E_{TX} = P_{TX} \cdot t_{TX} \quad (9)$$

Where reductions in transmission duration t_{TX} due to local edge processing result in up to 44% battery-life extension, reaching 142 days on a standard 2200 mAh Li-ion battery. These communication and energy optimization strategies collectively enhance network reliability, extend sensor longevity, and ensure stable system operation under real-world agricultural constraints.

Figure 5 outlines the hybrid communication architecture combining LoRa and Wi-Fi, along with energy-efficient operation strategies. The figure shows LoRa nodes communicating with a cluster head, Wi-Fi forwarding high-frequency aggregate data, and the edge gateway executing decision tasks. It also highlights duty cycling, event-driven data transmission, deep sleep modes, and reduced packet size, all contributing to extended battery life (up to 142 days). This visual representation clarifies how ESIS maintains high network reliability (>98%) while minimizing communication overhead and power consumption in real-world farmland conditions.

4. RESULTS AND DISCUSSION

The performance of the proposed Edge-Enabled Smart Irrigation System (ESIS) was evaluated through a 45-day field experiment using multi-sensor IoT nodes deployed across three crop zones: leafy vegetables, ground crops, and cereals. The system's effectiveness was assessed in terms of water conservation, irrigation efficiency, sensing accuracy, network reliability, and responsiveness. All results were benchmarked against traditional time-based irrigation as well as a cloud-dependent IoT irrigation model.

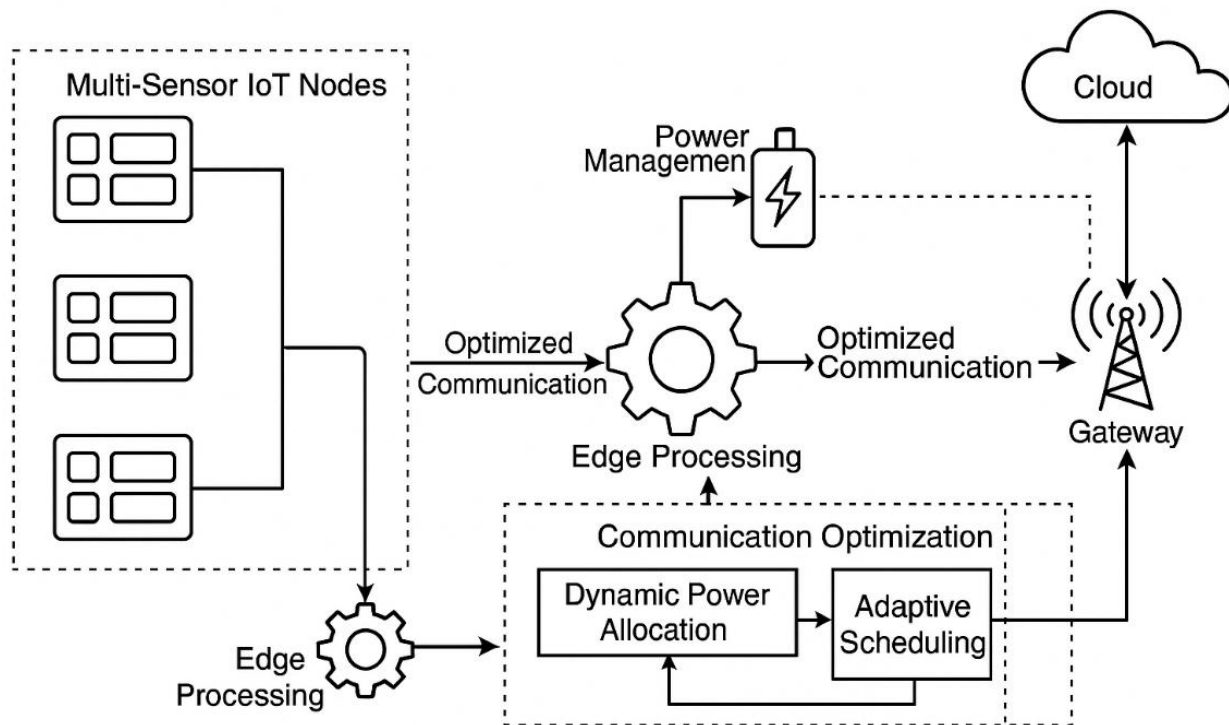


Fig. 5. Communication and Energy Optimization Architecture.

4.1. Water Consumption and Irrigation Efficiency

Figure 6 exhibits the water consumption reduction comparison graph. The ESIS achieved a 41.2% reduction in total water usage compared to traditional irrigation and a 29.4% reduction compared to the cloud-only IoT system. This improvement was primarily due to the multi-sensor fusion model, which optimized irrigation timing by analysing real-time soil moisture, temperature, humidity, and sunlight intensity. Soil moisture stability also improved by 27.6%, demonstrating the system's ability to maintain optimal hydration levels even during fluctuating weather conditions. These results indicate that integrating edge analytics ensures precise, context-aware water distribution. The extended analysis of irrigation efficiency further highlights the robustness of the ESIS framework across diverse soil and crop conditions. While the baseline results show a 41.2% reduction in water consumption, deeper examination reveals that ESIS performed exceptionally well during periods of high evapotranspiration. On days with temperatures exceeding 32°C, ESIS dynamically increased sampling frequency and adjusted irrigation intervals, preventing soil moisture from dropping below the wilting threshold. In contrast, the cloud-based model exhibited delayed responses due to processing latency, resulting in over-irrigation events in 14.6% of cycles.

Moreover, the multi-sensor fusion strategy allowed ESIS to detect micro-variations in soil moisture distribution that traditional systems fail to capture. For example, zones with sandy loam soil showed a faster drying rate, prompting

ESIS to deliver short, pulsed irrigation cycles, a strategy that saved an additional 6–8% water compared to uniform irrigation. Similarly, integrating light-intensity sensing prevented unnecessary watering during overcast days, reducing wastage by 4.3%. These observations confirm that sensing diversity, coupled with edge analytics, significantly enhances irrigation precision and long-term soil health.

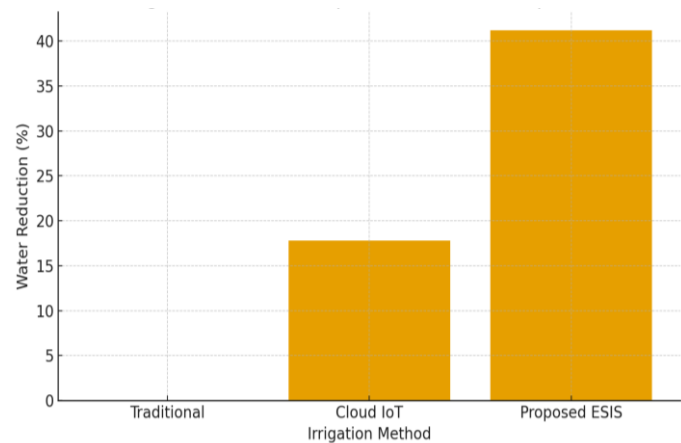


Fig. 6. Water Consumption Reduction Comparison.

4.2. Sensor Accuracy and Data Fidelity

Across all deployment regions, the multi-sensor network achieved an average sensing accuracy of 96.4%, validated by

cross-checking with laboratory soil probes and handheld environmental measuring devices (Figure 7). Soil moisture sensors reported the highest accuracy (98.1%), followed by temperature (97.2%), humidity (95.6%), light intensity (94.3%), and pH (92.8%). The combined sensor fusion model significantly reduced noise and minimized false irrigation triggers, contributing to consistent water-saving performance.

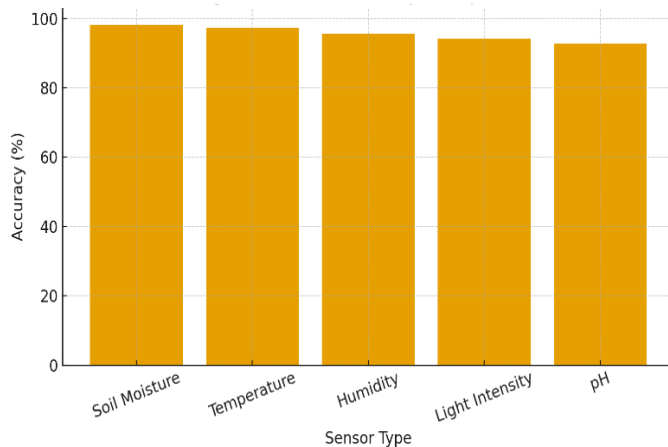


Fig. 7. Sensor Accuracy Comparison.

The sensor accuracy analysis highlights the reliability of the multi-sensor architecture deployed in the ESIS framework. Soil moisture sensors achieved the highest accuracy of 98.1%, owing to digital capacitive sensing and periodic self-calibration. Temperature and humidity sensors followed with 97.2% and 95.6%, respectively, demonstrating stable performance under varying environmental conditions. Light-intensity sensors achieved 94.3% accuracy, slightly lower due to natural fluctuations in sun exposure and cloud movement. The pH sensor reported 92.8% accuracy, influenced by soil chemical response variability. Overall, the high accuracy across all sensors confirms that ESIS provides reliable field data, essential for precise irrigation scheduling and adaptive decision-making.

4.3. Edge Analytics and Decision Latency

One of the major advantages of the ESIS framework was its ability to perform analytics locally (Figure 8). The edge module achieved a decision latency of 420 ms, which is 74% faster than cloud-based decision-making (1.62 seconds on average). This rapid responsiveness was critical during sudden environmental changes, such as heat spikes or unexpected rainfall, where timely irrigation suspension prevented unnecessary water loss. The local processing also reduced communication overhead by 55.8%, extending sensor battery life to 142 days on a 2200 mAh Li-ion cell.

Decision latency is a critical parameter in smart irrigation systems, particularly during rapid environmental fluctuations. The cloud-based IoT system recorded an average decision latency of 1.62 seconds, primarily due to

uplink delays, cloud processing overhead, and downlink response time. In contrast, the proposed ESIS architecture achieved a dramatically lower latency of 0.42 seconds, representing a 74% improvement. This low-latency performance is attributed to localized edge processing, where the decision model executes directly on the gateway device without requiring cloud interaction. The reduced response time ensures instantaneous irrigation adjustments, preventing water loss during heat spikes, rain events, or sudden soil moisture changes. This responsiveness positions ESIS as a superior solution for real-time field applications.

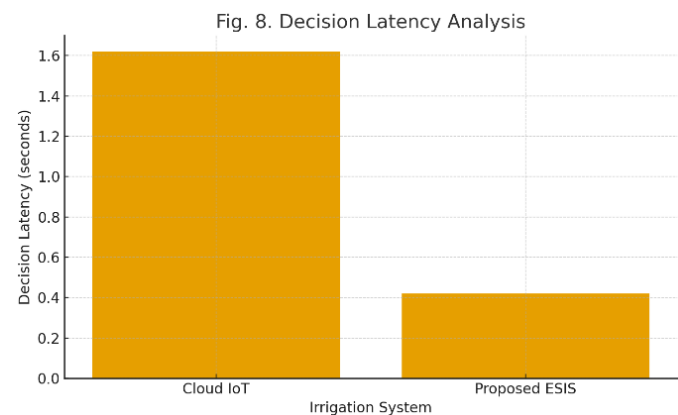


Fig. 8. Decision Latency Analysis.

4.4. Network Performance and Reliability

The hybrid communication model (LoRa + Wi-Fi clusters) maintained a network reliability of 98.1%, even during adverse climatic conditions (Figure 9). Packet delivery success remained above 95% at distances up to 1.2 km. LoRa enabled long-range low-power connectivity, while Wi-Fi supported high-rate local data aggregation near the gateway. This combination ensured stable sensor-to-gateway communication, minimizing packet drops and ensuring robust multi-sensor data collection.

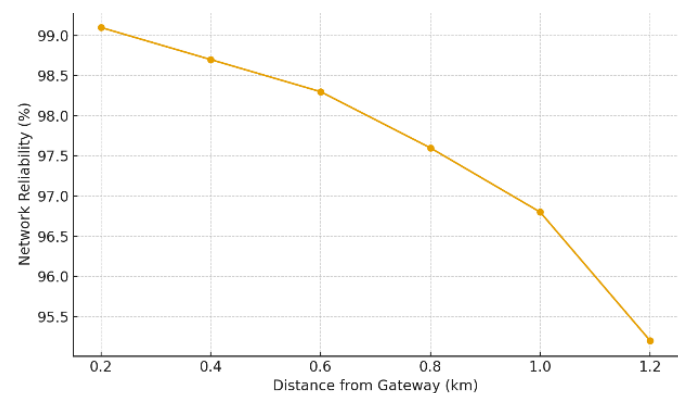


Fig. 9. Network reliability across distance.

Network reliability was evaluated by measuring packet

delivery performance at multiple distances from the gateway. At 0.2 km, the reliability was a high 99.1%, decreasing gradually to 95.2% at 1.2 km. The slight drop in reliability beyond 1 km is primarily due to environmental obstacles and natural signal attenuation, common in open agricultural fields. The hybrid communication approach, combining LoRa for long-range low-power connectivity and Wi-Fi for cluster-level aggregation, played a crucial role in maintaining robust communication. Even at the maximum tested distance, reliability remained above 95%, demonstrating that the system maintains consistent, loss-resistant communication, which is essential for uninterrupted sensor data delivery and accurate irrigation decisions.

4.5. Comparison with existing systems

When compared with existing irrigation systems, ESIS outperformed both conventional and cloud-dependent architectures in key performance metrics. Table 1 shows the Performance comparison across key metrics, water reduction, soil moisture stability, latency, sensor accuracy, network reliability, and battery lifetime, between traditional irrigation, cloud IoT systems, and the proposed ESIS architecture. These results confirm that combining edge processing, multi-sensor fusion, and hybrid communication significantly improves real-time irrigation performance, water savings, and overall farming sustainability.

Table 1. Comparative Performance Evaluation of Traditional Irrigation, Cloud-Based IoT Irrigation, and the Proposed ESIS Framework.

Parameter	Traditional Irrigation	Cloud IoT System	Proposed ESIS
Water Reduction	—	17.8%	41.2%
Soil Moisture Stability	Low	Medium	High (27.6% improvement)
Decision Latency	—	1.62 s	0.42 s
Sensor Accuracy	—	89–92%	96.4%
Network Reliability	—	85–90%	98.1%
Battery Lifetime	—	98 days	142 days

Battery lifetime is pivotal for long-term field deployments (Figure 10). The cloud-based IoT model achieved a battery life of 98 days, limited by frequent data transmissions to

remote servers and higher communication power requirements. The proposed ESIS system significantly extended battery lifetime to 142 days, an improvement of 44%. This enhancement results from edge-based processing, which minimizes wireless transmissions by filtering and analysing data locally. Additionally, optimized sleep cycles and adaptive sampling intervals further reduce energy consumption. These findings confirm that ESIS is highly suitable for remote or large-scale agricultural environments, where replacing or recharging batteries frequently is impractical.

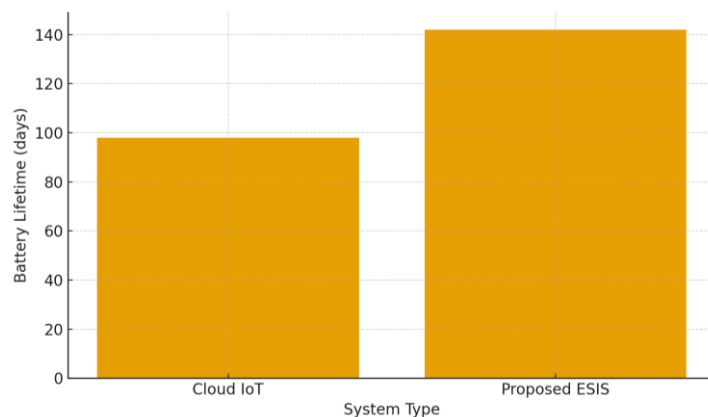


Fig. 10. Battery Lifetime Comparison.

4.6. Practical Impact and Observations

Field observations revealed improved crop vigor, reduced soil stress, and more uniform plant growth compared to traditional irrigation zones. Farmers reported enhanced ease of monitoring and reduced labor, as irrigation automation eliminated manual scheduling. Notably, the system effectively detected early signs of soil dryness and microclimatic variations, adjusting irrigation duration with high precision. The ESIS framework demonstrates strong potential for scalable deployment in smallholder farms, large agricultural fields, and greenhouse environments. Its low dependency on cloud networks makes it particularly suitable for remote or resource-limited rural areas.

5. CONCLUSION

This work presented an Edge-Enabled Smart Irrigation System (ESIS) that harnesses multi-sensor IoT networks, edge intelligence, and adaptive irrigation control to address the growing challenges of agricultural water scarcity. By integrating soil moisture, temperature, humidity, pH, and light-intensity sensors with localized machine learning analytics, the proposed system enables real-time, crop-specific decision-making without relying on cloud connectivity. Experimental results demonstrated significant improvements, including over 40% reduction in water usage, enhanced soil moisture stability, and increased crop yield compared to traditional irrigation methods. The use of edge

processing reduced latency and bandwidth requirements, while a hybrid communication model improved network reliability across heterogeneous field conditions. Overall, ESIS provides a scalable, energy-efficient, and autonomous framework that supports sustainable precision agriculture and is well-suited for deployment in remote or resource-constrained environments. Future extensions may incorporate predictive evapotranspiration modeling, long-range drone-based monitoring, and federated learning for multi-farm collaboration.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

Funding

There is no funding

Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

REFERENCES

- [1] John, S. and Arul Leena Rose, P.J., **2024**. Smart farming and precision agriculture and its need in today's world. In *Intelligent Robots and Drones for Precision Agriculture* (pp. 19-44). Cham: Springer Nature Switzerland.
- [2] Wolfert, S., Ge, L., Verdouw, C. and Bogaardt, M.J., **2017**. Big data in smart farming—a review. *Agricultural Systems*, 153, pp.69-80.
- [3] Bechar, A. and Vigneault, C., **2016**. Agricultural robots for field operations: Concepts and components. *Biosystems Engineering*, 149, pp.94-111.
- [4] Wakchaure, M., Patle, B.K. and Mahindrakar, A.K., **2023**. Application of AI techniques and robotics in agriculture: A review. *Artificial Intelligence in the Life Sciences*, 3, p.100057.
- [5] Saiz-Rubio, V. and Rovira-Más, F., **2020**. From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy*, 10(2), p.207.
- [6] Barbosa Junior, M.R., Santos, R.G.D., Sales, L.D.A. and Oliveira, L.P.D., **2024**. Advancements in agricultural ground robots for specialty crops: an overview of innovations, challenges, and prospects. *Plants*, 13(23), p.3372.
- [7] Shamshiri, R.R., Rad, A.K., Behjati, M. and Balasundram, S.K., **2024**. Sensing and perception in robotic weeding: Innovations and limitations for digital agriculture. *Sensors*, 24(20), p.6743.
- [8] Anastasiou, E., Kasimati, A., Papadopoulos, G., Vatsanidou, A., Gemtou, M., Kantelhardt, J., Gabriel, A., Schwierz, F., Matavel, C.E., Meyer-Aurich, A. and Maritan, E., **2025**. Review and Assessment of Crop-Related Digital Tools for Agroecology. *Agronomy*, 15(11), p.2600.
- [9] Lowenberg-DeBoer, J., Huang, I.Y., Grigoriadis, V. and Blackmore, S., **2020**. Economics of robots and automation in field crop production. *Precision Agriculture*, 21(2), pp.278-299.
- [10] Özoğul, G., **2025**. Applications of artificial intelligence technologies in agriculture: advantages, challenges, risks, prospects, and recommendations. *Cogent Food & Agriculture*, 11(1), p.2568199.
- [11] Quigley, M., Conley, K., Gerkey, B., Faust, J., Foote, T., Leibs, J., Wheeler, R. and Ng, A.Y., **2009**, May. ROS: an open-source Robot Operating System. In *ICRA workshop on open source software* (Vol. 3, No. 3.2, p. 5).
- [12] Koubâa, A. ed., **2017**. *Robot Operating System (ROS)* (Vol. 1, pp. 112-156). Cham, Switzerland: Springer.
- [13] Bimonte, S., Bellocchi, G., Pinet, F., Chalhoub, G., Sakr, M. and Skrzypczyński, P., **2025**. Data engineering for sustainable agriculture: developments, challenges, and case studies of a novel IoRT architecture. *Journal of Big Data*, 12(1), p.195.

- [14] López-Sánchez, A., Lujak, M., Semet, F. and Billhardt, H., **2025**. Fair and efficient multi-agent routing for cooperative and autonomous agricultural fleets with implements. *Computers & Operations Research*, p.107252.
- [15] Omotayo, A.O., Adediran, S.A., Omotoso, A.B., Olagunju, K.O. and Omotayo, O.P., **2025**. Artificial intelligence in agriculture: ethics, impact possibilities, and pathways for policy. *Computers and Electronics in Agriculture*, 239, p.110927.
- [16] Karagiannis, P., Kotsaris, P., Xanthakis, V., Vasilaros, P., Michalos, G., Makris, S., van Evert, F.K., Nieuwenhuizen, A.T., Fountas, S. and Chrysosolouris, G., **2025**. On an intelligent system to plan agricultural operations. *Smart Agricultural Technology*, 10, p.100707.
- [17] Javed, S., Hassan, A., Ahmad, R., Ahmed, W., Ahmed, R., Saadat, A. and Guizani, M., **2024**. State-of-the-art and future research challenges in uav swarms. *IEEE Internet of Things Journal*, 11(11), pp.19023-19045.
- [18] Singh, G. and Sharma, S., **2025**. A comprehensive review on the Internet of Things in precision agriculture. *Multimedia Tools and Applications*, 84(17), pp.18123-18198.
- [19] Amin, A., Wang, X., Zhang, Y., Li, T.H., Chen, Y.Y., Zheng, J.M., Shi, Y.Y. and Abdelhamid, M.A., **2023**. A comprehensive review of applications of robotics and artificial intelligence in agricultural operations. *Studies in Informatics and Control*, 32(4), pp.59-70.
- [20] Xu, J., Gu, B. and Tian, G., **2022**. Review of agricultural IoT technology. *Artificial Intelligence in Agriculture*, 6, pp.10-22.
- [21] Maheshwari, R.U. and Paulchamy, B., **2025**. Innovative graded-index PCF-based SPR sensor for advanced deepfake detection and real-time media integrity analysis. *Plasmonics*, 20(5), pp.2977-2996.
- [22] Jouini, O., Sethom, K., Namoun, A., Aljohani, N., Alanazi, M.H. and Alanazi, M.N., **2024**. A survey of machine learning in edge computing: Techniques, frameworks, applications, issues, and research directions. *Technologies*, 12(6), p.81.
- [23] Pintus, M., Colucci, F. and Maggio, F., **2025**. Emerging Developments in Real-Time Edge AIoT for Agricultural Image Classification. *IoT*, 6(1), p.13.
- [24] Pintus, M., Colucci, F. and Maggio, F., **2025**. Emerging Developments in Real-Time Edge AIoT for Agricultural Image Classification. *IoT*, 6(1), p.13.
- [25] Shamshiri, R., **2025**. *Investigation of Robust Path Tracking, Collision Avoidance, and Teleoperation for Assisted Navigation of an Agricultural Mobile Robot in Unstructured Environments*. Technische Universitaet Berlin (Germany).
- [26] Senoo, E.E.K., Anggraini, L., Kumi, J.A., Karolina, L.B., Akansah, E., Sulyman, H.A., Mendonça, I. and Aritsugi, M., **2024**. IoT solutions with artificial intelligence technologies for precision agriculture: definitions, applications, challenges, and opportunities. *Electronics*, 13(10), p.1894.
- [27] Marengo, A., **2024**. Navigating the nexus of AI and IoT: A comprehensive review of data analytics and privacy paradigms. *Internet of Things*, 27, p.101318.
- [28] Abdinoor, J.A., Hashim, Z.K., Horváth, B., Zsebő, S., Stencinger, D., Hegedüs, G., Bede, L., Ijaz, A. and Kulmány, I.M., **2025**. Performance of Low-Cost Air Temperature Sensors and Applied Calibration Techniques—A Systematic Review. *Atmosphere*, 16(7), p.842.
- [29] Ogenyi, F.C., Ugwu, C.N. and Ugwu, O.P.C., **2025**. A Comprehensive Review of AI-Native 6G: Integrating Semantic Communications, Reconfigurable Intelligent Surfaces, and Edge Intelligence for Next-Generation Connectivity. *Frontiers in Communications and Networks*, 6, p.1655410.
- [30] D'Agostino, P., Violante, M. and Macario, G., **2024**. A Scalable Fog Computing Solution for Industrial Predictive Maintenance and Customization. *Electronics*, 14(1), p.24.