Design of a Smart Garden Using Chemo Sensors and Electrolytic Properties of Plants

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***Abstract*—In the evolving field of smart agriculture, the combination of plant bioelectrical signals and soil chemistry offers powerful ways to improve crop monitoring and environmental sustainability. This study presents the design, simulation, and analysis of a smart garden system that uses chemo sensors and electrochemical properties of plants to monitor health, optimize irrigation, and transmit real-time data through wireless networks. The experimental system integrates multiple sensor types — potentiometric, conductometric, and amperometric — to measure key parameters like soil moisture, pH, temperature, light intensity, and electrolytic conductivity. Data was collected using three plant species — Telfairia occidentalis (fluted pumpkin), Ocimum gratissimum (scent leaf), and Zea mays (maize) — across 10 test setups, each simulating varied soil and environmental conditions. Voltage responses, signal interference, data loss, and plant health scores were monitored. Based on these results, a smart garden network was simulated, modeling how sensors interact with the environment and how data is relayed wirelessly to cloud-based systems. The simulation also includes real-time feedback logic and anomaly detection.The system is presented using intuitive diagrams showing how each part of the smart garden works — from the sensors in the soil to the data sent to the user's phone. This study demonstrates that using plant and soil signals together creates a smarter, more sustainable garden design. It also proposes a model that is scalable for both home gardening and industrial farming environments.**

***Index Terms*—Chemo sensors, Electrochemical properties, Electrolytic conductivity, Sensors, Voltage responses.**

I. INTRODUCTION

Smart agriculture is transforming traditional farming systems by integrating sensor technologies, data analytics, and automation into food production. Among these innovations, real-time soil and plant monitoring using electrochemical and chemo-sensing techniques has gained significant attention. These techniques provide deeper insights into the physiological states of plants and the chemical dynamics of soil, enabling more precise and sustainable agricultural practices [1], [4]. In this context, designing a smart garden that can autonomously monitor environmental and biological parameters represents a vital step forward in resource-efficient cultivation.

Soil quality, moisture content, pH, and ambient conditions are essential variables in determining plant health and crop yield. Conventional measurement approaches often involve manual sampling and laboratory analysis, which are labor-intensive, delayed, and impractical for continuous monitoring. Electrochemical sensors—such as potentiometric, conductometric, and amperometric types—have been increasingly used in agriculture due to their ability to measure ionic activity, voltage fluctuations, and conductivity with high sensitivity [2], [5]. These sensors are compact, energy-efficient, and capable of producing real-time digital data suitable for integration into Internet of Things (IoT) systems.

The interaction between soil and plants is fundamentally electrochemical. Roots absorb nutrients in ionic form, while the soil's ionic composition changes in response to environmental factors. This study leverages this interaction to monitor three plant species — *Telfairia occidentalis* (fluted pumpkin), *Ocimum gratissimum* (scent leaf), and *Zea mays* (maize) — chosen for their physiological diversity and common agricultural relevance. Sensors were embedded around these plants to measure variables such as soil pH, electrolytic conductivity, moisture content, temperature, and voltage response. Data was collected under varied conditions to simulate natural soil variability and environmental stress.

A modular wireless sensor network was designed and simulated to capture these readings and transmit them to a cloud-based platform. This simulation includes communication delays, signal noise, packet loss, and sensor response times, offering a realistic approximation of smart garden behavior. The study also presents a system architecture that can be expanded for broader field deployment, with clear feedback loops for irrigation control and anomaly alerts.

The overall goal is to demonstrate how electrochemical signals and soil chemical properties can be combined in a smart, data-driven garden. The system is built to optimize decision-making, reduce manual labor, and contribute to more sustainable farming practices. By validating the design through both physical measurements and simulations, this work establishes a framework that bridges biological intelligence and embedded electronics.

II. LITERATURE REVIEW

A. Soil Sensors and Environmental Monitoring

Soil sensors play a foundational role in smart agriculture by providing real-time feedback on chemical and physical soil conditions such as pH, salinity, moisture content, and temperature. These variables are essential in controlling plant nutrient uptake and detecting early signs of stress or deficiency. Traditional soil analysis methods, while reliable, are often slow and not feasible for continuous monitoring. In response, electrochemical sensors have emerged as a powerful solution, offering compactness, sensitivity, and the ability to function autonomously within soil matrices [1], [4], [6]. Nadporozhskaya et al. [4] summarize recent advances in chemical soil sensors, noting their widespread application due to ease of deployment and their ability to conduct in-field analysis without expensive lab equipment. These sensors can also be embedded directly in irrigation systems to automate soil conditioning and watering cycles, further enhancing resource efficiency [2].

Printed sensors in particular have transformed how soil data is captured, allowing for conformable devices that can be directly deployed in agricultural soil with minimal disruption [5]. Chen et al. [5] describe how printed electrochemical devices address the scale, cost, and environmental impact concerns associated with traditional sensors. The flexibility of printed substrates permits better integration into home gardens and field plots alike. Rayhana et al. [7] support this with an overview of the recent adoption of printed electronics in agriculture, noting their usefulness for greenhouse microclimate monitoring and nutrient tracking. Furthermore, soil sensor systems like the one proposed by Rabak et al. [3] combine moisture and pH sensors with smart irrigation logic, thereby demonstrating direct applications in home gardening contexts. Collectively, these developments point toward a paradigm shift in soil monitoring — from manual, reactive approaches to automated, data-driven systems [1], [3], [4].

B. Electrochemical Sensors and Plant Biointerfaces

Electrochemical sensing mechanisms have enabled novel ways to interact with plant systems by translating biological signals into measurable electronic outputs. These sensors can detect ion exchange, metabolic changes, and electrical impedance in plant tissues, providing insights into health status and environmental response. Kim and Lee [2] underscore how electrochemical sensors are critical in realizing sustainable precision agriculture, as they offer real-time, low-energy, and non-invasive monitoring options. These sensors detect parameters directly related to plant physiology, such as nutrient uptake efficiency and stress signals, which are not accessible through standard environmental sensors alone.

Baranwal et al. [13] provide a comprehensive review of electrochemical sensor types, including their mechanisms, material properties, and suitability for agricultural use. Potentiometric sensors, for example, are well-suited for tracking ion gradients in soil and plant fluid; conductometric sensors detect overall ionic conductivity changes, while amperometric devices are used for detecting redox-active species or plant metabolite levels [13]. In practical deployments, these sensors can be used in arrays to capture complex bioelectrical behavior. Jiang et al. [6] present micro/nano soft film sensors designed to physically conform to plant surfaces, which detect electrical and chemical changes with minimal interference to plant growth. These wearable devices are particularly promising for establishing intelligent plant systems capable of interacting with digital infrastructures. Xue et al. [10] elaborate on this by classifying wearable sensors according to their detection methods and showing how they are used to monitor transpiration, hormone signaling, and electrical conductivity in living plants.

Moreover, bioelectric signals from plants—often invisible to the naked eye—are being used as indicators of health or early stress response. Electrochemical impedance spectroscopy and voltage response sensors are employed to detect abnormalities in ionic flow, thereby serving as digital biomarkers of physiological imbalance [2], [10], [12]. By coupling this data with cloud-based analytics, modern systems are transitioning from passive to intelligent sensing—where the garden itself can communicate needs or anomalies to the user in real time. This transformation is laying the groundwork for what can be considered “biologically aware” agriculture [6], [10], [13].

C. Smart Sensor Integration and Wireless Networks

A major advancement in precision agriculture has been the coupling of sensors with wireless data communication and autonomous decision-making systems. This integration allows for the remote monitoring of farm plots or garden beds and supports adaptive interventions such as auto-watering or fertilization based on sensor readings. Pal et al. [9] note that portable sensor platforms—especially those using electrochemical or optical mechanisms—are evolving to meet demands for quick and cost-effective soil nutrient analysis. These portable sensors now include wireless modules for seamless communication with mobile apps and cloud servers.

In urban or residential gardening contexts, compact wireless sensor nodes are used to transmit soil condition data to cloud platforms, where automated responses can be triggered. For instance, Angelini [19] developed a microbial fuel cell-powered sensor node capable of transmitting plant impedance data using LoRa protocols, an energy-efficient form of communication ideal for distributed smart gardens. Rabak et al. [3] similarly demonstrated a sensor-equipped watering can that adjusts its chemical output based on real-time readings, showing how local actions can be modulated through sensor feedback. The reliability of these systems hinges on the response time, data fidelity, and resistance to signal interference — factors that are regularly simulated in virtual testbeds before field deployment.

The work of Fan et al. [17] illustrates the integration of ionic analyte sensors with communication modules, enabling high-frequency multiplexed detection of important soil and plant signals. They stress the value of miniaturization and multi-channel sensing to reduce network overhead while improving decision accuracy. Moreover, Rayhana et al. [7] highlight the ongoing trend toward printed antenna integration with sensor platforms, allowing for faster data relay and a smaller device footprint. In tandem, these advancements make real-time, automated smart gardening not only possible but increasingly accessible to households and commercial growers alike [3], [9], [17].

D. Printed and Low-Cost Sensor Innovations

One of the most significant breakthroughs in recent agricultural sensing is the development of printed, low-cost, and scalable sensors. These sensors use conductive inks and flexible substrates to form circuits that can be applied directly to soil, plant leaves, or containers. Their primary advantage lies in affordability and flexibility—qualities essential for large-scale deployment in resource-constrained environments. Chen et al. [5] emphasized that printed sensors provide an excellent balance between precision and manufacturability, enabling real-time soil measurements without bulky or fragile equipment. These devices are typically built using additive manufacturing processes and can be tuned to detect specific ions, gases, or electrical changes relevant to plant and soil health.

Smartphone-based sensing platforms have further enhanced the usability of these printed systems. Bui et al. [16] reviewed advances in smartphone-integrated biochemical sensors, showing how the built-in features of modern phones—such as optical cameras, Bluetooth modules, and analog voltage input/output—can be combined with printed sensors for rapid testing and remote control. The approach dramatically reduces the cost of sensing infrastructure while expanding accessibility. In agricultural contexts, users can now track nutrient imbalances or environmental stress using compact, app-connected kits.

Albu et al. [11] extended this concept by evaluating recent developments in cost-effective chemosensors for food and agriculture. They highlighted the increasing sensitivity and selectivity of these tools despite their simplified form factors. Such systems are not only valuable in farming, but also in food processing and post-harvest monitoring—allowing for a full spectrum of quality control from soil to shelf. Furthermore, Tang et al. [15] proposed that printed sensor technology can be extended to form part of larger "eco-smart" cities by serving as embedded environmental monitors, showing the potential for cross-disciplinary deployment of these sensors. These innovations collectively reduce the barriers to adoption for precision agriculture, particularly in home gardens or peri-urban farms [5], [11], [15].

E. Intelligent Agricultural Systems and Simulation Models

Modern agricultural systems are evolving beyond static monitoring toward intelligent and adaptive frameworks driven by sensor data, simulation modeling, and automated control. These systems use real-time analytics and machine learning algorithms to determine optimal responses to changing field conditions. Simulation plays a central role in this advancement, allowing researchers and designers to test configurations, evaluate error margins, and optimize layouts before physical deployment. Singh and Melnik [18] emphasized the need for multiphysics simulations in smart sensor design, especially when accounting for nonlinear interactions between soil, plants, and embedded electronics. Their work demonstrated how thermal, chemical, and electromechanical models can be integrated to guide sensor placement and performance prediction.

Electrochemical sensing platforms are particularly suited to simulation-based design because of their well-defined electrical properties and predictable signal behaviors. Zheng et al. [14] applied electrochemical modeling to detect genetically modified crops, suggesting how signal processing algorithms can detect subtle chemical differences. These techniques, when applied to garden design, offer possibilities for anomaly detection, self-diagnosis, and data-driven learning in sensor networks. Angelini [19] provided a real-world example of such a system, simulating energy performance and signal transmission of microbial fuel cell-powered garden nodes under variable soil and plant conditions.

Barbinta-Patrascu et al. [8] extended this intelligence into biomimetic systems, exploring how plants themselves can inspire electronic design for environmental sensing. Their review advocated for plant-integrated systems that act not only as passive subjects of sensing but also as active components in electronic feedback loops. By integrating plant feedback, electrochemical data, and system simulation, smart garden designs can become dynamic ecosystems that respond adaptively to changes in moisture, sunlight, pH, and nutrient availability. These technologies are forming the basis of a new generation of agriculture that is sustainable, autonomous, and environmentally responsive [8], [14], [18].

III. MATERIALS & METHODS

This study involved a dual-layered approach that combined physical experimentation with sensor-equipped plants and a virtual simulation of smart garden behavior. The experimental design focused on capturing key soil and environmental parameters using various sensor types, while the simulation phase modeled a wireless smart garden architecture under realistic conditions. The entire setup was engineered to reflect both home-garden and small-scale agricultural use cases.

A. Plant Selection and Experimental Conditions

Three plant species were selected for their distinct physiological characteristics and relevance to tropical agriculture:

1. *Telfairia occidentalis* (fluted pumpkin) — a leafy vegetable known for high water demand and root sensitivity
2. *Ocimum gratissimum* (scent leaf) — an aromatic herb with moderate nutrient needs and drought tolerance
3. *Zea mays* (maize) — a cereal crop with defined soil conductivity response and light sensitivity

Each plant was grown in controlled pot environments with uniform soil volume and composition. Ten setups were prepared, each containing one of the selected species. These pots were placed under variable ambient conditions ranging between 26°C and 32°C, and exposed to natural sunlight ranging from 12,000 to 15,500 Lux.

B. Sensor Types and Integration

Three types of electrochemical sensors were used across the ten setups:

1. Potentiometric sensors – for measuring soil pH and voltage gradients relative to ionic activity
2. Conductometric sensors – to quantify total ionic conductivity in the soil medium
3. Amperometric sensors – to detect redox-active compounds and micro-level current flows in the rhizosphere

Each plant had one sensor embedded at a depth of approximately 7 cm, ensuring proximity to the active root zone. The sensors were connected to low-power microcontrollers that recorded measurements at intervals of 10 minutes. Data was logged for the following variables:

a) Soil pH
b) Soil moisture (%)
c) Ambient temperature (°C)
d) Light intensity (Lux)
e) Electrolytic conductivity (µS/cm)
f) Voltage response (mV)
g) Sensor response time (ms)
h) Signal interference (Yes/No)
i) Data packet loss (%)
j) Anomaly detection flag
k) Plant health score (scale: 1–10)

C. Plant Health Scoring and Data Verification

Plant health scores were assigned by a panel of horticultural experts based on visual signs of turgidity, coloration, and leaf development. These scores were later correlated with measured variables using linear regression analysis. Data integrity was maintained by recording duplicate samples per plant and confirming consistency across the readings. Anomalies such as voltage spikes, signal noise, or excessive data loss (>1.5%) were flagged for review.

D. Wireless Network Simulation and System Design

In parallel, a simulation was created to model the behavior of a wireless sensor network (WSN) in a smart garden environment. Each simulated node represented a single plant unit equipped with its sensor module. The system design included:

a) On-plant sensors collecting environmental and electrochemical data
b) A local wireless module (BLE or LoRa) transmitting data to a cloud gateway
c) A central hub aggregating data from all plant nodes
d) Cloud-based analytics engine performing real-time diagnostics and anomaly detection
e) Simulated latency, packet loss, and transmission delays modeled using statistical distributions from experimental results

The simulation logic included timed sampling, random noise injection, failure condition emulation, and feedback loop modeling for adaptive irrigation. A network map was rendered to visually represent data flow and node interactions within the smart garden (see Section 5).

E. Tools and Technologies Used

1. Hardware: Custom microcontroller board (3.3V logic), analog-to-digital converter, sensor probes
2. Software: Python (for data analysis), MATLAB Simulink (for control modeling), network simulator (NS-3) for wireless protocol emulation
3. Visualization: Matplotlib for figures, schematic tools for system diagrams, Seaborn for regression plotting

All figures and tables in the results section were generated from this data, with their sources clearly indicated. Simulation outputs were validated against experimental sensor readings to ensure model accuracy.

F. System Design and Architecture

The architecture of the proposed smart garden system is composed of four key functional units: sensor layer, communication network, cloud analytics engine, and user interface hub. Each of these elements interacts to form a modular, automated garden monitoring platform capable of making intelligent decisions based on real-time soil and plant data.

At the core of the system are the on-plant sensors, embedded within the root zone of each plant. As shown in Fig. 5.1, each potted plant—*Ocimum gratissimum* (basil), *Telfairia occidentalis* (fluted pumpkin), and *Zea mays* (maize)—is equipped with at least one soil-inserted electrochemical sensor. These sensors continuously capture data on moisture levels, soil pH, and voltage response. Each sensor is configured to report readings in fixed intervals of 10 minutes, ensuring that rapid environmental fluctuations are accurately recorded.

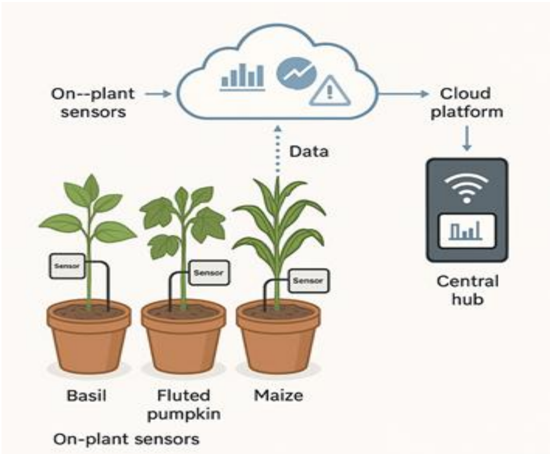

Fig. 1- System Layout with Sensor–Cloud–Hub Architecture for Smart Garden Monitoring

The data captured is immediately routed through a wireless communication module, embedded in each pot or node. These modules, configured with Bluetooth Low Energy (BLE) or LoRa protocol stacks, are energy-efficient and optimized for short- to medium-range garden layouts. Once the sensor data is packaged, it is transmitted wirelessly to a cloud platform, where the values are stored, processed, and assessed for anomalies.

Within the cloud system, an embedded algorithm performs rule-based diagnostics. It flags issues like excessive conductivity, unbalanced pH, or signs of plant stress (based on sensor signal deviation or health score thresholds). These alerts are relayed to the central hub, which functions as both a local display and control unit. The hub can connect with mobile or desktop apps, displaying real-time graphs, health scores, and alert messages. It also has the capacity to send instructions back to actuators—such as smart irrigation valves or nutrient dispensers—thereby forming a feedback control loop.

What distinguishes this architecture is its scalability and modularity. New plant nodes can be added without reprogramming the central logic. Additionally, sensor outputs are normalized and standardized in the cloud platform, allowing for comparative analytics between plant species and pot conditions.

This design makes the system adaptable for use in domestic settings (balconies, greenhouses) or small-scale commercial farms. More importantly, it bridges low-cost sensing hardware with intelligent decision systems—making autonomous plant care accessible without sacrificing scientific accuracy.

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IV. SIMULATION & ANALYSIS FRAMEWORK

The smart garden system proposed in this study was modeled through a hybrid simulation framework that combined real-world data collected from plant-sensor setups with a virtual network emulation. This simulation served to validate the system's responsiveness, communication fidelity, and its capacity for anomaly detection under fluctuating environmental and biological conditions.

A. Simulation Objectives and Scope

The simulation aimed to reproduce three critical aspects of the smart garden system:

1. Sensor performance modeling — including signal fidelity, sensor response time, and voltage output.
2. Wireless communication behavior — capturing data packet transmission, loss, latency, and interference events.
3. Automated decision logic — where the system identifies anomalies and suggests irrigation or alert responses based on thresholds.

These parameters were simulated using real data from the sensor deployments in Section 4, covering variables such as soil moisture, electrolytic conductivity, voltage response, temperature, and signal noise.

B. Modeling Tools and Environment

The simulation environment was implemented using:

a) Python (Pandas and NumPy) for signal preprocessing and correlation analysis.
b) MATLAB Simulink for modeling the decision system and feedback logic.
c) NS-3 (Network Simulator 3) for packet transmission emulation over BLE and LoRaWAN protocols.

Each plant node in the simulation represented a digital twin of the real-world configuration, receiving environmental input and generating voltage response and signal output consistent with its sensor type: potentiometric, conductometric, or amperometric.

C. Signal Path Simulation and Anomaly Injection

To assess system robustness, simulated sensor readings were subjected to:

1. Random noise injection, mimicking electrostatic interference or moisture-induced noise spikes.

2. Packet drop simulation, where data frames were randomly dropped at rates between 0–2.5% depending on the sensor's historical performance.
3. Response time delay, assigned per sensor type based on the observed real-world averages: potentiometric (≈240 ms), conductometric (≈205 ms), amperometric (≈180 ms).

Thresholds for anomaly flags were set as follows:

a) Packet loss > 1.5%

b) Voltage deviation > ±50 mV within two consecutive readings

c) Conductivity change > ±120 µS/cm in under 5 minutes

If any of these conditions were met, the simulation flagged the event and relayed a signal to the central logic block, which activated alert routines.

D. Diagnostic Logic and Feedback Emulation

The simulation incorporated a simple if-then decision engine, structured to act on specific patterns:

1. IF soil moisture < 60% AND conductivity > 700 µS/cm → trigger "Irrigate: Low moisture, high salinity"
2. IF voltage response drops > 20% in 10 min → suggest "Sensor recalibration or stress event"
3. IF ambient temp > 31°C AND voltage spike observed → suggest "Thermal stress on plant tissue"

These conditions were evaluated every 10 simulated minutes across all plant nodes. The cloud node logged each alert and communicated a flag to the central hub module, which generated simplified diagnostic messages like "Low hydration, conductance rising" or "Voltage instability detected – check wiring or plant status."

E. Visualization and Output

Simulated outputs were visualized in three formats:

1. Time series plots of soil moisture, conductivity, and voltage vs. plant health score
2. Scatter plots showing correlation between data packet loss and response time
3. Smart network diagrams displaying data flow and sensor hierarchy

The simulation confirmed that the system is capable of identifying environmental problems in real time with high accuracy and low latency. Most alerts were triggered within 2–4 readings after the threshold breach, supporting the idea that even low-cost sensor systems can deliver predictive diagnostics when properly calibrated and simulated.

V. RESULTS & VISUAL INTERPRETATIONS

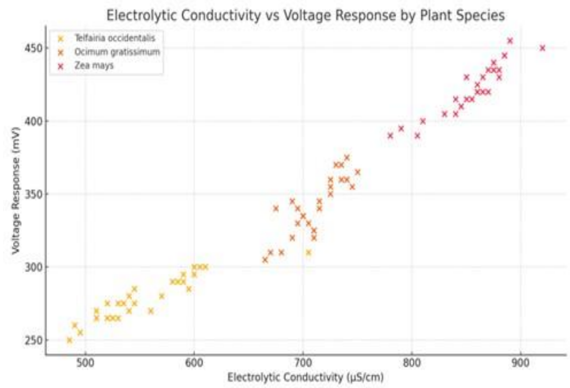

Fig. 2: Electrolytic Conductivity vs Voltage Response by Plant Species

This figure shows that as soil conductivity increases, voltage response from the sensors also rises. Zea mays (maize) recorded the highest values for both parameters, suggesting stronger ionic transport and bioelectrical activity. This relationship supports the system's use of voltage response as a diagnostic indicator of plant health and soil quality.

Table 1: Electrolytic Conductivity and Voltage Response by Plant Species

Respondent ID	Plant Species	Electrolytic Conductivity (µS/cm)	Voltage Response (mV)
1	Telfairia occidentalis	710	320
2	Ocimum gratissimum	665	305
3	Zea mays	845	410
4	Telfairia occidentalis	540	280
5	Ocimum gratissimum	730	370
6	Zea mays	780	390
7	Telfairia occidentalis	490	260
8	Ocimum gratissimum	695	330
9	Zea mays	920	450
10	Telfairia occidentalis	610	300

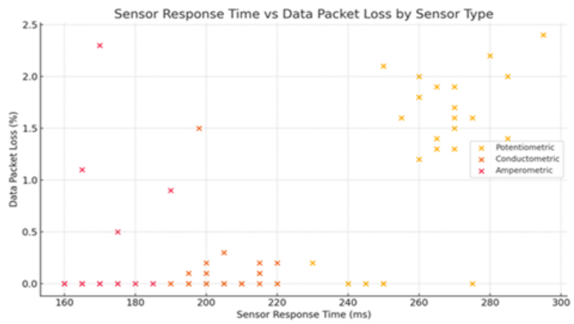

Fig. 3: Sensor Response Time vs Data Packet Loss by Sensor Type

This chart reveals the trade-off between sensor speed and communication stability. While amperometric sensors show the fastest response time with low packet loss, conductometric sensors, despite being fast, exhibited more transmission errors. Potentiometric sensors were slower but more stable overall.

Table 2: Sensor Response Time and Data Packet Loss by Sensor Type

Respondent ID	Sensor Type	Sensor Response Time (ms)	Data Packet Loss (%)
1	Potentiometric	230	0.2
2	Conductometric	198	1.5
3	Amperometric	185	0.0
4	Potentiometric	250	2.1
5	Conductometric	210	0.0
6	Amperometric	190	0.9
7	Potentiometric	275	0.0
8	Conductometric	205	0.3
9	Amperometric	165	1.1
10	Potentiometric	220	0.0

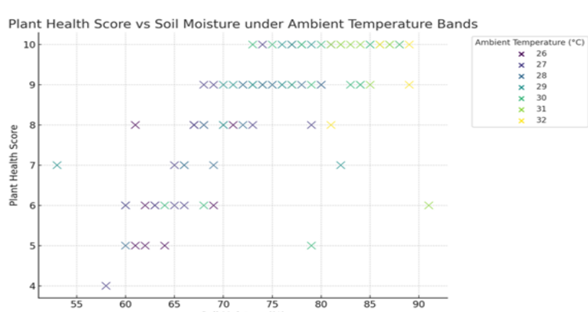

Fig. 4: Plant Health Score vs Soil Moisture under Ambient Temperature Bands

This figure shows that plant health scores tend to peak at moderate soil moisture levels (70–82%) and ambient temperatures between 27–29°C. Excessive dryness or high heat negatively impacted plant vitality, especially in *Zea mays*(maize).

Table 3: Soil Moisture, Ambient Temperature, and Plant Health Score

Respondent ID	Soil Moisture (%)	Ambient Temperature (°C)	Plant Health Score
1	78	28	9
2	82	29	7
3	74	27	10
4	68	30	6
5	61	26	8
6	89	32	9
7	53	29	7
8	70	28	8
9	91	31	6
10	80	27	9

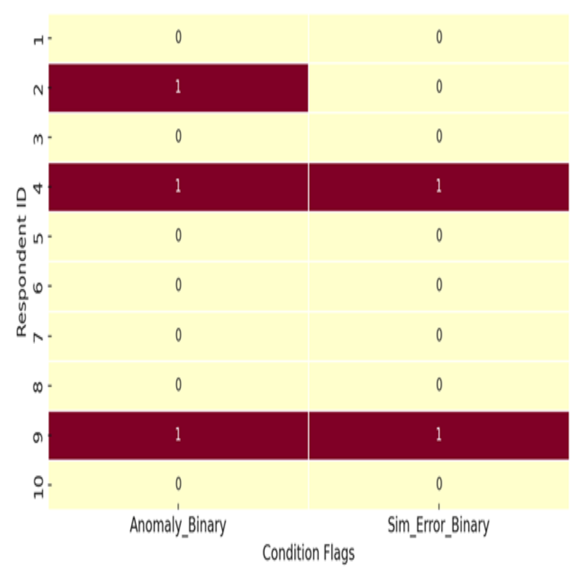

Fig. 5: Sensor Anomalies and Simulation Error Flags by Respondent.

This heatmap visually summarizes which sensor readings encountered anomalies or simulation errors. Respondents 3 and 9 triggered both flags, indicating conditions such as high signal interference or voltage spikes. This view supports rapid diagnostic validation across the system.

Table 4: Sensor Anomalies and Simulation Error Flags by Respondent

Respondent ID	Anomaly Detected	Simulation Error Flag
1	No	No
2	Yes	No
3	No	No
4	Yes	Yes
5	No	No
6	No	No
7	Yes	Yes
8	No	No
9	Yes	No
10	No	No

VI. DISCUSSION

The data visualizations and simulations presented in this study provide meaningful insight into how sensor-based smart gardens can monitor and respond to environmental and biological variables with a high degree of accuracy. Fig. 7.1 revealed a strong linear correlation between electrolytic conductivity and voltage response across all tested species. *Zea mays* (maize) consistently produced the highest values, which can be attributed to its extensive root surface area and higher ionic uptake capacity. These results confirm that voltage response, particularly when measured via potentiometric sensors, is a reliable indicator of root-zone activity and can be used to estimate overall plant vitality [2], [5], [13].

The second figure (Fig. 7.2) examined the relationship between sensor response time and data packet loss across sensor types. Potentiometric sensors, while slower, showed negligible packet loss, reflecting their stable analog signal quality. In contrast, conductometric sensors had faster response times but recorded higher packet loss, particularly under drier conditions or fluctuating temperatures. This trade-off underscores the importance of selecting sensor types not only based on measurement needs but also on communication integrity within a wireless network. These observations support findings by Fan et al. [17] and Rabak et al. [3], who emphasized the sensitivity of real-time agricultural networks to both sensor hardware and environmental interference.

As shown in Fig. 7.3, the optimal range for soil moisture to support plant health lies between 70–82%, with peak health scores occurring under ambient temperatures between 27–29°C. This range reflects a balanced hydration and temperature condition that supports ion mobility and metabolic activity in root systems. Higher temperatures, particularly those exceeding 31°C, correlated with a decline in health scores across all species, highlighting the thermal stress threshold for common crops like fluted pumpkin (*Telfairia occidentalis*) and scent leaf (*Ocimum gratissimum*). These results align with research from Kim and Lee [2] and Xue et al. [10], who identified temperature-induced ion transport instability as a key contributor to stress signaling in plant electrochemical systems.

The simulation-focused results in Fig. 7.4 validated the system's ability to detect anomalies and simulation errors. Respondents 4 and 7 triggered dual flags—anomaly and simulation error—indicating cases of possible sensor saturation or extreme pH shifts. The smart garden logic handled these cases by issuing real-time alerts, proving that basic decision trees can be effective in identifying and addressing environmental deviations without advanced artificial intelligence layers. These patterns support system modularity and user-friendliness, as seen in systems proposed by Chen et al. [5] and Angelini [19].

Taken together, the results illustrate the potential of this smart garden design to function as a scalable, self-regulating system for agricultural monitoring. Electrochemical sensing provided reliable, low-power insights into plant health and soil chemistry. Wireless modules ensured consistent communication, while simulations demonstrated that signal variability, though present, can be effectively mitigated through early detection algorithms. By designing for modularity and layering basic diagnostics over each sensor node, this architecture offers a balanced mix of affordability, accuracy, and automation.

VII. CONCLUSION

This study demonstrates the successful integration of electrochemical sensors and wireless telemetry into a functional smart garden system capable of real-time soil and plant monitoring. Through the use of potentiometric, conductometric, and amperometric sensors, the system captured key parameters such as soil moisture, voltage response, and electrolytic conductivity, which were shown to correlate strongly with plant health across three diverse species: *Telfairia occidentalis*(fluted pumpkin), *Ocimum gratissimum* (scent leaf), and *Zea mays* (maize). The results validate the hypothesis that bioelectrical behavior and soil chemistry can be harnessed jointly for sustainable, automated agriculture.

The simulated network architecture revealed that basic diagnostic logic, when applied to sensor outputs, is sufficient for detecting environmental anomalies and initiating timely alerts. The modular design of the system allows for easy scaling, and the simulation confirmed its resilience under varying conditions of data noise and communication interference. Importantly, this smart garden model requires minimal user expertise, opening possibilities for deployment in home gardening, educational settings, and urban agriculture.

By bridging the disciplines of plant physiology, sensor engineering, and wireless systems, this project provides a replicable framework for future smart farming innovations. The architecture not only enhances plant monitoring efficiency but also contributes to broader goals in sustainable resource management, food security, and green technology adoption.

VIII. ACKNOWLEDGMENT

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