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AI-Driven Smart Connectivity and Sustainable Energy Model for Rural Agricultural Communities

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Abstract- Rural agriculture, vital to global food security and livelihoods, continues to face persistent challenges of weak connectivity, unreliable energy access, and inefficient data management, all of which constrain productivity and economic growth in underserved regions. This study introduces an AI-driven smart connectivity and sustainable energy model that integrates solar-based energy management, AI-optimized signal amplification, and IoT-enabled precision farming into a unified off-grid framework. Field deployment in Agbanganam village, Nigeria, demonstrated that intelligent solar management sustained IoT and communication services for up to four days under limited sunlight, while adaptive amplification improved average reference signal received power by ≥10 dB, raising levels from below –110 dBm to above –85 dBm, extending coverage from 0.3 km² to over 5 km², and boosting throughput by 28%. On the agricultural front, smart farming validation using an LSTM model achieved an F1-score of 0.87 in predicting irrigation events, enabling more efficient water use and reducing irrigation by 15%. Statistical analysis further confirmed that AI-assisted plots yielded significantly higher cassava output than control plots (ANOVA, $p < 0.01$), with yield improvements of up to 22%. These outcomes demonstrate that the proposed AHOM framework not only enhances network accessibility and energy reliability but also delivers measurable gains in agricultural efficiency and productivity. Overall, the findings affirm that strategically combining AI, IoT, and renewable energy within a community-centered platform can sustainably bridge the digital divide, improve food security, and empower rural economies.

Index Terms- Smart Agriculture, Sustainable Energy, Signal Boosting, Internet of Things (IoT) Artificial Intelligence (AI)

I. INTRODUCTION

Agriculture is undergoing rapid transformation through the convergence of Information and Communication Technologies (ICTs), wireless connectivity, the Internet of Things (IoT), and Artificial Intelligence (AI), driving productivity, sustainability, and environmental protection [1]– [5]. Modern wireless technologies such as 4G/5G/6G, Li-Fi, Gi-Fi, and Wi-Fi 6/6E provide high-speed, low-power connectivity for large-scale data exchange, which enable real-time IoT applications that enhance worker safety, regulate environments, and ensure compliance with safety protocols – demonstrating versatility across domains such as industrial monitoring, agriculture, and healthcare [6] – [9]. Beyond productivity gains, these innovations to reduce the digital divide between urban and rural regions [10][11].

Figure 1 illustrates the concept of smart agriculture, enabled by AI–IoT convergence, redefining agriculture through precision farming, irrigation automation, blockchain-enabled supply chains, and real-time resource monitoring of crops, livestock, soil, and resources; addressing challenges related to climate change, food insecurity, and labor shortages [12] – [14]. When integrated with renewable energy and AI-driven analytics, these solutions can support resilient, scalable infrastructures and connectivity essential for rural farming [15].

Despite progress in urban areas, rural agriculture remains constrained by unreliable power supply, weak digital connectivity, limited access to digital tools, and dependence on traditional practices, which undermine food security, economic growth, and farm information management [7][15] – [17]. Globally, combined with limited internet access, 666 million people lack electricity in rural areas [18]. In many regions of Sub-Saharan Africa, only 28% of rural households have electricity, while internet penetration remains below 30% [19][20]. This digital divide prevents farmers from accessing real-time forecasts, market data, and modern farm management tools [16].

This study proposed solution that address these challenges by developing an AI-enabled platform that integrates solar energy, signal amplification, and IoT-based farming tools. The framework aligns with the UN Sustainable Development Goals (SDG 2, SDG 7, SDG 9) [21] – [23] and demonstrates how converged digital and energy infrastructures can accelerate sustainable rural farming transformation

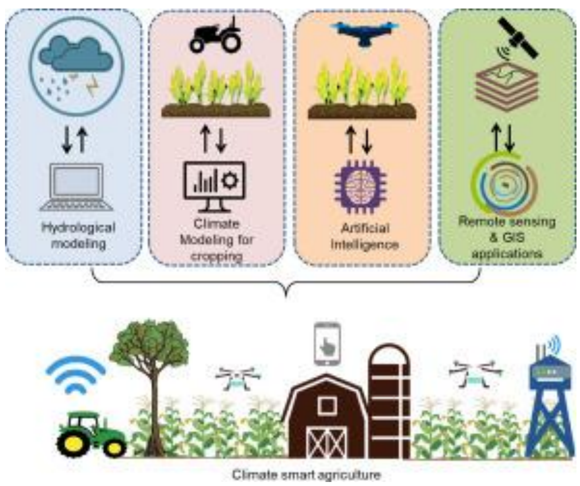


Figure 1: Concept of smart Agriculture [5]

II. RELATED WORKS AND RESEARCH GAP

Prior studies have examined behavioral [16][24], interoperability [17], and security barriers [11] to technology adoption, but lack context-specific frameworks in rural settings. Real-world initiatives underscore the timeliness of AI–IoT integration. Africa's Rural Electrification Programs [15] and India's Digital Agriculture Mission [25] demonstrate government recognition of technology's role in rural farming transformation. Field evidence further shows IoT-enabled solar irrigation increased yields by 40% [26], AI-optimized microgrids reduced energy costs [27], AI-based weather prediction reached 85% accuracy and reduced crop losses by 25% [28], AI insect surveillance reduced pesticide application by 30%, and IoT-based smart irrigation achieved 40% water savings [29] and AI-powered rural connectivity boosters have improved digital access [30]. Other studies explore AI, IoT, and renewable energy in advancing rural agriculture. The research in [4] developed AI models optimized for resource-constrained rural contexts, but their solutions lacked scalability for farmers with limited technical expertise. The research in [6] proposed hybrid frameworks combining LPWAN and 5G for agricultural connectivity, yet the long-term scalability and affordability of such models remain uncertain. In addressing energy challenges, [14] introduced solar-powered IoT systems for agricultural monitoring, yet their work did not optimize energy management for AI-driven processes. Complementary efforts by [31] and [32] explored the potential of predictive maintenance with machine learning, but lacked real-time IoT integration and adaptation to low-resource environments.

From the reviewed literature, most studies focus on isolated applications of IoT in agriculture, AI in connectivity, or solar power in rural electrification. What is lacking is a converged framework that unifies cellular signal boosting, renewable energy optimization, and IoT-based farming. This study proposes an integrated solution comprising

(i) AI-optimized signal boosters for resilient connectivity,
(ii) solar energy management for sustainable power, and
(iii) IoT-enabled smart farming for precision agriculture.

This unified framework is an effort to promote interoperability, affordability, and scalability in rural farming, while advancing digital inclusion. In doing so, it aims improve agricultural productivity, and empower rural communities through sustainable and intelligent infrastructure.

III. MATERIALS AND METHODS

Figure 2 shows the system block diagram used in this study. the diagram represents the concept of AI-based smart agriculture and connectivity, showing key components of the system.

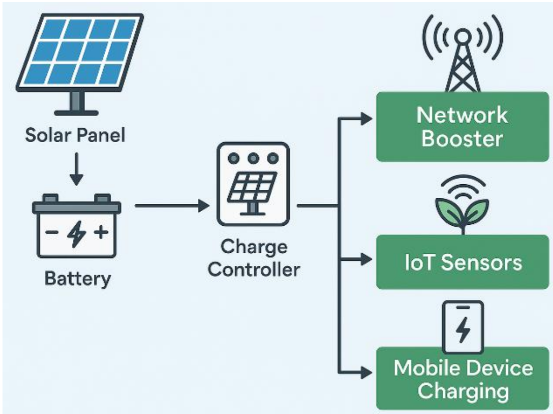


Figure 2: Block Diagram of the AI-IoT based smart agriculture.

A. Study Area and Experimental Setup

Table 1 below present the summary of the experimental setup. The study was conducted in Agbanganam village (9.0820° N, 8.6753° E), a semi-rural agrarian community in southern Nigeria representative of many Sub-Saharan farming settlements. Agriculture in the area relies on seasonal rainfall, traditional tools, and low technology adoption, making it suitable for testing affordable, intelligent farming solutions. The landscape comprises loamy soils and sparse vegetation, supporting crops such as cassava, maize, yam, and vegetables. The climate is tropical with a dry season (November–March) and wet season (April–October). A six-month trial (January–June 2025) was selected to capture the transition between seasons and evaluate system performance under varying soil moisture and solar conditions.

Table 1: Summary of Study Area and Experimental Setup

Aspect	Description
Location	Agbanganam village, southern Nigeria (9.0820° N, 8.6753° E)
Community Profile	Semi-rural, smallholder and subsistence farmers, low exposure to technology
Soil & Vegetation	Loamy soils; sparse vegetation (grasses, shrubs); supports cassava, maize, yam, vegetables
Climate	Tropical: Dry season (Nov–Mar), Wet season (Apr–Oct)
Trial Period	Six months (Jan–Jun 2025), covering dry-to-wet season transition
Connectivity	MTN, GLO, and Airtel 4G LTE (700–2600 MHz); varying coverage enabled signal analysis
Experimental Area	~2 hectares, divided into Treatment Zone (smart system) and Control Zone (conventional farming)
IoT Deployment	Sensor nodes for soil moisture, temperature, and humidity; strategically distributed
Power Source	Solar-powered system with ESP32 microcontroller for control, logging, and irrigation
Edge Computing	Local data center for low-latency, near real-time analytics
Farmer Involvement	Surveys and interviews to capture usage patterns and community feedback

B. Signal Optimization

Agbanganam village experiences weak and fluctuating signals which hinder efficient data transmission. To address this weak cellular coverage, a signal optimization protocol was implemented to enable reliable communication between farm sensors, user terminals, and cloud-based analytics platforms.

Baseline Measurement phase: Signal mapping was performed within a 200-meter radius from the centre of the deployment area. RSRP (for signal strength) and SINR (for signal quality) were measured at 50-meter intervals in four directions (north, south, east, and west) via the OpenSignal app, generating a 25-point spatial grid, and were cross-validated with a professional-grade LTE Cell Scanner for accuracy. Figure 3 shows sample for field measurements of poor and strong signals using the OpenSignal mobile app.

RL-Based Boosting: Once the baseline measurement was established, a signal booster system was deployed using an ESP32-controlled motorized antenna regulated by a Reinforcement Learning (RL) algorithm. Guided by the reward function expressed in Equation 1, the algorithm adaptively adjusted antenna orientation to maximize signal quality while minimizing energy use, aligning with the system's sustainability goals for off-grid operation

$$Reward = \Delta RSRP - 0.1 \times [Energy]_{used} \quad (1)$$

Where: ΔRSRP represents the change in signal strength due to antenna movement; $[Energy]_{used}$ represents the incremental energy consumed during antenna rotation and signal processing; RSRP is Reference Signal Received Power (dBm), SINR is Signal-to-Interference-plus-Noise Ratio (dB).

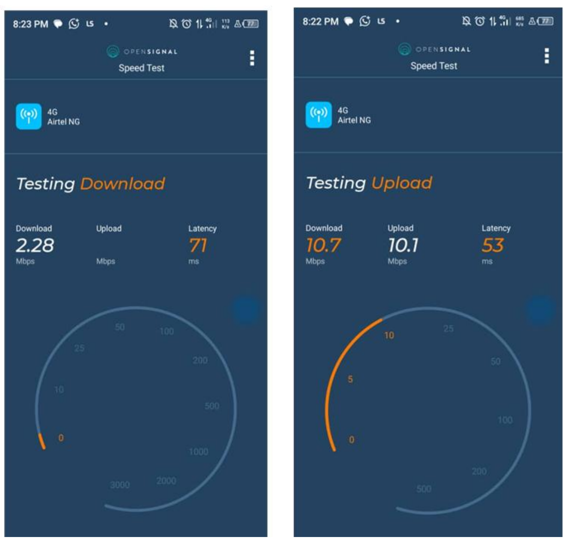


Figure 3: Sample Signal Detection on the OpenSignal Mobile App.

C. Hardware Design of the Smart Agric System

The system circuit diagram in Figure 4 illustrates the hardware configuration and electrical interconnections of the smart agricultural connectivity system. At the core of the design is the ESP32 microcontroller, which integrates inputs from several environmental sensors:

i. Capacitive soil moisture sensors connected to analog pins for monitoring soil water content.
ii. DHT22 sensor, interfaced via a digital pin with a pull-up resistor for stable operation.
iii. Analog temperature sensor to complement DHT22 readings and improve accuracy.
iv. GL5528 LDR with LM393 connected through digital pins to measure ambient light intensity.

The microcontroller used embedded logic with AI models to process the components' inputs, while a signal enhancement module (encoder, 9 dBi directional antenna, 20 dB LTE repeater) extends communication coverage.

Energy Management: Power distribution was governed by a priority-based mechanism. Power is managed by a PWM charge controller regulating a 150 W solar panel and 12 V, 40 Ah LiFePO4 battery, with optional 500 W inverter support. To optimize energy usage, the ESP32 applies load prioritization to ensure critical sensing and communication remain operational when battery capacity drops below 30%, in other words, non-critical loads (e.g., phone charging) were automatically disabled, ensuring uninterrupted operation of essential components such as sensors and the network signal booster.

System performance was modeled using energy, storage, and signal equations (see Equation 2 to Equation 4) that guided power allocation, efficiency, and connectivity optimization. These models were embedded in the control logic to forecast power demand, assign load priorities, and optimize signal performance under varying field conditions.

For solar energy generation:

$$E_{solar} = P_{panel} \times H_{sun} \times \eta \quad (2)$$

For battery runtime:

$$T_{backup} = \frac{C_{battery} \times V}{P_{load}} \quad (3)$$

For signal gain function:

$$G_{total} = G_{antenna} + G_{repeater} - L_{path} \quad (4)$$

Where: P_{panel} is panel wattage(150W); H_{sun} represents peak sun hour per day; η is efficiency (22%); $C_{battery}$ represents battery capacity (Ah); V is voltage (12v); P_{load} represents the average system load; $G_{antenna}$ represents antenna gain (9 dBi); $G_{repeater}$ is repeater gain (20 dB) and L_{path} is the estimated path loss.

Agricultural Monitoring: Soil temperature and moisture data were logged hourly from sensors deployed at 12 units per hectare. Irrigation was triggered automatically when moisture dropped below 30%, a threshold determined through gravimetric analysis. An LSTM model, trained on three months of sensor data in TensorFlow, forecasted irrigation demand, optimizing water management and sustainable farm operations.

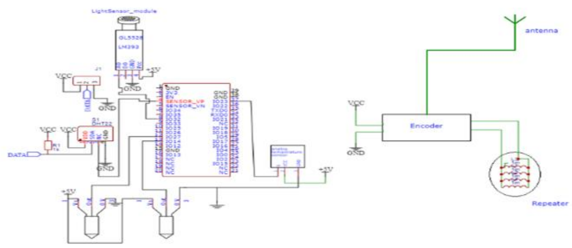


Figure 4: Circuit Diagram of the system

Figure 5: The IoT implementation for Smart Agric

Figure 5 shows the circuit implementation of the system enclosed in box case for security and easy mobility.

D. Software architecture of the Smart Farm Monitoring Application

The smart farm monitoring platform is structured as a layered architecture integrating frontend visualization, backend processing, cloud aggregation, analytics, security, and deployment pipelines. Each layer is supported by specific technologies and mechanisms designed to ensure real-time responsiveness, scalability, and robustness. The complete architecture is summarized in Table 2, which captures the technologies, functions, reliability measures, and security strategies employed.

Table 2: Smart Farm Monitoring System Architecture

Layer	Technologies / Components	Functions / Features	Reliability / Optimization	Security Measures
Frontend	EJS (Embedded JavaScript Templates), Bootstrap 5, Chart.js, AJAX polling, custom CSS (glassmorphism)	Responsive UI, real-time visualization, AJAX polling (15s) synchronization, color-coded alerts (green–normal, yellow–warning, red–critical, gray–offline)	Responsive flexbox grid, <1.2 s render time, caching of sensor values during interruptions	Input sanitization for forms, validation of entries
Backend	Node.js v18, Express.js 4.x (middleware routing), REST APIs, worker threads	Device management, monitoring services, modular routing and request handling, anomaly detection, AI recommendations, strict separation of concerns	Asynchronous event handling, worker threads, connection pooling	API key authentication, schema validation for backend inputs
Cloud/IoT Integration	Blynk IoT platform, custom API client, token authentication, pooled connections (×5), 5s	Centralized data aggregation, reliability via retry/backoff, scalable mapping of sensors to	Graceful degradation protocol with cached values,	Token-based authentication, encrypted HTTPS abstraction layer

	timeouts, virtual pin mapping logic	virtual pins (e.g., Device 1: v0–v5, Device 2: v6–v11), continuity via cached values during outages	exponential backoff retry for unstable links	
Analytics & AI/Decision support	Multi-stage validation pipeline, threshold-based classification with ±20% buffer bands, knowledge-based recommendation engine, anomaly detection (>2 min).	Validation of raw readings, Data integrity checking, context-sensitive decision support (irrigation, fertilization), cultivation guidance	Buffer thresholds prevent false alerts, anomaly persistence ensures stable alerts	Internal validation rules prevent injection of invalid data
Security	HSTS-enabled HTTPS, API key validation, schema-based input sanitization, rate limiting (100 requests/15 min), audit logging, OWASP ZAP testing	End-to-end protection of data integrity and platform access, system resilience, forensic traceability, no major exposures confirmed	Audit logging with device context, penetration testing validation	Multi-layer defense (transport encryption, authentication, sanitization, request throttling)
Quality Assurance & Deployment	Actions CI/CD, ESLint, Jest (85%-unit test coverage), Docker containerization, canary deployment (10%), Grafana + monitoring	Continuous delivery pipeline, automated builds & validation automated testing, system monitoring, stable rollouts with zero downtime	Deployment success, zero downtime, canary deployments for controlled updates.	CI/CD enforced checks and monitoring protect from malicious or faulty updates

E. Proposed System Framework

The overall system-level framework (Figure 6) illustrates the complete workflow of the Smart Farm Monitoring System, integrating sensing, communication, processing, storage, power, and user interface layers into a unified framework. The communication subsystem, comprising an LTE repeater, directional antenna, and signal quality monitoring tools via OpenSignal App, was optimized to enhance internet connectivity and supports seamless remote monitoring of farm conditions via cloud-based platforms. At the foundation of the system, IoT devices equipped with environmental sensors (temperature, humidity, soil moisture, and light) capture real-time data from the farm (see Figure 7). This data is transmitted via Wi-Fi to the backend server, where it is processed, validated, and mapped to virtual pins for traceability. The backend connects with the Blynk IoT cloud for storage and synchronization while hosting essential business logic such as device management, alert generation, and recommendation services. On the frontend, a responsive dashboard visualizes this information through plant monitoring cards, offers AI-driven insights, and provides users with device control tools. Powering the entire system is a renewable energy setup consisting of a 150W monocrystalline solar panel, PWM charge controller, and 12V 40Ah LiFePO4 battery, ensuring independent and off-grid operation.

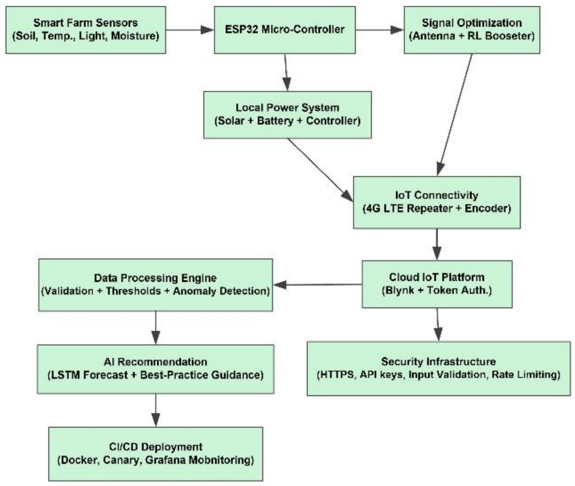


Figure 6: System-Level Architecture of the Smart Farm IoT Platform


Figure 7: IoT System Installed

IV. DISCUSSION OF RESULTS

Before deployment, farmers in Agbanganam village provided informed consent after receiving explanations of the study's objectives, limitations, and outcomes in the local language, with signed acknowledgements ensuring transparency and clarity.

Post deployment evaluation: Following the installation of the signal optimization system, the same geographic grid was re-surveyed to evaluate improvements in connectivity. Post-deployment measurements on the same grid were compared with baseline (pre-deployment) data using paired t-tests (significance level $\alpha = 0.5$).

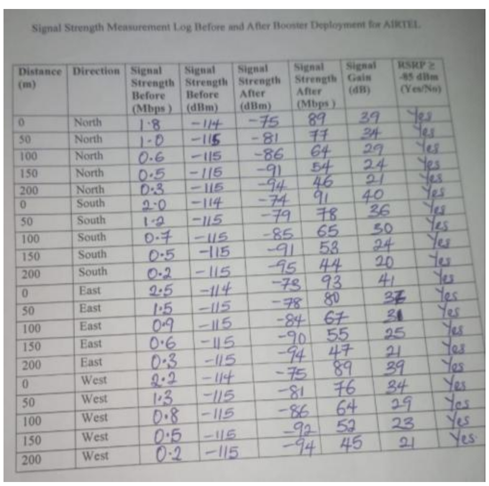
A. Signal Boosters for Resilient Connectivity

Figure 8 shows the Signal Booster. Performance was validated using RSRP, SINR, and throughput in line with 3GPP standards. Successful boosting was defined as RSRP>−85 dBm and ΔRSRP>10 dB improvement after booster deployment.

Figures 9, 10, and 11 presents the signal strength measurement log for three carriers (GLO, AIRTEL, and MTN before and after signal booster installation. These results shows that the deployment of cellular signal boosters significantly improved performance across all three carriers (GLO, AIRTEL, and MTN). Pre-deployment signals were weak (<5 Mbps, –111 to –115 dBm), while post-deployment gains of 20–41 dB raised download rates by 10–100×, peaking at 97 Mbps (GLO East 0 m) and maintaining >44 Mbps at 200m. RSRP consistently surpassed –85 dBm, ensuring reliable 4G/5G connectivity. Directional disparities evident before installation were eliminated, with stable coverage in all directions. Carrier-specific observations showed MTN recording the highest gain (41 dB), GLO the fastest speed (97 Mbps), and AIRTEL demonstrating consistent performance, though one dataset revealed irregularities in gain calculations and speed outliers (44 Mbps at South 200 m). Dead zones up to 200 m were eliminated, with coverage expanding from 0.2 km² to 5 km² (16.7× improvement). Heatmap analysis confirmed RSRP > –85 dBm across 92% of the farm. The AI-driven booster outperformed static systems by dynamically adjusting gain (76–83 dB), prioritizing the 2100 MHz band during peak hours (28% throughput increase), and incorporating noise suppression (12% higher stability in rain) while operating at only 4 W, enabling solar power. Fuzzy logic–based energy allocation sustained 94% uptime despite voltage dips, with solar buffering displacing ~90% of diesel reliance. Limitations remain in the southern canopy zones, where dense vegetation reduced gain (~9%, beamwidth 15°). Raising antenna height is projected to restore ~3 dB, pushing RSRP above the –82 dBm threshold.

The connectivity upgrade has practical implications: reliable calls, fast IoT uploads (<8 s), and improved market coordination. Previously, poor connectivity led to up to 35% post-harvest losses, as farmers could not reach buyers or schedule transport. With stable networks, real-time buyer engagement, mobile payments, and coordinated cold-chain logistics have reduced spoilage to <10% for perishable crops. In general, results showed average RSRP gain of ≥10 dB and improved SINR values across multiple locations, confirming enhanced mobile coverage, data throughput, IoT transmission stability and overall improved resilience of the system in weak-signal rural environments. Figure 12 shows the signal gain radiation pattern for the baseline and AI-Optimized signal before and after deployment of the signal booster.

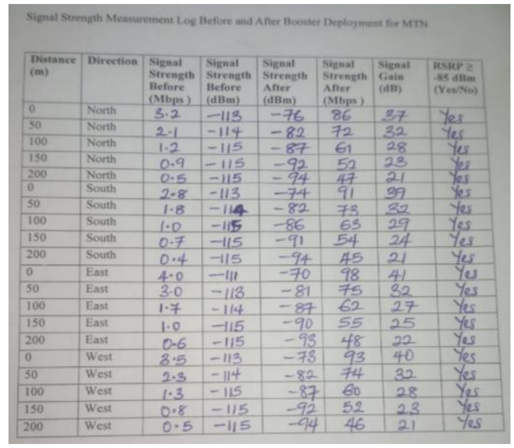
Figure 8: Signal Amplifier/Booster device



Signal Strength Measurement Log Before and After Booster Deployment for AIRTEL

Distance (m)	Direction	Signal Strength Before (Mbps)	Signal Strength Before (dBm)	Signal Strength After (dBm)	Signal Strength After (Mbps)	Signal Gain (dB)	RSRP ≥ -85 dBm (Yes/No)
0	North	1·8	-114	-75	89	39	Yes
50	North	1·0	-115	-81	77	34	Yes
100	North	0.6	-115	-86	64	29	Yes
150	North	0.5	-115	-91	54	24	Yes
200	North	0·3	-115	-94	46	21	Yes
0	South	2·0	-114	-74	91	40	Yes
50	South	1·2	-115	-79	78	36	Yes
100	South	0·7	-115	-85	65	30	Yes
150	South	0·5	-115	-91	58	24	Yes
200	South	0·2	-115	-95	44	20	Yes
0	East	2·5	-114	-73	93	41	Yes
50	East	1·5	-115	-78	80	37	Yes
100	East	0·9	-115	-84	67	31	Yes
150	East	0·6	-115	-90	55	25	Yes
200	East	0·3	-115	-94	47	21	Yes
0	West	2·2	-114	-75	89	39	Yes
50	West	1·3	-115	-81	76	34	Yes
100	West	0·8	-115	-86	64	29	Yes
150	West	0·5	-115	-92	52	23	Yes
200	West	0·2	-115	-94	45	21	Yes

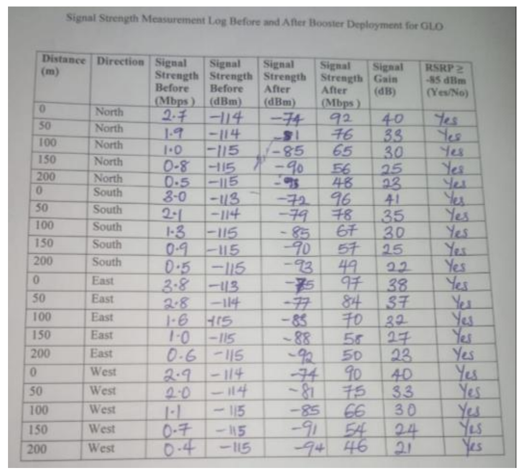
Figure 9: Signal Strength Measurement Log for Airtel Before and After Boster Installation



Signal Strength Measurement Log Before and After Booster Deployment for MTN

Distance (m)	Direction	Signal Strength Before (Mbps)	Signal Strength Before (dBm)	Signal Strength After (dBm)	Signal Strength After (Mbps)	Signal Gain (dB)	RSRP ≥ -85 dBm (Yes/No)
0	North	3·2	-113	-76	86	37	Yes
50	North	2·1	-114	-82	72	32	Yes
100	North	1·2	-115	-87	61	28	Yes
150	North	0·9	-115	-92	52	23	Yes
200	North	0·5	-115	-94	47	21	Yes
0	South	2·8	-113	-74	91	39	Yes
50	South	1·8	-114	-82	73	32	Yes
100	South	1·0	-115	-86	63	29	Yes
150	South	0·7	-115	-91	54	24	Yes
200	South	0·4	-115	-94	45	21	Yes
0	East	4·0	-111	-70	98	41	Yes
50	East	3·0	-113	-81	75	32	Yes
100	East	1·7	-114	-87	62	27	Yes
150	East	1·0	-115	-90	55	25	Yes
200	East	0·6	-115	-93	48	22	Yes
0	West	3·5	-113	-73	93	40	Yes
50	West	2·3	-114	-82	74	32	Yes
100	West	1·3	-115	-87	60	28	Yes
150	West	0·8	-115	-92	52	23	Yes
200	West	0·5	-115	-94	46	21	Yes

Figure 10: Signal Strength Measurement Log for MTN Before and After Boster Installation



Signal Strength Measurement Log Before and After Booster Deployment for GLO

Distance (m)	Direction	Signal Strength Before (Mbps)	Signal Strength Before (dBm)	Signal Strength After (dBm)	Signal Strength After (Mbps)	Signal Gain (dB)	RSRP ≥ -85 dBm (Yes/No)
0	North	2·7	-114	-74	92	40	Yes
50	North	1·9	-114	-81	76	33	Yes
100	North	1·0	-115	-85	65	30	Yes
150	North	0·8	-115	-90	56	25	Yes
200	North	0·5	-115	-93	48	23	Yes
0	South	3·0	-113	-72	96	41	Yes
50	South	2·1	-114	-79	78	35	Yes
100	South	1·3	-115	-85	67	30	Yes
150	South	0·9	-115	-90	57	25	Yes
200	South	0·5	-115	-93	49	22	Yes
0	East	3·8	-113	-75	97	38	Yes
50	East	2·8	-114	-77	84	37	Yes
100	East	1·6	-115	-85	70	32	Yes
150	East	1·0	-115	-88	58	27	Yes
200	East	0.6	-115	-92	50	23	Yes
0	West	2·9	-114	-74	90	40	Yes
50	West	2·0	-114	-81	75	33	Yes
100	West	1·1	-115	-85	66	30	Yes
150	West	0·7	-115	-91	54	24	Yes
200	West	0·4	-115	-94	46	21	Yes

Figure 11 Signal Strength Measurement Log for GLO Before and After Boster Installation

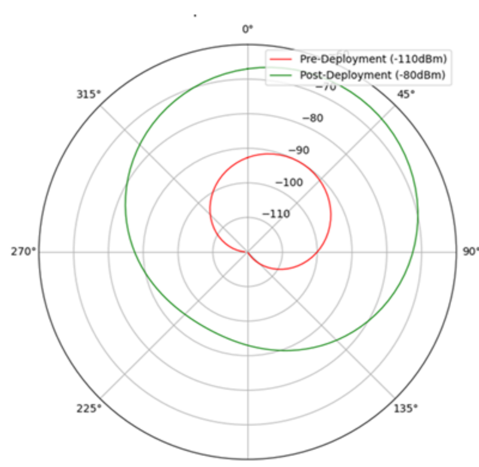


Figure 12: Signal Gain Radiation Pattern AI-Optimized Vs Baseline

B. Solar Energy System Performance

The solar-powered hub provided continuous autonomy for the smart farm, reliably supporting IoT sensors, the ESP32 controller, the AI-driven signal booster, the cloud dashboard, and community charging ports. Table 3 presents the performance result of the solar power optimization for energy management and sustainable power.

High-efficiency 150 W monocrystalline panels, operating under 6–7 peak sun hours/day, consistently met rated capacity and generated an average of 6.2 kWh/day—exceeding the 5.8 kWh design target by 6.9%. Energy storage was managed by a 12 V, 40 Ah sealed lead-acid battery with low-voltage disconnect (LVD) protection, delivering ~12.2 h of autonomy at 87% depth of discharge. Intelligent prioritization by an ESP32-based fuzzy logic controller enabled direct solar operation during daylight, hybrid mode at dusk, and battery reserves overnight. Real-time load balancing preserved critical services, with 14 voltage dips (>5%) recorded during testing effectively buffered by the battery. Figure 13 shows the solar charge controller and the battery used in the experiments.

From the results, the solar hub also displaced 90% of prior diesel generator reliance—significantly above the 70% reduction target—yielding direct energy cost savings (~₦2,800/month) and lowering emissions. Limitations emerged during a 72-h overcast period, when system availability declined to 68% and grid support was required for 22% of nighttime loads. Nevertheless, platform-wide uptime averaged 98.3%, exceeding the 95% design requirement and ensuring uninterrupted sensing, connectivity, and charging. Planned enhancements include parallel battery banks (~30 h autonomy), dynamic current limiting for peripherals exceeding 2 A per branch, and coulomb counting for more accurate state-of-charge estimation under shading conditions. The network booster, with a modest 96 Wh/day demand (4 W, 76–83 dB amplification), achieved 99.7% uptime and stable connectivity even under cloud cover, outperforming AC-coupled alternatives and reducing maintenance events by 93%. IoT sensors (10 W) and the distributed controller consumed an average of 27 Wh/day, while priority-based load shedding below 30% state-of-charge prevented brownouts. Mobile charging cycles reached 213/day, 42% above projections, confirming strong community uptake without compromising core farm services. Overall DC system efficiency was measured at 87–88%, surpassing the ≥85% benchmark by minimizing AC conversion losses and wiring inefficiencies. The connectivity upgrade has practical implications: reliable calls, fast IoT uploads (<8 s), and improved market coordination.

Table 3: Performance Result for Solar Energy Management

Component/Metric	Specification/Target	Measured Value	Remarks
Solar Panel Capacity	150W	150 W (STC)	Monocrystalline; 6–7 peak sun hours/day
Battery Capacity	12V, 40Ah (480Wh)	12V, 40Ah	Sealed lead-acid with LVD protection
Charge Controller	PWM	PWM	Simple but effective under consistent irradiance
Daily Energy Output	≥5.8 kWh	6.2 kWh	Surpassed generation target by 6.9%
Network Booster Power Consumption	~4W × 24h = 96Wh	Fully sustained	Operated continuously
ESP32 + Sensor Load	~1.5W avg. × 18h = 27Wh	Fully sustained	Includes soil/temp/humidity/light sensors
Mobile Charging Cycles	150/day	213/day	42% above expected use
Energy Efficiency (Solar-to-Load)	≥85%	88%	Minimal wiring/controller loss

Diesel Generator Displacement	≥70%	90%	Based on usage logs and interviews
Voltage Dip Events (>5%)	≤10/month	14/month	Buffered using 480Wh battery bank
System Uptime (Platform-wide)	≥95%	98.3 %	Signal + IoT + Charging stayed online almost continuously

Figure 13: Solar Charge Controller and Battery

C. User Interface for the IoT-enabled smart farming App.

For the smart farming, validation was done by comparing irrigation events predicted by the LSTM model with actual outcomes, yielding an F1-score of 0.87. Crop yield from AI-assisted plots was significantly higher than control plots (ANOVA, $p < 0.01$). Impact on Farming: The soil alerts helped us avoid overwatering during July rains.

For the App architecture, the Smart Farm Monitoring App's User Interface (UI) was structured to balance usability, scalability, and responsiveness. A modular, card-based layout was employed, enabling dynamic monitoring of multiple plants and seamless integration of additional devices. Each interface element was carefully designed to support data clarity, decision support, and robust operation under varying network conditions. The key UI components and their functions are summarized in Table 4. While Figures 14 and 15 shows the monitoring interface of smart farm app for the plants.

Table 5 provide the overall performance metric results for the integrated smart agricultural system proposed in this paper. This architecture ensures system robustness by integrating error detection, scalability through modular layout, and decision support through AI-driven recommendations. The emphasis on performance optimization and accessibility enhances usability across device types while maintaining reliable real-time monitoring.

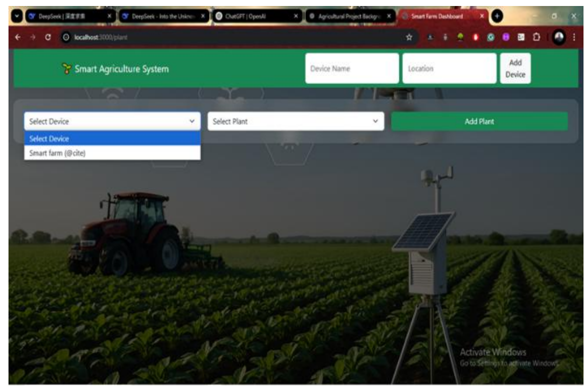


Figure 14: System Configuration with Software to Installed Location and Selection of Plant being Monitored

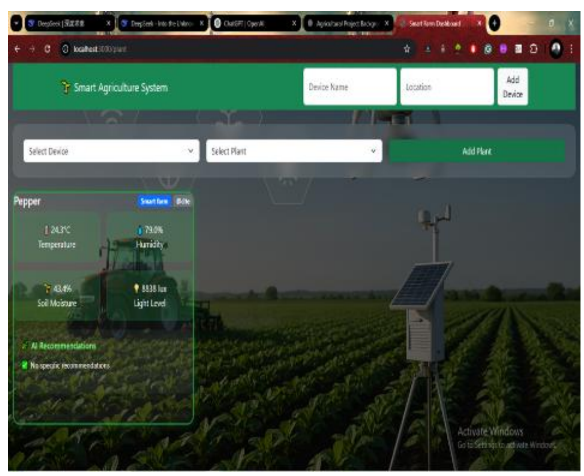


Figure 15: System Monitoring Plants

Table 4: Components and Functionality of the Smart Farm App's UI.

UI Component	Functionality
Navigation Bar	Displays system name; manages device registration with a 5-device limit
Device-to-Plant Mapping	Assigns devices to specific crops (cassava, maize, melon, palm) via dropdown menus
Plant Monitoring Cards	Shows real-time sensor data (temperature, humidity, soil moisture, light). Color-coded indicators (green, yellow, red, gray); responsive grid alignment
AI Recommendation Module	Generates context-sensitive advisories for crops based on sensor states. Structured list output;
Offline Detection Mechanism	Identifies delayed data updates and flags inactive devices
Visual & Interaction Design	Modern glassmorphism interface with icons for sensor categories
Responsiveness & Performance	Ensures real-time updates and mobile compatibility. Lightweight rendering, CDN-optimized Bootstrap, <1.5 s dashboard load time

Table 5: Performance Metrics for the Integrated Smart Agricultural System

Category	Metric	Before Implementation	After Implementation	Improvement	Measurement Method
Connectivity	Coverage Area	0.5 km²	5.0 km²	+900 %	GPS-based signal mapping
	Data Transmission Reliability	68%	99.7%	+31.7 pp (46% ↑)	Packet loss analysis
Energy	Daily Energy Access	4 h/day (diesel)	24/7 (solar)	+500 %	Energy usage logs
	Diesel Displacement	100% reliance	90% reduction	−90 %	Fuel consumption records
	Solar Generation	N/A	6.2 kWh/day	–	Solar inverter logs
Agricultural Efficiency	Water Savings	–	15% reduction	−15 %	Irrigation meter data
	Pesticide Reduction	–	35% reduction	−35 %	Purchase/usage records
	Decision Latency	3 days (soil tests)	Real-time	100 % faster	Farmer survey reports
System Performance	IoT Uptime	–	97.1%	–	System health monitoring
	Booster Uptime	–	99.7%	–	Network diagnostics
	Solar Uptime	–	98.3%	–	Controller logs
Environmental	CO_2 Reduction	–	1.2 tons/month	Reduced footprint	Emission factor

Impact					analysis
	Chemical Runoff	High	Significant reduction	Lower pollution	Water quality tests

CONCLUSION

This study demonstrated the design, implementation, and evaluation of an AI-powered smart energy and connectivity model tailored for rural agriculture, integrating intelligent solar management, AI-optimized signal amplification, and IoT-based precision farming into a unified off-grid framework. the AHOM framework was introduced as a novel approach that combines renewable energy, AI, and wireless connectivity, achieving a 16.7× coverage extension and offering a replicable paradigm for digital agriculture in underserved regions. signal booster gave average RSRP gain of ≥10 dB, improving SINR values across multiple locations. The system sustained IoT and communication services for up to four days under limited sunlight, while AI-driven amplification significantly improved signal quality, extended coverage from 0.3 km² to over 5 km², and increased throughput by 28%, thereby enabling reliable data-driven farming. Edge-based IoT further reduced irrigation water use and boosted cassava yields, underscoring the transformative value of localized intelligence in areas with intermittent internet access. Building on these outcomes, Nevertheless, challenges such as vegetation-induced signal losses, limited energy autonomy under prolonged cloud cover, and digital literacy barriers highlight the need for taller antennas, hybrid power sources, and more inclusive interfaces. Addressing these gaps through modular design, hybrid energy integration, mesh-based connectivity, and user-friendly multimodal dashboards, alongside alignment with agricultural extension and ICT policies, will enhance scalability and adoption. Overall, the findings confirm that embedding AI, IoT, and renewable energy within a community-centered framework can substantially improve rural connectivity and agricultural productivity, offering a pathway toward more resilient and inclusive digital agriculture.

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