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Controlling Food Security with AI and IoT for Smart Farming Among Low-Income Earners

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Abstract: It has become imperative that certain concerns arising from food scarcity should receive prompt attention. Since a large quantity of our agricultural products emanates from the rural areas, peasant low-income farmers must be well thought-out while arriving at a suitable solution. Interloping Internet of Things (IoT) and Artificial Intelligence can transpose into an intensified, enhanced and navigable framework for smart agricultural practices with a spotlight on guaranteeing food security in a resource-constrained environment, having eminent climate unpredictability. This study enforces the integration of IoT using real-time data and weather forecasting derivable(s) to optimize expected and moderate rainfalls, improve soil fertility and massive crop yielding mechanism output as against the traditional farming practices. The Machine Learning (ML) component strengthens the knowledge of the system and the farmers in line with the global expectations towards accurate decision making, precision, evaluation, impact assessments and validation within a farming cycle. For the participatory implementation framework that will set off affordability, usability, and data accessibility, both enhanced and traditional farming methodology would be compared in terms of data collection, implementation and usability. Symposiums and technical talks were significant enough to bridge the digital inequalities gravely experienced thus far by low-income farmers. The findings authenticated that integrating IoT for smart and large-scale agricultural practises within a cost-sensitive, friendly and limited architecture can notably ensure food security, demystify digital ignorance and scatter the barriers of hunger and poverty.

Keywords: *Optimization, Low-Income Farmers, Precision Forecasting, IoT Integration, Cost-Sensitive, Framework, Resource-Constrained, Food Security, Internet of Things, Artificial Intelligence, Traditional Farming Practice, Intentional Farming.*

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I. INTRODUCTION

They are records of massive improvement over the year in agricultural practices. Moving from basic subsistence practices to advanced industrial systems. The Industrial Revolution, for example, introduced mechanization and high-yield crop varieties, culminating in the Green Revolution of the mid-20th century. While these advances significantly increased global food production and security, they also introduced new challenges, such as overdependence on chemical inputs, soil degradation, and reduced environmental sustainability (Smith, 2020). In the present era, agriculture faces even greater pressures and uncertainties including climate change, water scarcity, unpredictable weather patterns, and labour shortages, which threaten productivity and food security (Jones & Lee, 2021). This research observed in first-hand the struggles of peasant and low-income farmers, who relied heavily on traditional farming methods and practices. These methods demanded extensive manual labour, lacked precision in resource application, and often resulted in low yields despite significant effort. Such experiences highlighted the limitations of conventional practices and underscored the urgent need for smarter, technology-driven approaches that could ease farmers' burdens while improving productivity and sustainability.

Contrary to the norm, integrating Internet of Things (IoT), Artificial Intelligence and Machine Learning (ML) offer transformative opportunities for modern agriculture. IoT enables the deployment of interconnected sensors and actuators to collect real-time data on key environmental factors such as soil moisture, temperature, humidity, and light intensity. This data, when processed with ML algorithms, can generate predictive insights on crop growth, irrigation needs, and pest infestation risks. Blending IoT and ML provide the foundation for precision agriculture systems that not only optimize resource utilization but also reduce manual intervention, making farming more efficient, scalable, and sustainable.

➢ *Problem Statement*

Before now, low-income farmers did not have certain level of control over significant farming practices that will yield enormous production due to environmental and climatic

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unpredictability, resource-constrained fixation, diehard traditional approaches, technological adoption barriers and fragmented smart solution. Therefore, there arises a pressing need for an integrated, cost-effective smart agricultural system that combines IoT, AI and ML to optimize decision-making, improve resource management, and enhance productivity, while it remains accessible to low-income farmers. This research seeks to address this gap by empirically comparing both smart and traditional agricultural practices for sustainable precision and intentional farming.

➢ *Aim and Objectives*

The aim of this paper is to conceptualize IoT integration for smart agricultural practices among low-income farmers as it leverages on AI for food security. With the following objectives:

- Conceptualize a feasible prototype for smart agricultural system that integrates IoT sensors for monitoring soil moisture, temperature, humidity, and light intensity.
- Integrate the AI-ML models with the IoT framework to enable real-time, data-driven decision-making for irrigation and resource management to predict crop growth patterns, irrigation requirements, and potential disease outbreaks.
- Assess the potential benefits of the system for sustainable farming, including resource optimization, reduced manual labour, and improved crop yield.

II. TRADITIONAL AGRICULTURAL PRACTICES AND FARMING METHODS

Traditional agriculture in rural communities has historically relied on practices such as shifting cultivation, subsistence farming, mixed crop–livestock systems, crop rotation and intercropping, manual irrigation, and animal-drawn farm power. Shifting cultivation, where land is cleared and farmed for a few years before being left fallow, once sustained livelihoods under low population densities but is now associated with deforestation, biodiversity loss, and soil degradation when practiced unsustainably (Nkonya et al., 2023; Chanthorn et al., 2019). Subsistence farming for low-income earners aims at the cultivation for household consumption using hand tools, remains important for food security but is labour-intensive and yields are often low compared to mechanize systems (FAO, 2020; Jayne et al., 2019).

With respect to ancient farming practices mostly by low-income farmers, hard work, dedication, reliance on manual labour, imprecise resource use, and boxed techniques often resulted in low yields and high drudgery. This human dimension highlights not only the productivity and environmental limitations of traditional agriculture but also the social cost of relying on outdated methods. These realities underscore the need for integrating technological innovations such as IoT-enabled sensing and machine learning-based decision support into agriculture to increase efficiency, reduce labour intensity, and make farming more sustainable and resilient in the face of modern challenges (Wolfert et al., 2017; Klerkx et al., 2019).

Low-income farmers basically cultivate for household consumption with limited surplus for commercial markets. Irrigation depends largely on rainfall, making productivity highly susceptible to drought and climate variability. Organic fertilizers, animal manure, and plant residues are commonly used to maintain soil fertility, while pest control often relies on herbs or manual removal. These methods promote ecological balance but lack the efficiency and predictive capacity required for modern food production to ensure food security.

➢ *Block diagram of the Traditional Farming System*

The block diagram of the traditional farming system has been shown in *Figure 2. The* key limitation is that they heavily rely on manual systems which give rise to low scalability, poor resilience, and limited profitability. The weaknesses of the traditional system highlight the need for modernization. While traditional practices preserve culture and biodiversity, they cannot fully meet the challenges of food security, climate change, and global competitiveness. Integrating IoT and Machine Learning (ML) provides a pathway to address these limitations by enabling real-time monitoring, predictive insights, and automation.

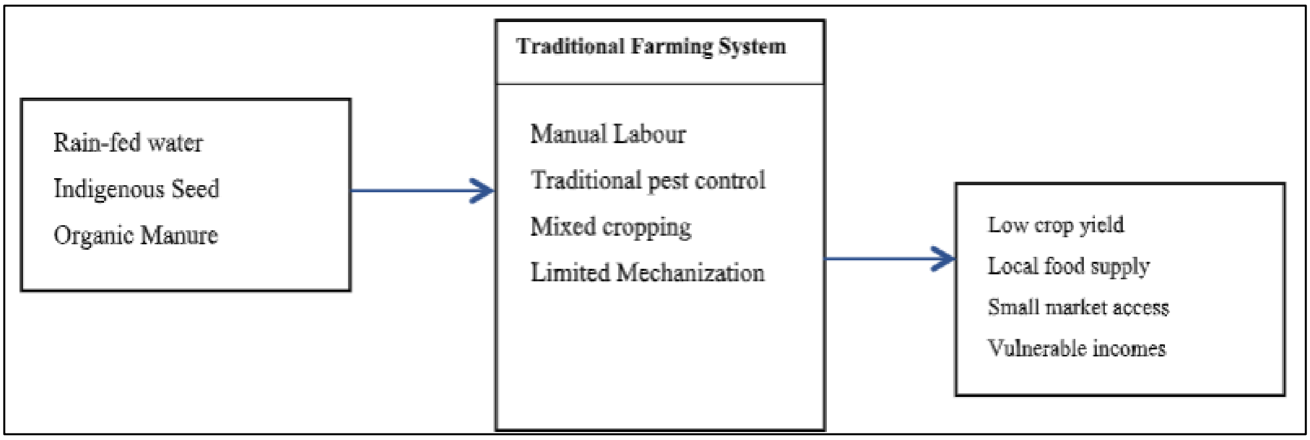

Fig 1 Block Diagram of the Existing System

- *Limitations of Traditional Farming*

✓ Low productivity due to limited mechanization.
✓ High vulnerability to pests, diseases, and erratic rainfall.
✓ Heavy dependence on manual labour.
✓ Minimal use of data and analytics for decision-making.

As global food demand rises, these challenges highlight the need to modernize traditional farming systems through IoT- and AI-based solutions that retain ecological wisdom while introducing automation, data precision, and efficiency. Although, the strange believe in shifting from traditional or fundamental paradigm to an improved approach is one that requires planning, studying and implicit implementation (Mba & Mbeledogu, 2024).

➢ *Facets of Traditional Farming*

- *Manual Labour and Animal Power*

Farming activities such as ploughing, planting, and harvesting are primarily carried out by hand or using animal-drawn implements. This method, while labour-intensive, supports employment in rural communities but limits scalability and productivity.

- *Subsistence Farming*

Most traditional farmers produce mainly for household consumption, with minimal surplus for market sales. This limits income potential and the ability to invest in improved farming inputs or technologies.

- *Rain-Fed Agriculture*

Watering depends largely on natural rainfall, with little or no irrigation infrastructure. Consequently, productivity is highly vulnerable to droughts and changing weather patterns.

- *Crop Rotation and Mixed Cropping*

Farmers often rotate crops or plant different crops together to maintain soil fertility and reduce pest infestations. Though ecologically beneficial, yields are typically lower compared to intensive modern systems.

- *Use of Organic Manure and Natural Inputs*

Instead of synthetic fertilizers, traditional farmers rely on compost, animal dung, and plant residues to enrich the soil. This enhances long-term soil health but may not provide sufficient nutrients for high-yield crops.

- *Indigenous Pest and Weed Control*

Local knowledge of herbs, plant extracts, and manual weeding are employed to manage pests and diseases. These methods are eco-friendly but less effective for large-scale production.

- *Limited Use of Technology and Data*

Traditional systems rely on farmers' experience and observation rather than data analytics or automated monitoring. This often leads to inefficient resource use and unpredictable output.

➢ *Smart Agricultural Practices and Farming Methods*

Smart agriculture or precision agriculture represents the modern evolution of traditional farming systems through the integration of advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), remote sensing, and automation. These innovations enable farmers to make data-driven decisions that enhance productivity, optimize resource utilization, and improve sustainability. Smart agricultural practices are characterized by real-time data collection, automated control, and predictive analytics. Unlike conventional farming, where decisions are based on observation and experience, smart agriculture relies on sensor data, computational intelligence, and cloud-based analytics to provide actionable insights.

- *IoT in Smart Agriculture*

The Internet of Things (IoT) refers to a network of interconnected devices that communicate with each other and collect real-time data from the environment. In agriculture, IoT plays a crucial role in precision farming by enabling continuous monitoring of various environmental and crop conditions.

- *Areas of IoT Application in Agriculture*

✓ *Soil and Crop Monitoring*

IoT sensors can measure essential soil parameters such as moisture levels, temperature, pH, and nutrient content. Studies by Kumar et al. (2020) and Singh et al. (2021) emphasize how IoT sensors deployed in fields allow for real-time monitoring of soil health, enabling farmers to make timely decisions about irrigation, fertilization, and pest management.

✓ *Weather Monitoring*

IoT-based weather stations are increasingly used to gather data on temperature, humidity, wind speed, and precipitation. According to Ghosh et al. (2019), weather forecasting models incorporating IoT data have improved the accuracy of agricultural planning, helping farmers anticipate weather patterns and adjust their operations accordingly.

✓ *Livestock Monitoring*

IoT devices, such as wearable sensors, are used to monitor animal health and behavior, including tracking movements, feeding patterns, and vital signs. Gupta et al. (2020) highlight that IoT sensors help improve livestock management by enabling early disease detection, reducing losses, and improving animal welfare.

- *Facets of Smart Farming*

✓ *IoT-Based Monitoring Systems*

Smart farming employs a network of IoT sensors to continuously monitor environmental parameters such as soil moisture, temperature, humidity, and light intensity. These sensors provide real-time data that inform critical decisions on irrigation, fertilization, and pest control. Data is transmitted through wireless networks (Wi-Fi, LoRa, or GSM) to edge or cloud servers for processing.

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✓ *Automated and Precision Irrigation*

IoT-enabled irrigation systems automatically regulate water flow based on soil moisture readings and weather forecasts. This ensures crops receive optimal water levels, significantly improving water-use efficiency and reducing wastage. AI models further enhance irrigation precision by predicting plant water requirements under changing climatic conditions.

✓ *AI-Driven Decision Support Systems (DSS)*

Machine learning algorithms analyze collected data to detect patterns, forecast yield outcomes, and identify potential pest or disease outbreaks. For instance, Random Forest and LSTM models can predict irrigation schedules, crop growth rates, and anomalies in field conditions. This predictive intelligence helps farmers take proactive actions rather than reactive measures.

✓ *Remote Sensing and Drone-Based Imaging*

Drones and satellite imaging technologies provide high-resolution data for mapping crop health, identifying nutrient deficiencies, and assessing land variability. These images, analyzed through AI tools, support precision management of large agricultural fields.

✓ *Smart Fertilization and Pest Control*

Sensor data and AI algorithms determine the appropriate amount and timing of fertilizer and pesticide applications, reducing input costs and minimizing environmental pollution. Automated sprayers and drones can deliver inputs with precision based on geospatial data.

✓ *Blockchain and Traceability Systems*

In some advanced implementations, blockchain technology is used to record data from farm to market, ensuring transparency and trust in the agricultural supply chain. This system supports food safety and quality assurance for both producers and consumers.

➢ *Machine Learning in Smart Agriculture*

Machine Learning (ML) refers to the application of algorithms that allow computers to learn from data without explicit programming. In smart agriculture boring a leave from traditional practices, Mba and Mbeledogu (2024) verified that improved machine learning algorithms can analyse data from parsley and densely population areas. In using IoT devices to provide predictive and prescriptive insights that improve farm management, farmers can leverage on modernize input to ensure food availability.

- *Facets of ML in Agriculture*

✓ *Crop Yield Forecasting*

ML models can analyse historical and real-time data from IoT sensors to predict crop yields, helping farmers make better decisions about planting, irrigation, and harvesting schedules. Hussain et al. (2020) and Patel et al. (2019) demonstrate that ML algorithms, such as regression models and neural networks, are increasingly used for accurate crop yield forecasting.

✓ *Pest and Disease Detection*

ML algorithms, combined with image recognition techniques, can detect pests and diseases early by analysing data from cameras, drones, and other IoT-based monitoring systems. Studies by Chen et al. (2020) and Sharma et al. (2021) highlight the use of deep learning methods for real-time pest detection and automated response actions.

✓ *Irrigation Optimization*

ML models, when applied to data from soil moisture sensors and weather forecasts, can optimize irrigation schedules, reducing water usage and improving crop health. Soni et al. (2018) suggest that decision support systems based on ML can adjust irrigation in real-time based on environmental factors and crop requirements.

✓ *Precision Fertilization*

ML algorithms help determine the optimal amount of fertilizer needed for specific crops based on soil composition and environmental factors. According to Tiwari et al. (2021), this reduces over-fertilization, prevents nutrient runoff, and enhances soil health.

➢ *Challenges in Implementing IoT and ML in Agriculture*

Despite the immense potential of IoT and ML in agriculture, several challenges hinder widespread adoption:

- *High Initial Investment*

The cost of implementing IoT sensors and ML systems can be prohibitive, especially for small-scale farmers. Patel et al. (2020) argue that financial support and subsidies are necessary to make these technologies more accessible.

- *Data Security and Privacy*

IoT devices collect vast amounts of data, raising concerns about data security and privacy. Sharma et al. (2020) discusses the need for secure data protocols and privacy regulations to protect sensitive agricultural information.

- *Data Overload*

The sheer volume of data generated by IoT sensors can overwhelm farmers, making it difficult to extract meaningful insights. Zhao et al. (2021) highlight the challenge of data management and the need for advanced analytics tools that can efficiently process large datasets.

➢ *Benefits of Smart Agricultural Methods*

- *Smart Agricultural Practices Offer a Range of Measurable Benefits*

Enhanced productivity and yield: Real-time monitoring and predictive analytics ensure optimal growing conditions.

- *Resource Efficiency*

Automated irrigation and fertilization minimize waste of water, fertilizers, and energy.

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- *Reduced Labour Dependency*

Automation decreases manual intervention, saving time and effort.

- *Climate Resilience*

AI-based forecasting tools help mitigate risks associated with unpredictable weather.

- *Economic Empowerment*

Data-driven insights enable low-income farmers to make informed, cost-effective decisions.

III. METHODOLOGY

➢ *System Design and Architecture for Implementing AI in Agriculture*

The proposed system consists of an IoT layer which is a distributed network of sensors to capture soil moisture, temperature, humidity, and light intensity. This layer was manually implemented in other to accommodate the deficiencies of low-income farmers.

The layer is logically divided into two; data interface model and application model. They are:

- *Data Interface Model*

✓ Data Understanding
✓ Data Preparation
✓ Data Modelling
✓ Data Evaluation

- *Application Model*

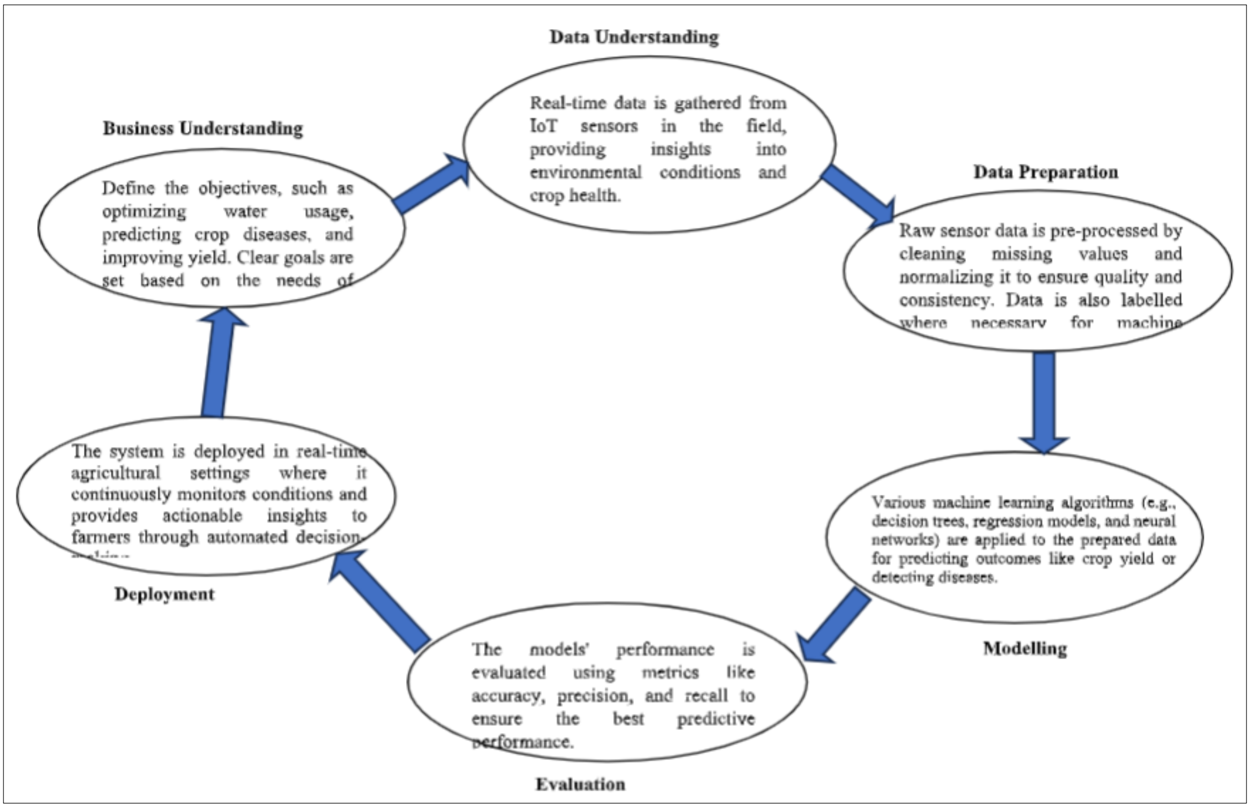

Fig 2 IoT Layer Model Outlook

✓ Deployment
✓ Business understanding

Figure 2 below holds a detail description of each of the models and how the inter-operate within the IoT layer to capture in real time soil moisture, temperature, humidity and light intensity which are the main ingredients need for controlled and stabilized farming of which the resultant effect in large production.

The communication between the sub-layers is such that uses wireless connectivity to transmit sensor data, and the processing layer, which uses edge computing concepts for local data pre-processing and temporary storage. This is for the smart and IoT enabled farming.

➢ *The AI-ML Layer*

This is a predictive models trained to forecast irrigation requirements, crop growth, and disease likelihoods whose core work is to control irrigation and crop growth.

Two major ML models are deployed in the AI-ML layer;

- Random Forest: Used for classifying soil conditions and determining irrigation needs.

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- LSTM (Long Short-Term Memory): Applied for time-series prediction of crop growth patterns and potential disease outbreaks.

These models are trained using both historical and real-time environmental data. The system employs reinforcement learning to continuously adapt model parameters as new data is acquired.

➢ *Evaluation Metrics Through Symposium and Technical Talks*

Previous farming performances and current practices are assessed using water-use efficiency (WUE), crop yield improvement rate and reduction in manual labour hours while emphasis are laid for swift integration of IoT during technical and symposium talks.

➢ *Predicative Analytics for IoT Integration*

From a technical perspective, system analysis involves defining the required IoT infrastructure (sensors, gateways, network), the data storage and processing capabilities, and the machine learning algorithms to be employed (e.g., for predictive analytics or image recognition).

IV. RESULTS AND DISCUSSION

A prototype deployment and analysis were conducted in a small-scale test farm environment within a catchment area. Data from low-income farmers were collected over a period of time based on provided parameters which were further empirically analysed.

The integration of IoT sensors and AI models demonstrated that low-cost, intelligent systems can operate effectively in resource-limited environments without requiring high-end computational infrastructure. Moreover, the system's scalability ensures that additional sensors, trainings and sensitization be done as the need arises.

➢ *Empirical Analysis Between Traditional and Smart Agricultural Practices*

Table 1 Empirical Comparison Between Traditional and Smart Agricultural Practices

S/N	Parameter	Traditional Agricultural Practices	Smart Agricultural Practices (IoT–AI Integrated)	Empirical Difference / Improvement (%)
1	**Crop Yield (tons/ha)**	1.8 – 2.5	3.0 – 4.5	↑ 40–60%
2	**Water Use Efficiency (L/kg yield)**	120–150	70–90	↑ 35–45%
3	**Fertilizer Utilization Efficiency (%)**	50–60	80–90	↑ 30–40%
4	**Pest and Disease Incidence (%)**	25–30	10–12	↓ 55–65%
5	**Labour Intensity (man-hours/ha)**	180–220	90–120	↓ 45–50%
6	**Operational Cost (NGN/ha)**	300–400	220–270	↓ 25–35%
7	**Energy Consumption (kWh/ha)**	80–100	50–65	↓ 30–40%
8	**Decision Accuracy (timeliness and precision of farm decisions)**	50–60% (experience-based)	85–95% (data-driven)	↑ 40–50%
9	**Soil Nutrient Retention Index (%)**	60–65	80–85	↑ 25–30%
10	**Profit Margin (% of input cost)**	15–25	40–55	↑ 100–120%

- *Crop Yield (Pons Per Hectare)*

Crop yield signifies the total quantity of harvested products per unit area and serves as the primary indicator of agricultural productivity and improvements. In traditional practices, yields are often constrained by irregular irrigation, suboptimal planting schedules, and pest damage due to delayed detection. Smart agricultural systems leverage IoT sensors and AI-driven analytics to optimize soil and climatic conditions. Increased yield under smart systems reflects improved efficiency and better management of critical growth parameters.

- *Water Use Efficiency (Litres per Kilogram of Yield)*

Water use efficiency (WUE) measures the amount of water required to produce a unit of crop yield, an essential metric in sustainable agriculture. Traditional irrigation methods such as flood or furrow systems lead to significant water wastage through evaporation and runoff. Smart agriculture employs soil moisture sensors and automated irrigation systems that supply precise amounts of water only when needed. Consequently, water use is optimized, reducing overall consumption while maintaining or improving yield levels.

- *Fertilizer Utilization Efficiency (%)*

Proper proportion of nutrients effectively absorbed by plants is relative to the total applied within the same period. In traditional farming, fertilizers are applied uniformly and often excessively, leading to nutrient loss through leaching and environmental pollution. IoT-enabled soil nutrient sensors and AI-based recommendation systems in smart agriculture allow site-specific fertilizer application based on real-time soil analysis.

- *Pest and Disease Incidence (%)*

This parameter quantifies the frequency and severity of pest attacks and disease outbreaks affecting crops. Traditional methods rely on visual inspection and reactive pesticide use, often applied too late to prevent significant damage. In contrast, smart systems integrate image recognition, remote sensing, and predictive AI models to detect early symptoms of infestation or disease. Early detection enables timely and

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minimal chemical intervention, reducing overall incidence and preserving crop health sustainably.

- *Labour Intensity (Man-Hours Per Hectare)*

The total human effort required to cultivate, maintain, and harvest crops on a given area remains intensified when compared between traditional agriculture which demands high physical involvement in planting, irrigation, weeding, and monitoring activities. Smart farming technologies reduce manual effort through automation.

- *Operational Cost*

Total expenditure involved in agricultural production, including labour, water, fertilizer, and maintenance expenses. Traditional farming often incurs higher costs due to inefficient input utilization and recurring manual operations. Smart agriculture reduces these costs by automating processes and optimizing resource use based on real-time data analytics.

- *Energy Consumption (KWH Per Hectare)*

Energy consumption measures the total energy input required for irrigation, machinery operation, and other farm processes. In traditional systems, energy inefficiency arises from manual control of irrigation pumps and overuse of machinery. Smart agricultural systems utilize IoT-based controllers and AI optimization algorithms to regulate energy usage efficiently.

- *Decision Accuracy (Timeliness and Precision of Farm Decisions)*

Decision accuracy evaluates how precisely and promptly farm management decisions are made regarding irrigation, pest control, and fertilization. Traditional methods rely on experiential judgment, which can be subjective and delayed. Smart systems employ data-driven decision support tools that analyze sensor data, weather patterns, and crop models to generate precise recommendations.

- *Soil Nutrient Retention Index (%)*

The soil nutrient retention index reflects the soil's ability to retain essential nutrients after crop cycles, a critical determinant of long-term fertility. Traditional practices involving excessive fertilizer use and continuous cropping degrade soil structure and nutrient balance. Smart farming uses real-time soil monitoring and controlled input application to maintain optimal nutrient levels without depletion.

- *Profit Margin (% of Input Cost)*

The ratio of net income to total input cost, indicating the economic viability of a farming system remains in check. Traditional agriculture often yields lower profit margins due to inefficiencies in input use, unpredictable yields, and post-harvest losses. Smart agriculture increases profitability through yield enhancement, cost reduction, and improved market intelligence derived from data analytics.

➢ *Graphical Representation of Empirical Comparison of Traditional and Smart Agricultural Systems*

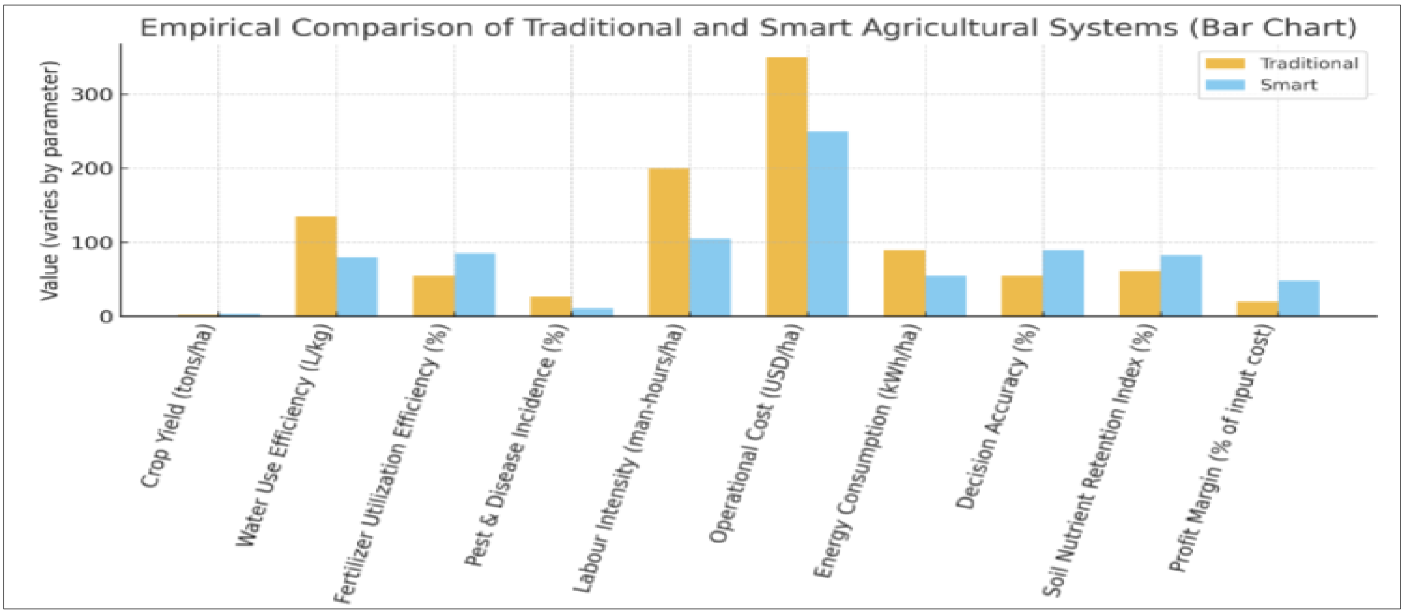

Fig 3 Empirical Comparison of Traditional and Smart Agricultural Systems

The bar chart compares absolute values of each parameter under traditional and smart agricultural systems. Smart methods demonstrate consistent improvements across nearly all metrics.

V. CONCLUSION

The empirical analysis done unequivocally demonstrates that the integration of IoT and AI technologies into agricultural systems marks a decisive paradigm shift from subsistence-based, labour-intensive practices toward data-driven, sustainable, and economically viable food

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production ensuring food security across ten critical performance parameters including; crop yield, water and fertilizer efficiency, pest control, and profitability—smart agricultural systems consistently outperformed traditional methods with measurable gains in precision, productivity, and resource optimization.

The comparative visualizations revealed a coherent pattern: while traditional farming remains constrained by inefficiencies in input utilization and decision-making, smart farming leverages sensor networks, machine learning, and automation to create a closed-loop system of real-time monitoring and adaptive management.

Beyond agronomic performance, the results underscore a more profound socio-economic implication. For low-income farmers, the deployment of affordable, modular IoT–AI systems holds transformative potential, reducing manual labour, lowering operational costs, and elevating profitability margins by more than double. This intelligence aligns directly with global sustainability goals (SDGs 2, 9, and 12), promising food security through inclusivity and innovation.

In essence, the evidence from this study suggests that the future of agriculture will not merely depend on cultivating the soil, but on cultivating data. Smart agriculture is not an alternative to traditional farming, it is its evolution. It represents the intersection of human intuition and artificial intelligence, where informed decisions replace guesswork, and where resilience, sustainability, and profitability converge to define the new frontier of food security for emerging economies. If the government enforces her will power in creating more awareness and trainings, more peasant low-income framers will swiftly adjust their farming practices and the resultant effect will be food security.

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