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Security Challenges in IoT Networks: A Block chain-Based Approach

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Abstract: *The evolution of agriculture from traditional to precision-based practices has been significantly accelerated by the integration of Internet of Things (IoT), edge computing, and Artificial Intelligence (AI). This research presents a comprehensive study on the design, implementation, and evaluation of an IoT-based smart agriculture system enhanced with edge computing and AIoT (Artificial Intelligence of Things) capabilities. Unlike conventional cloud-based models, the proposed edge-AIoT architecture enables real-time decision-making for irrigation, pest detection, and environmental monitoring through localized data processing using lightweight AI models. Experimental results show that edge systems reduce inference latency by over 80%, lower bandwidth consumption by up to 75%, and maintain comparable accuracy levels (above 91%) in pest detection and irrigation forecasting when benchmarked against cloud-based systems. The study also compares communication protocols, highlighting the superior efficiency of LoRaWAN in rural deployments compared to NB-IoT. Furthermore, the paper explores the feasibility of deploying lightweight Large Language Models (LLMs) at the edge for multimodal reasoning, enabling autonomous agricultural analytics with minimal cloud reliance. The findings suggest that edge-AIoT frameworks not only enhance operational efficiency and scalability in smart farming but also offer a viable, cost-effective solution for smallholder and rural farmers. The research concludes with future directions including LLM-powered edge assistants, drone integration, federated learning, and sustainable energy models to further advance autonomous agriculture ecosystems.*

Keywords: Edge Computing, Smart Agriculture, Artificial Intelligence of Things (AIoT), Precision Farming, IoT Sensor Networks

I. INTRODUCTION

Agriculture remains the backbone of many economies, especially in developing regions, where it not only ensures food security but also sustains livelihoods for a majority of the population. However, traditional farming methods are under severe stress due to rapid population growth, urbanization, water scarcity, soil degradation, and unpredictable climate patterns. To meet the rising demand for food while ensuring environmental sustainability, there is a pressing need to transform conventional agriculture into a smart, data-driven system that optimizes resource usage and maximizes crop yield.Smart agriculture, also known as precision farming, involves the use of advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and edge computing to collect and analyze real-time data from the field. This technological ecosystem enables farmers to make informed decisions regarding irrigation, fertilization, pest control, and harvesting. In a smart agriculture system, IoT devices like soil moisture sensors, temperature and humidity sensors, drones, and cameras are deployed across farmland to continuously monitor environmental and crop conditions. These devices generate vast amounts of data, which when processed effectively, can drastically improve decision-making efficiency and reduce dependency on guesswork. Traditionally, data collected from the field is transmitted to cloud servers for processing. However, this cloud-centric model introduces challenges such as high latency, limited internet connectivity in rural areas, increased bandwidth usage, and privacy concerns. This is where edge computing plays a critical role. Edge computing allows data to be processed locally—close to the data source—on small, powerful

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edge devices like Raspberry Pi, Jetson Nano, or microcontrollers. By performing AI-driven analytics directly at the edge, the system can respond to real-time events such as sudden pest infestations or soil moisture drops without relying on cloud connectivity. This significantly improves the responsiveness and reliability of the smart agriculture ecosystem.
Moreover, integrating AI models at the edge enables intelligent decision-making with minimal delay. Lightweight AI algorithms can classify pests from images, predict irrigation needs using time-series sensor data, and detect anomalies in climate patterns. This AIoT (Artificial Intelligence of Things) approach minimizes human intervention while enhancing precision, efficiency, and sustainability in agriculture.This paper investigates the integration of IoT with edge-based AI to develop an efficient smart farming system. It examines the design architecture, performance benchmarks (accuracy, latency, energy usage), and communication trade-offs (LoRaWAN vs. NB-IoT), while proposing future enhancements like lightweight large language models (LLMs) for multimodal analysis and decision support at the edge. Through simulation and analytical modeling, the study aims to validate that edge-AIoT systems can serve as a scalable and cost-effective solution for modern agriculture, particularly in rural and infrastructure-limited regions.

II. LITERATURE REVIEW

Smart agriculture is an emerging interdisciplinary field that intersects agricultural science, computer engineering, data analytics, and environmental monitoring. The growing interest in this domain is driven by the urgent need to improve crop yield, resource efficiency, and sustainability through data-driven technologies. This section synthesizes key literature on IoT applications in agriculture, the evolution of edge computing as a response to cloud limitations, and the emerging role of AI and AIoT (Artificial Intelligence of Things) in achieving real-time, intelligent decision-making on the farm.

The integration of IoT technologies into agriculture began with the adoption of remote sensing, wireless sensor networks (WSNs), and GPS-enabled devices. These technologies enabled farmers to monitor variables such as soil moisture, ambient temperature, and rainfall levels with unprecedented granularity. According to Kumar et al. (2020), IoT-based monitoring systems have been successfully used in precision irrigation, resulting in up to 30% water savings in certain deployments. However, these systems typically rely on cloud infrastructure for data aggregation and analysis, which presents limitations in bandwidth, latency, and continuous internet availability—especially in rural or underdeveloped areas. Edge computing has emerged as a transformative solution to address the bottlenecks posed by centralized cloud processing. In an edge architecture, data is processed locally—on-site—through edge devices such as microcontrollers, Raspberry Pi, or NVIDIA Jetson modules. These systems drastically reduce the time taken to respond to events such as irrigation needs, pest attacks, or disease detection. Solis et al. (2022) emphasized that edge computing minimizes network congestion, ensures lower latency, and enables offline functionality, which are all critical for farms located in regions with poor internet connectivity. AI plays a pivotal role in converting raw IoT data into actionable insights. Machine learning (ML) models are used to predict soil conditions, detect pest infestations, forecast crop yield, and even automate irrigation schedules. Habib et al. (2023) applied a CNN-based deep learning model for pest detection in strawberry farms, achieving over 92% classification accuracy. These AI models traditionally require significant computational resources, which is why they were initially restricted to cloud platforms.

However, with advances in edge AI, lightweight models can now be deployed directly on edge devices. For instance, using TensorFlow Lite or PyTorch Mobile, researchers have implemented real-time disease detection systems on Jetson Nano and Raspberry Pi devices, enabling autonomous decision-making at the farm level. Indra Gandhi et al. (2023) reported a successful AIoT poultry monitoring system where edge-deployed ML models achieved 99.72% classification accuracy in detecting abnormal temperature and humidity conditions. In a comparative study, Ebrahimi et al. (2023) demonstrated that edge-based crop monitoring systems reduced average decision latency by over 60% compared to cloud-only systems. This is significant in scenarios requiring time-sensitive interventions, such as pesticide spraying following early-stage pest detection. Moreover, edge computing enhances data privacy, as sensitive environmental and geolocation data need not be transmitted to third-party servers.AI plays a pivotal role in converting raw IoT data into actionable insights. Machine learning (ML) models are used to predict soil conditions, detect pest infestations, forecast crop yield, and even automate irrigation schedules. Habib et al. (2023) applied a CNN-based deep learning model for

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III. OBJECTIVES OF THE STUDY

The overarching goal of this study is to explore the integration of Internet of Things (IoT) with edge computing and Artificial Intelligence (AI) to build a robust, scalable, and real-time smart agriculture system. In particular, this research investigates how AIoT systems deployed at the edge can enhance agricultural decision-making by reducing latency, minimizing bandwidth requirements, and enabling autonomous farm management.Secondary

Primary Objectives

1. To develop and test a smart agriculture architecture that combines IoT devices, edge computing nodes, and AI models for localized crop monitoring, irrigation management, and pest detection.
2. To evaluate the performance of edge-AIoT systems against traditional cloud-centric systems using key metrics such as:
3. Latency (response time)
4. Data accuracy (pest/disease detection, irrigation forecasting)
5. Energy consumption (per device/per session)
6. Bandwidth utilization (communication protocol efficiency)
7. To identify the most suitable communication protocols (e.g., LoRaWAN, NB-IoT) for different deployment scenarios in agriculture based on cost, range, and power efficiency.
8. To simulate and analyze real-world agricultural scenarios, including greenhouse climate control and open-field crop monitoring, through case studies and controlled experiments.
9. To assess the feasibility of deploying lightweight AI models and LLMs at the edge, enabling multimodal analytics (sensor + image data) without reliance on cloud connectivity.

Secondary Objectives:

1. To understand deployment challenges in rural settings, including hardware costs, maintenance requirements, and network infrastructure limitations.
2. To explore future enhancements such as federated learning, mobile UAV integration, and solar-powered edge nodes for sustainable farming.

IV. HYPOTHESES

This study is guided by a series of testable hypotheses that align with the core objectives:

H_1: Edge-AIoT systems offer equivalent or superior accuracy in pest detection and crop condition monitoring when compared to cloud-based models, with significantly reduced latency.

H_2: Integrating LoRaWAN-based communication with edge computing results in lower bandwidth usage and energy consumption than NB-IoT or cloud-only alternatives in low-infrastructure rural settings.

H_3: Lightweight AI models (e.g., KNN, CNN, LSTM) deployed on edge platforms like Raspberry Pi or Jetson Nano can perform real-time analytics without exceeding acceptable energy and processing limits for continuous field deployment.

H_4: Deploying multimodal lightweight LLMs at the edge is feasible and improves the system's ability to perform context-aware, cross-modal reasoning using weather, image, and sensor data with minimal cloud intervention.

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V. METHODOLOGICAL FRAMEWORK

This research adopts a **mixed-methods design** that combines experimental prototyping, simulation-based modeling, and analytical performance evaluation. The choice of methodology is driven by the multidisciplinary nature of the study, which encompasses aspects of embedded systems, artificial intelligence, wireless communication, and agricultural field dynamics. A mixed approach allows the integration of **quantitative performance metrics** (latency, accuracy, energy use) with **qualitative analysis** of deployment feasibility, infrastructure needs, and environmental constraints.

The research is conducted in three main phases:

Phase I: System Architecture and Prototype Development

In this phase, a **smart agriculture architecture** was developed using:

- **IoT sensors** (soil moisture, humidity, temperature, light intensity),
- **Edge devices** (Jetson Nano, Raspberry Pi 4),
- **AI models** (CNN for image classification, LSTM for irrigation prediction),
- **Communication protocols** (LoRaWAN and NB-IoT for comparison).

The system was deployed in a controlled environment simulating open-field and greenhouse settings. IoT sensors collected real-time data and transmitted it via both protocols. Edge nodes processed this data using onboard AI models to detect pest outbreaks, assess irrigation needs, and activate actuators (simulated as digital switches for pumps and sprayers).

Phase II: Experimental Benchmarking

This phase involved **benchmarking system performance** under realistic agricultural scenarios. For consistency, the tests were conducted over fixed intervals (30-minute cycles) over a simulated 48-hour agricultural workweek. Key performance indicators included:

- Inference latency (time taken for AI models to generate a decision),
- Accuracy (pest detection/classification, irrigation prediction),
- Energy consumption (per task, per hour),
- Data bandwidth (amount of data transmitted per day).

A comparative test was run using a **cloud-based system** that transmitted the same data to a cloud server for centralized processing. This allowed for direct benchmarking of the edge-AIoT system against conventional architectures.

Phase III: Statistical and Analytical Evaluation

Collected data was analyzed using **descriptive statistics and inferential tests**. A **t-test** was applied to evaluate latency differences between edge and cloud systems, while a **Chi-Square test** assessed the impact of communication protocols on reliability and response. **Correlation analysis** was conducted to understand the trade-offs between energy consumption and model accuracy on different edge devices. Findings were visualized using Python and Grafana.

The design was validated through peer reviews and by replicating trials in different environmental conditions (wet, dry, night/day) to ensure robustness. Finally, a qualitative assessment was conducted to evaluate the practicality of deploying such systems in rural or low-infrastructure areas.

VI. DATA COLLECTION TECHNIQUES

- System Log Analysis: Captured transaction data, smart contract events, and authentication failures.
- Network Monitoring: Used Wireshark and Grafana dashboards to monitor packet flow, latency, and network load.
- Power Usage: Measured via USB power meters to understand the overhead introduced by blockchain operations.

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- Interviews: Conducted semi-structured interviews with 5 IoT engineers and 3 blockchain developers to gain insights into real-world implementation feasibility.
- Comparative Benchmarking: Traditional vs. blockchain-based models were tested under identical environmental variables for comparative analysis.

In this research, the term "sample" refers to the hardware and software components, datasets, and network configurations used to build and evaluate the smart agriculture prototype. A purposive sampling technique was adopted to select components that reflect real-world constraints, such as energy limitations, cost-efficiency, environmental durability, and processing capability **in rural agricultural contexts.**

6.1 Sample Composition

Edge Devices:

- Jetson Nano Developer Kit: Used for running AI models (CNN, LSTM) for real-time image and sensor analysis.
- Raspberry Pi 4 Model B: Used for control logic, data acquisition, and lighter AI tasks.

IoT Sensors:

- Capacitive soil moisture sensor v1.2
- DHT11 temperature and humidity sensor
- Light-dependent resistors (LDR)
- Analog water flow meter sensor

Communication Modules:

- LoRa SX1276 transceivers (for long-range, low-power communication)
- NB-IoT SIM7000E module (for cellular-based M2M communication)

AI Models:

- CNN-based pest classifier: Trained on open-source crop pest image datasets.
- LSTM-based irrigation predictor: Trained on time-series soil moisture and temperature data.

Deployment Environment:

A mock farm setup was created indoors and outdoors, consisting of three plots:

1. Simulated greenhouse (controlled conditions),
2. Open-field dry crop,
3. Moist environment crop (simulating paddy or wet soil farming).

Sensor nodes and edge devices were rotated among plots to ensure all conditions were represented across trials.

6.2 Sampling Rationale

The sample was deliberately curated to meet the following criteria:

- Scalability: All components can be replicated in larger deployments.
- Cost-effectiveness: Each node was built under $100 USD.
- Power compatibility: Edge and sensor modules supported solar power and battery operation.
- Real-world applicability: The sensors and protocols used are available and field-tested.

The sample size—five IoT nodes (with identical configurations), two edge processors, and two wireless protocols—was sufficient for collecting over 5,000 data points during the trials. This volume allowed for statistically meaningful analysis of the performance gaps between edge-AIoT and cloud systems.

6.3 Sample Limitations

While the sample reflected realistic rural farming conditions, certain limitations were acknowledged:

- Simulation of pests was done using images rather than real-time environmental events.

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- Wireless interference and large-scale LoRa mesh network behavior were not fully tested due to spatial constraints.
- The use of synthetic datasets in model training may not account for unpredictable real-world conditions like sensor noise or weather anomalies.

Despite these limitations, the sampling approach offered a practical, low-cost, and flexible testbed that emulates conditions faced by farmers in small to medium-sized agricultural settings.

VII. DATA ANALYSIS

The data analysis phase focused on evaluating the performance, efficiency, and accuracy of the proposed edge-AIoT-based smart agriculture system compared to a conventional cloud-based IoT setup. Various quantitative metrics were measured across multiple trials, followed by statistical tests to validate the hypotheses laid out earlier. Analysis was carried out using Python (Pandas, NumPy, SciPy), with visualization done via Matplotlib and Grafana dashboards.

7.1 Key Performance Metrics

The core metrics analyzed include:

- Latency (ms): Time taken from data capture to actionable output.
- Energy Consumption (mAh): Power usage per hour by edge and cloud systems.
- Pest Detection Accuracy (%): Accuracy of AI models deployed at the edge vs. the cloud.
- Bandwidth Usage (KB/day): Total transmission load generated by each system.
- Anomaly Detection Rate (%): Frequency and reliability of identifying deviations in soil, moisture, or temperature.

The experiments were conducted over 48-hour cycles under similar environmental conditions across three agricultural plots (controlled greenhouse, dry soil field, wet field).

7.2 Descriptive Statistics

Metric	Edge-AIoT System	Cloud-Based IoT System
Avg. Inference Latency (ms)	130	870
Pest Detection Accuracy (%)	91.6	92.8
Soil Moisture Prediction Error (%)	6.5	6.3
Bandwidth Usage (KB/day/node)	290	1,260
Energy Consumption (mAh/hour)	280	190 (IoT node only)
Anomaly Response Time (sec)	3.8	10.7

7.3 Inferential Statistics

A. Latency (t-test)

- Null Hypothesis (H_0): No significant difference in latency between edge and cloud systems.
- $t(98) = 12.56$, $p < 0.001$

Interpretation: The edge system shows significantly lower latency than the cloud system, strongly supporting H_1.

B. Pest Detection Accuracy (Paired t-test)

- Accuracy edge = 91.6%; cloud = 92.8%
- **$t(98) = -1.18$, $p = 0.24$**

Interpretation: No statistically significant difference in accuracy between edge and cloud deployments. This supports **H_3**, indicating lightweight edge models perform comparably.

C. Bandwidth Usage (Chi-Square Test)

- LoRaWAN vs. NB-IoT transmission logs showed drastic differences:

Protocol	<500 KB/day	>500 KB/day	Total
LoRaWAN	46	4	50
NB-IoT	13	37	50

- **$\chi^2(1) = 34.91, p < 0.001$**

Interpretation: Bandwidth usage is significantly lower with **LoRaWAN**, validating $\mathbf{H_2}$.

D. Correlation (Pearson's r) Between Energy and Accuracy

- $r = -0.12$, $p = 0.18$

Interpretation: A weak and statistically insignificant correlation indicates energy consumption is not directly tied to detection accuracy, supporting that optimized edge models are viable.

7.4 Visual Analysis

- **Latency Heatmaps**: Displayed faster responses from edge systems across all field types.
- **Power Curves**: Jetson Nano showed stable draw at ~4.8W; Raspberry Pi at ~3.2W. Spikes only during AI inference.
- **Data Flow Charts**: LoRaWAN networks had less congestion and packet loss compared to NB-IoT, particularly during peak collection times.

7.5 Discussion

The results confirm that edge-based AIoT systems significantly improve response time and reduce dependency on cloud infrastructure. While the cloud-based model yielded slightly higher accuracy in pest detection, the difference was not statistically significant, demonstrating the efficacy of deploying lightweight AI models at the edge. Additionally, the edge system conserved up to 75% bandwidth, which is crucial for scalability in low-bandwidth rural areas. The higher energy consumption on the edge (particularly Jetson Nano) was an expected trade-off for reduced latency. However, this can be mitigated through solar power integration or duty-cycling models that only activate inference when significant data anomalies are detected. Ultimately, the edge-AIoT system offered comparable accuracy, faster response, and lower operational costs than cloud systems, making it more suitable for precision agriculture in resource-constrained environments.

VIII. RESULTS AND DISCUSSION

This section presents and interprets the findings from the comparative evaluation between the edge-AIoT smart agriculture system and a traditional cloud-based IoT system. The results highlight the strengths and trade-offs of using edge computing combined with AI in precision farming, particularly in resource-constrained or rural environments.Chi-Square Analysis: Unauthorized AccessTo determine whether the use of blockchain significantly impacts the prevention of unauthorized access, a Chi-Square test of independence was conducted. The frequency table used is presented below:

8.1 System Performance Overview

The edge-AIoT system consistently outperformed the cloud-based alternative in latency, bandwidth efficiency, and real-time responsiveness:

- Inference Latency: Edge devices completed AI-driven pest detection and irrigation prediction tasks within an average of 130 milliseconds, compared to 870 milliseconds in the cloud system. This 6.7x improvement in speed is crucial for time-sensitive agricultural operations.

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- Bandwidth Utilization: The edge system required only 290 KB/day/node, while the cloud model consumed over 1,260 KB/day/node, making the edge-AIoT system more viable in regions with limited connectivity.
- Accuracy: Both systems showed similar results in prediction accuracy (~91.6% for edge vs. 92.8% for cloud), confirming that edge models, when optimized, can perform as well as cloud-based models.

These outcomes strongly support Hypotheses H_1 and H_3: edge-AIoT systems provide low-latency decisions with comparable AI accuracy, while reducing bandwidth reliance.

8.2 Communication Protocol Trade-offs

The study compared LoRaWAN and NB-IoT in edge device communication:

- LoRaWAN exhibited significantly lower bandwidth usage and power consumption, making it ideal for farms with energy and infrastructure constraints.
- NB-IoT, while providing higher data rates, consumed more energy and incurred telecom costs.

A Chi-Square test ($\chi^2(1) = 34.91$, $p < 0.001$) confirmed that LoRaWAN offered a statistically significant reduction in bandwidth usage, validating Hypothesis H_2.

Conclusion: LoRaWAN is better suited for low-data-rate agricultural applications where cost and power consumption are primary concerns.

8.3 Energy Consumption and Device Feasibility

The Jetson Nano required ~4.8 W during active inference, while Raspberry Pi 4 consumed ~3.2 W. Though higher than IoT-only nodes, these energy levels are manageable with solar panels or intermittent scheduling. Lightweight devices with hardware accelerators for AI (like Google Coral) could further optimize this.

There was no significant correlation between energy use and AI accuracy (Pearson $r = -0.12$, $p = 0.18$), suggesting that edge AI can be efficient without compromising prediction performance, reinforcing Hypothesis H_3.

8.4 Real-Time Decision Making and Anomaly Response

The anomaly detection response time—the interval between detecting unusual sensor readings and triggering a corrective action—was reduced from 10.7 seconds in the cloud system to 3.8 seconds on the edge. This enabled timely intervention in irrigation misfires and pest outbreaks, demonstrating the value of local processing in agriculture.This responsiveness directly impacts yield quality and resource conservation, especially in climates where fast action can prevent crop loss or disease spread.

8.5 Lightweight LLM Integration Potential

Though not deployed in full scale, simulation using Farm-LightSeek (Jiang et al., 2025) demonstrated that edge devices with 8–16 GB RAM can support LLM-based multimodal reasoning for small datasets. These models combined weather forecasts, soil sensor data, and crop images to suggest interventions—offering a glimpse into next-gen autonomous farming assistants.This supports Hypothesis H_4, indicating that edge deployment of compact language models is feasible for agricultural use cases, particularly for decision support systems.

8.6 Limitations and Challenges

Despite promising results, the study faced the following constraints:

- Controlled Environment: Real farm deployments involve unpredictable factors like wildlife interference, variable weather, and sensor degradation, which were only partially simulated.
- Power Supply: Although solar-assisted designs were theorized, actual integration was not tested in this phase.
- AI Generalization: The models were trained on pre-existing datasets, which may not account for regional pest or crop variety differences.

8.7 Overall Implications

The results strongly indicate that **edge-AIoT systems are practical, scalable, and cost-effective** for smart agriculture—particularly in **low-infrastructure rural regions**. With faster response times, reduced bandwidth dependency, and acceptable accuracy, such systems empower farmers to make timely and data-driven decisions. Additionally, the ability to run AI inference on-site opens opportunities for **privacy-preserving, autonomous agriculture**, paving the way for more intelligent, climate-resilient farming ecosystems.

IX. CONCLUSION AND FUTURE SCOPE

The convergence of **IoT, edge computing, and artificial intelligence (AI)** has opened a new frontier in precision agriculture, providing farmers with real-time, data-driven tools to enhance productivity, sustainability, and decision-making. This study has demonstrated that integrating **AI-enabled edge computing with IoT devices (AIoT)** significantly enhances the performance of smart farming systems when compared to conventional cloud-based models.
The research findings confirm several key advantages of edge-AIoT architectures:

- **Reduced Latency**: Real-time decisions—such as activating irrigation or alerting for pest outbreaks—can be made in under 150 milliseconds at the edge, compared to nearly 900 milliseconds in cloud-dependent setups.
- **Improved Bandwidth Efficiency**: LoRaWAN-based communication significantly minimizes network congestion, making the system feasible for rural or low-bandwidth environments.
- **High Accuracy**: Lightweight AI models deployed at the edge can achieve pest detection and irrigation forecasting accuracies above 90%, comparable to cloud AI models.
- **Scalability and Autonomy**: Decentralized processing reduces reliance on internet connectivity, making the solution more scalable and suitable for remote and infrastructure-constrained farms.

While the study showcased the effectiveness of deploying **deep learning and time-series models (CNN, LSTM)** at the edge, it also hinted at future possibilities—especially the integration of **lightweight large language models (LLMs)** for cross-modal reasoning using diverse data streams like sensor logs, weather data, and crop imagery.
However, challenges remain. Energy consumption by edge nodes, particularly GPU-powered boards like Jetson Nano, needs to be optimized for field longevity. Additionally, variability in local conditions, hardware costs, and farmer adoption rates must be studied through long-term field deployments.In conclusion, the edge-AIoT approach represents a **transformative and accessible technology** for smallholder farmers, government agencies, and agritech startups alike. It can accelerate the transition from traditional farming to **autonomous, AI-driven agriculture**, offering tangible solutions to food security, climate change resilience, and water conservation.

Future Scope

Building on the findings of this research, several directions emerge for future investigation:

1. **Deployment of Lightweight LLMs at the Edge**
   With advancements in edge hardware and model compression, running LLMs (like TinyGPT, DistilBERT) on local processors is becoming feasible. These models can enable real-time question-answering, multilingual interfaces for farmers, and intelligent decision support systems for disease diagnosis, market prediction, and farm planning.
2. **Federated Learning in Agriculture**
   Future systems can adopt federated learning, where models are trained across multiple farms without centralizing data—preserving privacy while improving model generalization for different crops and environments.
3. **UAV and Drone Integration**
   Combining UAV-based aerial imaging with edge-AIoT systems could expand real-time monitoring coverage. Drones can capture field-wide data, which can be processed by mobile edge nodes for anomaly detection, plant counting, or weed segmentation.

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4. **Sustainable Energy Integration**
   To support always-on edge analytics, future work should focus on **solar-powered edge devices**, energy-efficient chipsets, and power-aware scheduling algorithms for inference tasks.
5. **Long-Term Field Trials with Real Farmers**
   To evaluate socio-technical feasibility, the proposed system should be field-tested with smallholder farmers across diverse regions and climates. This would provide insight into adoption challenges, human-computer interaction issues, and economic impacts.
6. **Policy and Platform Development**
   Governments and agricultural departments could use these findings to build **open AIoT platforms** with standardized protocols, sensor APIs, and deployment kits that make smart agriculture accessible even to small rural cooperatives.

By bridging cutting-edge technologies with grassroots agricultural practices, this research lays the groundwork for a future where intelligent, responsive, and self-learning farms become the norm—empowering farmers not only to survive but to thrive in the face of uncertainty.

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