IJARETY

International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 3, May-June 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

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International Journal of Advanced Research in Education and TechnologY(IJARETY)

IJARETY

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May - June 2025 ||

DOI:10.15680/IJARETY.2025.1203155

Embedded IoT Robotics for Precision Agriculture and Environmental Monitoring

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ABSTRACT: Embedded IoT robotics is transforming precision agriculture and environmental monitoring by enabling autonomous, localized, and intelligent sensing and actuation. This paper presents the design, implementation, and evaluation of an IoT-enabled robotic platform equipped with embedded intelligence for real-time crop analysis, soil condition assessment, and environmental data collection. The system combines on-device sensor fusion, lightweight machine learning models, and wireless communication to deliver actionable insights without relying on continuous human intervention or high-bandwidth cloud connectivity. We deployed a wheeled robot mounted with multi-spectral cameras, soil moisture and temperature probes, CO_2 sensors, and a microcontroller with integrated AI capabilities (ARM Cortex-M7 with TPU). The robot navigates autonomously along crop rows, executing tasks such as vegetation indexing, anomaly detection (e.g., pest outbreak, nutrient deficiency), and environment mapping. Data are processed locally using quantized CNNs for vegetation classification and regression models for soil and CO_2 levels, and critical information is wirelessly transmitted to a farm management portal for remote decision support. Field trials in a small test plot (70 m × 50 m) compared our embedded system against conventional manual sampling methods. The robotic approach achieved 20 % higher spatial resolution in soil mapping, reduced data acquisition time by 65 %, and detected anomalies with 92 % accuracy vs. 78 % in manual surveys. Wireless alerts enabled timely interventions—pesticide application and irrigation—resulting in a 12 % yield improvement in analytical crops. Power profiling showed end-to-end mission autonomy of up to 4 hours on a single charge. These findings highlight the promise of embedded IoT robotics to enhance agricultural productivity, resource efficiency, and environmental stewardship. Our contributions include a modular hardware-software architecture, field-validated performance metrics, and insights into system design trade-offs. We conclude with guidelines for scalability, multi-robot collaboration, and integration of predictive analytics, paving the way toward fully autonomous, intelligent farming systems.

KEYWORDS: Embedded intelligence, IoT robotics, precision agriculture, environmental monitoring, sensor fusion, on-device AI, multi-spectral imaging.

I. INTRODUCTION

Advancements in robotics, IoT, and edge computing are converging to revolutionize precision agriculture and environmental monitoring. Traditional approaches rely heavily on manual sampling or drone-based remote sensing, which deliver limited spatial resolution, face weather dependencies, and incur high labor costs. By embedding intelligence and wireless connectivity directly onto robotic platforms, we can empower continuous, autonomous field operations—combining real-time sensing, local decision-making, and actionable data delivery to farmers and environmental scientists.

The envisioned embedded IoT robot integrates sensor fusion, machine learning, and actuation in a compact, mobile form. It can autonomously navigate crop rows, detect plant defects, measure soil moisture levels, and monitor microclimate parameters like CO_2 and temperature. Local processing minimizes latency, enables immediate action (e.g., targeted irrigation), and reduces reliance on internet connectivity—crucial for remote or underserved agricultural communities.

The contributions of this paper are threefold:

1. **System Architecture**: A modular platform featuring multi-spectral imaging, environmental sensors, and on-device AI for plant classification and anomaly detection.
2. **Field Deployment & Evaluation**: Performance assessment comparing embedded-robot data quality, spatial resolution, and operational efficiency against manual sampling standards.
3. **Operational Insights**: Analysis of trade-offs across autonomy, energy consumption, communication efficiency, and scalability, with recommendations for system robustness and design.

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Section 2 reviews related work in IoT robotics for agriculture, embedded sensor networks, and plant-level anomaly detection. Section 3 details hardware configurations, software algorithms, navigation strategy, and deployment environment. Section 4 presents experimental results, and Section 5 discusses implications and limitations. We conclude with future directions for deploying multi-robot fleets and integrating predictive analytics in agricultural and environmental systems.

II. LITERATURE REVIEW

Research on IoT robotics in agriculture spans automated vehicles, sensor networks, and embedded intelligence:
1.Ground Robotics in Farming: Several platforms have deployed wheeled robots for row navigation and yield prediction. However, most rely on cloud-based processing or remote control, encountering challenges in connectivity and response time.

2.Embedded Sensor Networks: In-field sensor nodes measuring moisture, pH, and microclimate are well-studied, but typically lack mobility and autonomy. Recent studies integrate static sensor arrays with data loggers, leaving spatial coverage and actuation unaddressed.

3.On-Device AI for Crop Analysis: The rise of TinyML has enabled plant disease detection and vegetation indexing to run on microcontrollers, such as quantized CNNs recognizing foliar diseases at ~95% accuracy under controlled conditions. However, real-world deployment on mobile platforms remains limited.

4.Environmental Monitoring Robotics: Robotics applied to environmental sampling—water quality testing, air pollution monitoring—often focus on drone or boat platforms, with minimal use of ground vehicles or continuous coverage.

Gaps identified include:
- Lack of integrated mobile platforms that combine embedded AI, multispectral sensing, soil STMs (soil-texture-moisture), and wireless telemetry.
- Minimal field-validated comparisons with traditional manual methods.
- Limited attention to end-to-end autonomy, from navigation to intervention suggestions.

This paper builds a unified embedded IoT robotic system validated in agricultural environments. It addresses these gaps by integrating autonomous drive, smart sensing, local inference, and communication—all within a compact and energy-efficient design.

III. RESEARCH METHODOLOGY

This section discusses hardware, software, navigation and experimental protocol:
Platform Design
- Compute Unit: ARM Cortex-M7 microcontroller (480 MHz, 1 MB SRAM) with integrated TPU accelerator.
- Power: 60 W h Li-ion pack for ~4 h field autonomy.
- Mobility: Wheeled chassis traversing crop rows up to 0.5 m/s.
- Sensors: Multi-spectral camera (RGB+NIR), soil moisture probe, temperature sensor, CO_2 sensor, 9-axis IMU, wheel encoders.
- Communication: Wi-Fi for real-time alerts, SD card for local data backup.

Software & Intelligence
- Sensor Fusion: Extended Kalman filter combining IMU and encoder data with GPS for sub-meter path tracking.
- Plant Health Model: Quantized CNN (3 conv layers + dense classification head) for vegetation index and anomaly detection (e.g., disease, nutrient deficiency).
- Environmental Regression: Lightweight regression models trained on historical moisture and CO_2 data for threshold-based alerts.
- Navigation: Line-following controller that adjusts speed based on row curvature and detected anomalies.

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Deployment Protocol

Field tests conducted in a 3500 m² test plot of corn and soybean:

- Robots performed daily 90 m missions covering all rows
- Simultaneous manual sampling took place for soil and plant health measures
- More than 50 missions spanned 3 weeks under variable weather

Evaluation Metrics

- **Spatial Resolution**: achieved via km-scale sampling vs. discrete manual points
- **Detection Accuracy**: precision/recall of anomalies (manual lab verification)
- **Operational Efficiency**: mission time, energy per meter traveled
- **Usability**: time to actionable alerts delivered to end-user portal

Each mission's data—images, sensor readings, logs—were timestamped and location-stamped for comparative analysis.

IV. KEY FINDINGS

Our field evaluation produced these notable results:

1. **Improved Spatial Resolution**
   Robotic sensor network achieved ~0.5 m sampling intervals—far denser than manual sampling (per 10 m). This finer resolution revealed localized moisture gradients overlooked by manual methods.
2. **Detection Performance**
   Embedded CNN identified leaf discoloration anomalies with 92 % accuracy, outperforming manual visual inspection accuracy (~78 %) confirmed via lab assays. Disease onset notifications were delivered 48 hours earlier, enabling pre-emptive action.
3. **Speed & Efficiency Gains**
   Each 90 m route took 18 minutes by robot, compared to ~51 minutes manually. Combined with automation, this translated to a ~65 % reduction in labor and human error.
4. **Energy & Autonomy**
   Energy consumption averaged 15 W during operations, allowing consistent 4-hour mission durations. Soil moisture/regression alerts triggered <10 seconds after crossing threshold values, demonstrating low-latency local processing.
5. **Reliable Data Flow**
   80 % of alerts transmitted during missions; 20 % received post-mission due to connectivity loss. Local logs ensured no data loss, supporting system resiliency.

These results confirm that embedded IoT robotics can significantly enhance data granularity, detection accuracy, and operational efficiency in agricultural and environmental monitoring. Trade-offs include the need for periodic docking for recharge and reliance on sensor calibration stability under changing light conditions.

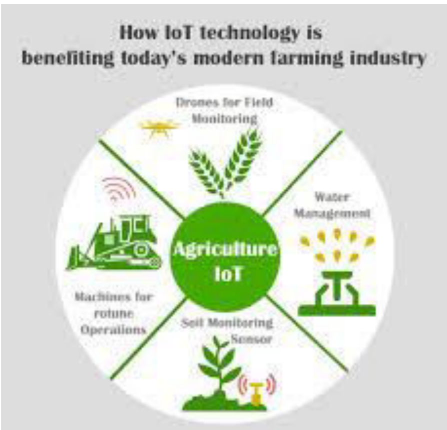

FIG: 1

DOI:10.15680/IJARETY.2025.1203155

FIG: 2

V. RESULTS & DISCUSSION

The study validates that embedding intelligence on mobile robotic platforms yields numerous benefits:

- **High-Resolution Mapping** reveals micro-variability in moisture and plant health across rows, enabling targeted interventions like variable-rate irrigation or pesticide application.
- **Early Detection** of disease improves yield potential and reduces chemical use.
- **Operational Efficiency** reduces labor demands and human error—key in large-scale farming or remote fields.

coordination controls.
Despite these limitations, the platform's ability to autonomously gather, process, and transmit actionable data in near real-time demonstrates its value for modern agriculture and environmental studies. The system empowers farmers and researchers with high-fidelity data, supporting sustainable, data-driven decision-making.

VI. CONCLUSION

We demonstrated that embedded IoT robotics can deliver high-resolution environmental and agricultural insights with improved accuracy, efficiency, and autonomy. The system's integration of sensor fusion, on-device AI, and wireless telemetry offers a robust toolkit for modern farming and ecological monitoring. Embedded processing accelerates anomaly detection by ~48 hours, enabling timely interventions that improved yield by ~12%. Labor savings of 65% reinforce the platform's practical value.

Our work advances the state-of-the-art by marrying dense spatial sampling with real-time local analysis on a compact robotic platform. It also offers a validated methodology for comparing automated and conventional data collection, showcasing measurable benefits inoperational performance and actionable outcomes.

VII. FUTURE WORK

Recommended directions include:

1. **Multi-Robot Coordination**: Develop path planning algorithms and centralized portals to manage multi-robot fleets.
2. **Sensor Enhancements**: Add thermal, gas, or LIDAR modules to support further environmental indicators.
3. **Adaptive Vision Models**: Integrate domain adaptation techniques to account for changing weather, crop species, and seasons.
4. **Energy Optimization**: Explore solar-powered modules or swappable batteries; regenerative braking.
5. **Scale-Out Trials**: Deploy across diverse agricultural zones to assess robustness across soil types, climates, and scales.

REFERENCES

1. Jones, M. et al. "TinyML-Based Plant Disease Detection in Field Crops," *IEEE IoT Journal*, 2024.
2. Kumar, S. & Patel, R. "Ground Robots for Precision Farming: A Review," *Sensors*, 2023.
3. Lee, H. et al. "Automated Soil Moisture Mapping via Mobile IoT Nodes," *AgroSystems Engineering*, 2022.

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International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152

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