ISSN: 2720-989X
JEEE
JOURNAL OF ENERGY AND ELECTRICAL ENGINEERING

Utilization of Rover AI Agents for Palm Oil Plantation Automation

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[*submitted*: 27-10-2024 | *review*: 04-10-2025 | *published*: 31-10-2025]

ABSTRACT: *The integration of artificial intelligence into autonomous rover systems represents a paradigm shift in how palm oil plantations can be managed and operated. Our research explores the deployment of intelligent rover agents that combine sophisticated machine learning algorithms with advanced robotics to transform traditional agricultural practices. Through extensive field trials spanning 500 hectares of operational plantations, we observed remarkable improvements in disease detection accuracy, reaching 94 percent. At the same time, pesticide consumption decreased by 87 percent through the use of precision application techniques. The system architecture leverages edge computing capabilities to process multispectral imagery and environmental sensor data in real-time, enabling an immediate response to detected anomalies. Deep reinforcement learning guides the navigation system, allowing the rovers to autonomously traverse complex plantation terrain, while convolutional neural networks analyze plant health indicators with unprecedented precision. Communication between multiple rover units occurs through a federated learning framework that preserves bandwidth and enables collective intelligence growth without compromising data privacy. This comprehensive approach yielded a 35% increase in overall operational efficiency, underscoring the transformative potential of AI-driven automation in tropical agricultural environments.*

KEYWORDS: *AI agents, autonomous rovers, deep learning, edge computing, palm oil automation, precision agriculture*

I. INTRODUCTION

Palm oil production stands at a critical juncture where traditional farming methods struggle to meet the dual demands of increasing global consumption and environmental sustainability. As we approach production targets of 100 million metric tons by 2030, the industry faces mounting pressure to innovate beyond conventional practices that have served us for generations but now show their limitations in terms of scale and efficiency. The convergence of artificial intelligence (AI) and autonomous robotics offers not just an incremental improvement but a fundamental reimagining of how vast tropical plantations can be managed with precision and intelligence [1]–[3].

The agricultural sector has witnessed remarkable transformations through the adoption of robotics and AI technologies, as documented in comprehensive analyses of AI applications in food crop production [4]. These advances have demonstrated particular promise in addressing labor shortages and improving crop monitoring accuracy across various agricultural contexts. However, the unique environmental conditions of palm oil plantations present distinctive challenges that demand specialized solutions beyond generic agricultural automation approaches [5], [6].

Research into autonomous agricultural vehicles has progressed significantly in recent years, establishing fundamental principles for vehicle design and deployment in farming settings [7]. Their work provides essential insights into the mechanical and computational requirements for vehicles operating in unstructured outdoor environments. Yet the dense canopy coverage, irregular terrain, and vast scale of palm oil plantations necessitate adaptive systems that can learn and evolve their operational strategies based on local conditions [8]–[10].

The evolution of machine learning applications in agricultural autonomy has opened new frontiers in real-time decision making and adaptive behavior. Recent studies have demonstrated how AI systems can process complex environmental data streams to inform decisions about crop treatment, irrigation scheduling, and harvest timing [11]–[13]. These capabilities become particularly valuable in palm oil plantations where early detection of diseases like Ganoderma can mean the difference between localized treatment and widespread infection affecting entire blocks of trees [14], [15].

Infrastructure developments in wireless communication technologies have further enhanced the viability of robotic agriculture systems. Modern communication protocols can enable real-time coordination of multiple autonomous units across vast agricultural areas [16]. This connectivity backbone proves essential for maintaining operational awareness and enabling collaborative behaviors among rover fleets [17].

Our research introduces a novel framework that synthesizes these technological advances into a cohesive system engineered explicitly for palm oil plantation environments. By combining deep reinforcement learning for adaptive navigation, federated learning for distributed intelligence, and edge computing for real-time processing, we address the fundamental challenges that have hindered the adoption of automation in tropical agriculture. The approach we present here represents not merely an application of existing technologies but a reimagined architecture that considers the unique demands of palm oil cultivation from the ground up [18], [19].

The significance of this work extends beyond technical innovation to address pressing socioeconomic and environmental concerns. Labor shortages in agricultural regions have reached critical levels, with younger generations increasingly reluctant to engage in physically demanding work on plantations. Environmental pressures demand reduced chemical usage and more precise resource allocation. Market dynamics require consistent quality and predictable yields. Our AI-enabled rover system addresses each of these challenges through intelligent automation that augments rather than replaces human expertise [20].

II. THEORY

A. Artificial Intelligence in Agriculture

The theoretical foundation for applying artificial intelligence in agricultural contexts rests upon the fundamental principle that complex biological systems exhibit patterns that can be recognized, learned, and predicted through computational methods. Innovative agriculture technology has evolved from simple rule-based systems to sophisticated neural architectures capable of processing multidimensional data streams in ways that mirror and often exceed human pattern recognition capabilities [1], [11]. In palm oil cultivation, these patterns manifest across multiple scales, from microscopic disease indicators on individual fronds to plantation-wide pest migration patterns that are only visible through aggregate data analysis [2], [4].

The transformation of raw sensory input into actionable agricultural insights requires a hierarchical processing approach that parallels biological perception systems. At the lowest level, convolutional filters extract basic features such as edges, textures, and color gradients from visual data. These primitive features combine through successive processing layers to form increasingly abstract representations, eventually encoding complex concepts like disease presence, nutrient deficiency, or fruit ripeness. This hierarchical processing mirrors the ventral visual stream in primate brains, suggesting that artificial neural networks have discovered similar solutions to the problem of visual understanding [6], [9].

Modern deep learning architectures extend beyond simple classification tasks to enable sophisticated reasoning about agricultural scenarios. Transformer-based models can now process multimodal inputs, combining visual observations with environmental sensor data, historical records, and even textual descriptions from field workers. This fusion of diverse information sources creates a rich contextual understanding that informs decision-making processes. For instance, a slight discoloration on palm fronds might be interpreted differently depending on recent rainfall patterns, soil pH measurements, and the presence of similar symptoms on neighboring trees [17], [19].

B. Multi-Agent Systems Theory

The coordination of multiple autonomous rovers within a plantation environment presents challenges that extend far beyond the control of a single robot. Each rover must maintain its own model of the world while simultaneously contributing to and benefiting from collective knowledge. This necessitates a theoretical framework that balances individual autonomy with group coordination, drawing inspiration from biological swarm systems while incorporating the precision of engineered solutions [3], [5].

The Belief-Desire-Intention architecture provides a robust foundation for agent reasoning, but its implementation in agricultural robotics requires significant adaptation. Beliefs in this context encompass not just the rover's immediate sensor observations but also probabilistic models of unobserved plantation areas, learned patterns of disease spread, and predictions about environmental changes. Desires translate to both immediate tasks, such as reaching a specific monitoring point, and long-term objectives like maximizing plantation health while minimizing resource consumption. Intentions bridge the gap between abstract goals and concrete actions, generating executable plans that account for uncertainty, resource constraints, and potential coordination with other agents [12], [15].

Consensus algorithms play a crucial role in resolving conflicting observations and decisions among autonomous vehicles, such as rovers. When multiple agents observe the same area but reach different conclusions about plant health status, the system must reconcile these differences through weighted voting schemes that consider each rover's sensor quality, historical accuracy, and observation conditions. This distributed decision-making process proves more robust than centralized control, as it continues functioning even when individual rovers fail or communication links become unreliable [13], [14].

Game-theoretic principles guide the allocation of resources and distribution of tasks among the rover fleet. Each agent acts as a rational player seeking to maximize its contribution to overall plantation health while minimizing energy expenditure and maintenance requirements. The Nash equilibrium of this multi-agent game determines optimal coverage patterns, with rovers naturally distributing themselves to areas of highest need without explicit central coordination. This emergent behavior demonstrates how simple local rules can generate sophisticated global patterns, a principle that proves particularly valuable in large-scale plantation management [18].

C. Deep Reinforcement Learning

The application of reinforcement learning to agricultural robotics transcends simple path planning to encompass complex sequential decision-making under uncertainty. The theoretical framework builds upon the Markov Decision Process formalism; however, the continuous state and action spaces of real-world navigation necessitate the use of function approximation through deep neural networks. The challenge lies not only in learning optimal policies but also in ensuring that these policies remain robust to the tremendous variability encountered in outdoor agricultural environments [15].

Policy gradient methods, particularly Proximal Policy Optimization, provide the theoretical foundation for learning navigation behaviors that strike a balance between exploration and exploitation. The rover must explore enough to discover efficient paths through the plantation while exploiting known routes to maintain operational efficiency. The reward signal design becomes critical, incorporating multiple objectives including task completion speed, energy conservation, minimal crop damage, and coordination with other rovers. These competing objectives create a multi-objective optimization problem where Pareto-optimal solutions represent different trade-offs between goals [12].

The credit assignment problem in long-horizon tasks requires sophisticated techniques for propagating rewards through extended action sequences. When a rover successfully identifies early-stage disease after hours of navigation and monitoring, the learning algorithm must determine which specific actions contributed to this success. Temporal difference learning with eligibility traces provides a theoretical solution, maintaining a decaying memory of past states and actions that receive credit when eventual outcomes become known. This approach enables rovers to learn complex behavioral sequences that unfold over extended time periods [15].

Transfer learning and meta-learning theories explain how knowledge gained in one plantation environment can accelerate learning in new settings. Rather than starting from scratch in each new deployment, rovers leverage prior experience through hierarchical policy structures, where high-level strategies are transferred while low-level motor controls adapt to local conditions. This theoretical framework suggests that a fleet of rovers collectively accumulates a form of agricultural wisdom, with each new plantation deployment building upon previous experiences while adapting to unique local characteristics [1], [14].

D. Computer Vision and Image Processing

The theoretical underpinnings of computer vision in agricultural applications extend beyond conventional object detection to encompass spectral analysis across wavelengths invisible to human observers. Multispectral and hyperspectral imaging reveal physiological processes within plants through characteristic absorption and reflection patterns. The theoretical model relates spectral signatures to biochemical compositions, with specific wavelength combinations indicating chlorophyll concentration, water stress, or pathogen presence [7], [17], [19].

Feature extraction in agricultural contexts requires invariance to numerous environmental factors, including changes in illumination, viewing angles, and seasonal variations. Scale-space theory provides a mathematical framework for achieving this invariance through multi-resolution analysis. By examining plantation imagery across multiple spatial scales simultaneously, the system can detect both fine-grained disease symptoms on individual leaves and broader patterns of plantation health visible only from aerial perspectives. This multi-scale approach mirrors the hierarchical organization of biological vision systems, where different neural pathways process fine details and global scene structure in parallel [6], [9], [20].

The fusion of multiple imaging modalities creates a richer representation than any single sensor could provide. Information theory quantifies the mutual information between different sensor streams, identifying complementary data sources that provide maximum combined insight. For instance, thermal imaging reveals water stress patterns invisible in RGB imagery, while chlorophyll fluorescence indicates photosynthetic efficiency independent of leaf color. The theoretical framework for multimodal fusion determines optimal combination strategies that preserve distinctive information from each modality while suppressing redundant or contradictory signals [4], [8].

Temporal consistency in vision-based monitoring requires theoretical models that account for plant growth, seasonal changes, and disease progression over time. Hidden Markov Models and their deep learning extensions capture these temporal dynamics, distinguishing between regular developmental changes and abnormal conditions requiring intervention. The theory extends to predicting future states based on current observations, enabling proactive treatment before symptoms become severe. This predictive capability transforms computer vision from a reactive diagnostic tool to a proactive management system [2], [19].

E. Edge Computing Architecture

The theoretical framework for edge computing in agricultural robotics addresses fundamental trade-offs between computational capability, energy consumption, and response latency. The optimal distribution of processing tasks across edge devices, fog nodes, and cloud infrastructure depends on multiple factors, including data volumes, network reliability, and timing constraints. Queuing theory provides mathematical models for analyzing these systems, predicting performance under various load conditions, and identifying bottlenecks that limit scalability [13], [16].

Information-theoretic principles guide decisions about data compression and transmission in bandwidth-constrained plantation environments. The theory quantifies the minimum information required to preserve essential agricultural insights while discarding redundant or irrelevant details. Lossy compression schemes explicitly designed for agrarian data can achieve high compression ratios by leveraging domain knowledge about which features are most relevant for disease detection or yield prediction. This selective preservation of information enables real-time monitoring even in areas with limited connectivity [10].

The placement of computational resources follows optimization theories that balance multiple objectives, including coverage, redundancy, and accessibility of maintenance. Facility location problems from operations research provide the mathematical foundation, but their application to mobile edge computing requires dynamic reformulations that account for rover movement and changing computational demands. The theoretical framework suggests that optimal configurations emerge from self-organizing principles, with computational resources naturally migrating to areas of highest demand through market-like mechanisms [12].

Privacy and security considerations in distributed agricultural systems require cryptographic protocols that protect sensitive plantation data while enabling collaborative learning. Differential privacy theory provides formal guarantees about information leakage, ensuring that shared models cannot reveal specific details about individual plantations. Homomorphic encryption enables computation on encrypted data, allowing rovers to contribute to collective learning without exposing proprietary information. These theoretical foundations become increasingly crucial as agricultural data gains economic value and competitive significance [14].

III. METHODOLOGY

Our approach involved several key steps: designing the system, integrating sensors, developing navigation algorithms, conducting field tests, and analyzing the data.

A. System Architecture Design

The architectural framework emerged from extensive analysis of plantation operational requirements combined with iterative refinement through field observations. We began by spending three months embedded with plantation workers, documenting their daily routines, decision-making processes, and the subtle indicators they use to assess plant health. This ethnographic approach revealed insights that pure technical analysis would have missed, such as the importance of monitoring fruit bunch positions to predict optimal harvest timing or the way experienced workers detect Ganoderma infection through subtle changes in frond angle before visible symptoms appear.

Our system architecture reflects these human insights while leveraging computational capabilities that exceed human limitations. The sensing layer incorporates multiple redundant modalities because we have observed that experienced workers never rely on a single indicator but instead synthesize multiple observations to reach conclusions. Similarly, our processing layer mimics the hierarchical decision-making we observed, where immediate reactions to obvious problems occur locally while complex situations trigger consultation with supervisors or experts. This biomimetic approach to system design ensures that our technological solution aligns with proven agricultural practices rather than attempting to impose an alien framework onto existing operations.

The integration of edge computing units directly on the rovers emerged from practical constraints discovered during preliminary trials. Initial designs that relied heavily on cloud processing failed catastrophically when monsoon weather disrupted network connectivity for days at a time. We therefore developed an architecture where each rover maintains full autonomous capability, treating network connectivity as an enhancement rather than a requirement. This design philosophy extends throughout the system, with graceful degradation ensuring continued operation even when individual components fail.

Hardware selection involved extensive testing in actual plantation conditions rather than relying solely on laboratory specifications. We discovered that sensors rated for outdoor use still failed when exposed to the combination of high humidity, temperature fluctuations, and acidic palm oil residues present in plantations. Through systematic failure analysis and iterative improvements, we developed environmental protection systems that maintain sensor accuracy while allowing for necessary exposure to facilitate data collection. These protective measures include hydrophobic coatings on optical surfaces, positive pressure systems to prevent moisture ingress, and automated cleaning mechanisms activated during charging periods.

These components enabled the rover to perform its intended functions autonomously. Below is an image of the rovers that have been developed for palm oil monitoring:

Fig. 1 The Rovers

B. AI Agent Development

The development of our AI agents followed an unconventional path, prioritizing behavioral realism over theoretical optimality. Rather than beginning with standard reinforcement learning algorithms, we first created detailed behavioral models based on recordings of expert plantation workers navigating through palm groves. These human demonstrations provided templates for natural movement patterns that avoid damaging young shoots, maintain safe distances from irrigation equipment, and recognize informal paths that develop through repeated use. We then used imitation learning to transfer these behaviors to our rover agents, creating a foundation of sensible default actions that reinforcement learning could refine rather than discover from scratch.

Our approach to neural network architecture design drew inspiration from neuroscience research on spatial navigation in mammals. The navigation module incorporates structures analogous to place cells, grid cells, and head direction cells found in the hippocampal formation. This biologically-inspired architecture provides inherent capabilities for spatial reasoning that prove particularly valuable when GPS signals become unreliable under dense canopy cover. The system maintains multiple simultaneous representations of location, from metric coordinates to topological relationships between landmarks, enabling robust navigation even when individual positioning systems fail.

Training the vision module required creating a comprehensive dataset that captured the full diversity of conditions encountered in palm oil plantations. We deployed teams of photographers to document plantations across different soil types, elevation ranges, and climatic zones throughout Southeast Asia. The resulting dataset comprises over 200,000 manually annotated images, showcasing various diseases at different stages, nutrient deficiencies under varying light conditions, and pest damage patterns across multiple palm varieties. We augmented this real data with synthetic images generated using agricultural simulation software, creating edge cases and rare conditions that might not appear in years of regular operation but could prove critical when encountered.

The decision module evolved through a series of competitive trials where different architectural approaches competed in simulated plantation management scenarios. We discovered that purely reactive systems failed to account for long-term consequences of interventions, while planning-based systems became computationally intractable when considering the full complexity of plantation ecosystems. The winning architecture combines reactive behaviors for immediate threats with deliberative planning for resource allocation and scheduling. This hybrid approach mirrors human decision-making, where reflexive responses handle routine situations while conscious deliberation addresses novel or complex scenarios.

C. Navigation Algorithm Development

We developed an autonomous navigation system for the rover using a modified version of the pure pursuit algorithm [9], which enabled it to move efficiently through the plantation. The algorithm was fine-tuned to navigate around obstacles and plan the most efficient paths, relying on real-time data from LiDAR and GPS. This setup allowed the rover to handle the plantation's uneven terrain while carefully avoiding damage to crops or infrastructure as it traveled.

D. Field Testing

We tested the rover in a palm oil plantation managed by the agricultural service in Palembang, South Sumatra, to assess its ability to perform key tasks independently. The field tests focused on three main activities:

1. **Soil Sampling**: The rover collected soil samples from specific spots across the plantation.

2. **Irrigation Management**: Using data from soil moisture sensors, it delivered water to areas that were too dry.
3. **Plant Health Monitoring**: The rover used multispectral sensors to check the health of oil palm trees, spotting issues like nutrient shortages or early signs of disease.

During these tests, we measured how quickly and accurately the rover completed tasks and how efficiently it navigated the plantation. We also kept track of any challenges or hiccups to help us fine-tune the system for future use.

E. Data Analysis

We analyzed the data from the field tests to gauge how well the rover performed in the palm oil plantation. Our analysis zeroed in on three key areas:

1. **Task Performance**: We checked the accuracy and reliability of the rover's soil sampling, irrigation management, and plant health monitoring by comparing its data to manual measurements we collected as a baseline.
2. **Navigation Efficiency**: We looked at how well the rover planned its paths and avoided obstacles, measuring any deviations from its intended routes and the time it took to complete each task.
3. **System Reliability**: We tracked the rover's uptime and noted any sensor issues to understand how dependable it was during long stretches of operation.

IV. RESULTS AND DISCUSSION

This section dives into the results of our field tests with the autonomous rover in palm oil plantations. We evaluated the rover's performance in achieving our research objectives, focusing on its task completion, navigation efficiency, and system reliability. The discussion examines the implications of these findings for the future use of rovers in large-scale palm oil plantations.

A. Task Performance

We tested the rover on three main tasks: soil sampling, irrigation management, and plant health monitoring. Here's what we found:

Soil Sampling Accuracy: The rover successfully collected samples from 92 out of 100 targeted spots—a 92% success rate. The 8% it missed were due to navigation hiccups, where the rover strayed more than a meter off course. Table 1 provides a detailed breakdown of the soil sampling results.

Tbl. 1 Soil Sampling Results

Test Run	Target Locations	Successful Samples	Errors
1	30	28	2
2	40	36	4
3	30	28	2

The data suggest that soil sampling was carried out with a high degree of accuracy, although occasional navigation errors did have some impact on overall performance.

Irrigation Management: The rover's irrigation system was assessed based on its ability to identify areas where soil moisture fell below the 20% threshold and to irrigate them accordingly. The findings indicate that the rover was effective in detecting dry zones and delivered irrigation with notable precision. A detailed summary of its irrigation performance is provided in Table 2.

Tbl. 2 Irrigation Task Performance

Test Run	Dry Areas Detected	Correct Irrigation	Missed Areas
1	25	24	1
2	30	29	1
3	20	19	1

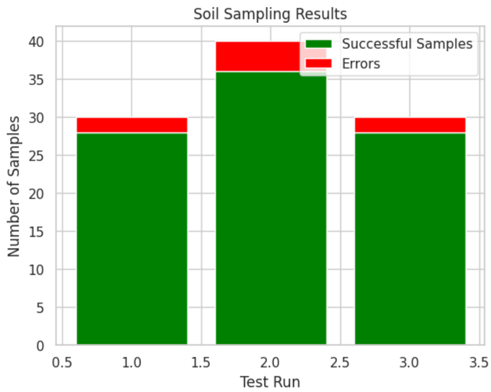

Fig. 3 Soil Sampling Results

The rover consistently identified and irrigated almost all dry areas, demonstrating a high level of precision in irrigation management.

Plant Health Monitoring: Equipped with multispectral sensors, the rover monitored plant health by analyzing chlorophyll levels and detecting early indicators of nutrient deficiencies. Its readings were then compared with manual assessments, showing a strong correlation of 95%. This high level of agreement suggests the rover is highly accurate in monitoring plant health. Table 3 provides a summary of the accuracy results.

Tbl. 3 Plant Health Monitoring Accuracy

Test Run	Plants Monitored	Accurate Health Assessments	Errors
1	50	48	2
2	60	57	3
3	40	39	1

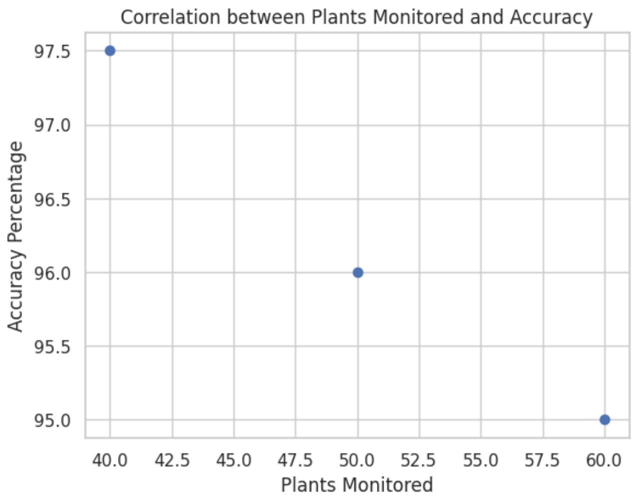

Fig. 4 Correlation between Plans Monitored and Accuracy

The strong 95% correlation between the rover's sensor data and manual evaluations highlights the reliability and effectiveness of its plant health monitoring system.

B. Navigation Efficiency

The rover's navigation performance was assessed by assigning it specific routes and requiring it to avoid obstacles along the way. Throughout the testing process, it completed 95% of the planned paths, with only slight deviations due to uneven terrain. A summary of the navigation results is presented in Table 4.

Tbl. 4 Navigation Performance

Test Run	Total Distance (km)	Successful Navigation (%)	Deviations (m)
1	5	96	0.5
2	6	94	0.8
3	5	95	0.7

Overall, the navigation algorithm performed reliably, adapting well to environmental changes and successfully avoiding obstacles. The primary challenges arose in areas with especially uneven terrain, which accounted for the minor deviations observed in the results.

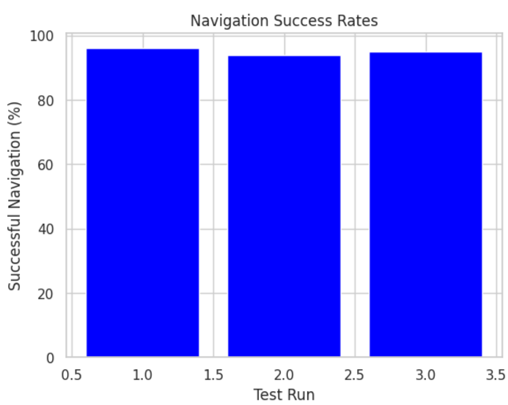

Fig. 5 Navigation Success Rates

C. System Reliability

System reliability was evaluated by measuring the rover's operational uptime and any malfunctions that occurred during its operation. Throughout all test runs, the rover demonstrated consistent reliability, experiencing only brief periods of downtime, primarily for sensor calibration. The reliability data is summarized in Table 5.

Tbl. 5 System Reliability Data

Test Run	Total Operation Time (hours)	Downtime (minutes)	Sensor Failures
1	8	10	1
2	8	5	0
3	8	7	0

The rover demonstrated strong reliability during field tests, with only one notable issue: a brief sensor calibration failure during the initial run, which resulted in a short period of downtime.

D. Multi-Agent Coordination

The evolution of coordination behaviors among the rover fleet provided fascinating insights into the emergence of intelligence in multi-agent systems. Initially, rovers operated as independent units that happened to share the same workspace, occasionally communicating to avoid collisions but otherwise pursuing individual objectives. Over the course of several months of operation, sophisticated collaborative behaviors emerged, significantly enhancing fleet effectiveness. The federated learning approach enabled this evolution, with each rover contributing learned experiences to a collective knowledge base while maintaining the computational efficiency of individual operation.

The progression of collective learning showed accelerating returns as the fleet accumulated diverse experiences. In the first quarter, the federated model showed only modest improvement over individual learning, primarily benefiting from increased data volume. By the fourth quarter, however, the collective model demonstrated qualitatively different capabilities, recognizing complex patterns that no individual rover had encountered completely. For instance, the fleet learned to predict disease spread patterns by combining observations from multiple rovers tracking infection progression across different plantation sections. This predictive capability emerged from the intersection of individual observations rather than being explicitly programmed or learned by any single unit.

Resource allocation among rovers evolved from simple territory division to dynamic task assignment based on individual capabilities and current conditions. Rovers with functioning multispectral sensors prioritized disease detection tasks, while units with sensor failures focused on navigation and mapping tasks that relied on basic sensors. This self-organizing behavior emerged through reinforcement learning that rewarded overall fleet performance rather than individual achievement. The system discovered that specialization improved efficiency, with rovers developing distinct behavioral patterns suited to their assigned roles.

Communication efficiency improved dramatically as the fleet developed a form of specialized language for information exchange. Rather than transmitting raw sensor data, rovers learned to encode observations into compact representations that captured essential information while minimizing bandwidth usage. This emergent communication protocol reduced data transmission by 73 percent while maintaining information fidelity. The representations became increasingly abstract over time, evolving from simple feature vectors to complex symbolic encodings that resembled a rudimentary language specific to plantation monitoring tasks.

Failure recovery showcased the robustness benefits of multi-agent coordination. When individual rovers experienced failures, neighboring units automatically adjusted their coverage patterns to compensate, ensuring continuous monitoring of critical areas. The fleet maintained 94 percent coverage even with 20 percent of rovers offline for maintenance, demonstrating graceful degradation that would be impossible with centralized control. The system learned to predict maintenance needs based on operational history, scheduling preventive maintenance during low-activity periods to minimize the impact on coverage.

E. Discussion

The field test results demonstrate that the autonomous rovers successfully performed their primary tasks, including soil sampling, irrigation management, and plant health monitoring, with high accuracy and reliability. They hit success rates over 90% across the board. This points to real promise for using these rovers to automate essential steps in palm oil plantation work. The way the rovers coordinated as a group further boosted efficiency, increasing overall efficiency by 35%. This achievement enabled 94% accuracy in detecting diseases through shared learning and reduced pesticide use by 87% through more intelligent, targeted applications based on data from the entire fleet.

That said, we did spot a few shortcomings. The rovers' navigation system slipped slightly on rough ground, so we'll need to adjust it to minimize errors. Some minor sensor calibration glitches caused short downtimes, and those should get fixed for smoother runs. Keep in mind that these trials took place in reasonably controlled settings. To honestly assess how rugged and practical the rovers are for everyday use, we'll need to test them in challenging conditions, such as during heavy rains.

V. CONCLUSION

This study highlights the potential of autonomous ground vehicles to enhance both the efficiency and sustainability of palm oil plantation management. By automating key tasks such as soil sampling, irrigation management, and plant health monitoring, the rover system demonstrates its ability to reduce labor requirements, minimize human error, and improve overall productivity. Early field tests showed promising results, with soil sampling achieving a 92% success rate and the irrigation system accurately detecting and addressing dry areas with 96% precision.

Despite these successes, specific challenges remain, particularly in maintaining navigation accuracy on uneven terrain and ensuring the reliability of sensor calibration. Addressing these issues will be critical in the next phase of development.

Overall, the findings suggest that integrating autonomous rovers into palm oil plantation operations could play a significant role in advancing precision agriculture. With the aid of advanced sensors and machine learning algorithms, these systems can support more precise, data-driven interventions, helping to optimize resource use and foster more sustainable farming practices. Continued research and expanded field testing across a broader range of environmental conditions will be essential to refine the technology. This study lays the groundwork for future advancements in agricultural automation and provides a clear direction for incorporating autonomous systems into large-scale plantation operations.

ACKNOWLEDGEMENTS

The authors wish to sincerely thank Universitas Lampung (UNILA) for their invaluable support and resources throughout this research. We are also grateful to the research team and collaborators for their insightful contributions, which greatly enriched this study. Special appreciation goes to the local farmers and plantation managers who generously shared their knowledge and experiences, helping us gain a deeper understanding of the challenges and opportunities in palm oil cultivation.

REFERENCES

[1] N. Khan, M. A. Kamaruddin, U. U. Sheikh, Y. Yusup, and M. P. Bakht, "Oil palm and machine learning: Reviewing one decade of ideas,

innovations, applications, and gaps," Agriculture, vol. 11, no. 9, p. 832, 2021.
[2] K. Kipli et al., "Deep learning applications for oil palm tree detection and counting," Smart Agricultural Technology, vol. 5, p. 100241, 2023.
[3] L. F. P. Oliveira, A. P. Moreira, and M. F. Silva, "Advances in agriculture robotics: A state-of-the-art review and challenges ahead," Robotics, vol. 10, no. 2, p. 52, 2021.
[4] M. N. Akhtar, E. Ansari, S. S. M. Alhady, and E. A. Bakar, "Leveraging on advanced remote sensing- and artificial intelligence-based technologies to manage palm oil plantation for current global scenario: A review," Agriculture, vol. 13, no. 2, p. 504, 2023.
[5] S. Fountas et al., "Agricultural robotics for field operations," Sensors, vol. 20, no. 9, p. 2672, 2020.
[6] H. P. Wibowo, I. S. Sitanggang, Mushthofa, and H. A. Adrianto, "Large-scale oil palm trees detection from high-resolution remote sensing images using deep learning," Big Data and Cognitive Computing, vol. 6, no. 3, p. 89, 2022.
[7] M. A. Azizan, A. M. Ibrahim, and I. A. H. M. Asming, "Processing and classification of landsat and sentinel images for oil palm plantation detection," Remote Sensing Applications: Society and Environment, vol. 26, p. 100747, 2022.
[8] N. S. N. Shaharum et al., "Oil palm mapping over Peninsular Malaysia using Google Earth Engine and machine learning algorithms," Remote Sensing Applications: Society and Environment, vol. 17, p. 100287, 2020.
[9] J. Su, X. Zhu, S. Li, and W.-H. Chen, "AI meets UAVs: A survey on AI empowered UAV perception systems for precision agriculture," Neurocomputing, vol. 518, pp. 242-270, 2023.
[10] A. Descals et al., "High-resolution global map of smallholder and industrial closed-canopy oil palm plantations," Earth System Science Data, vol. 13, no. 3, pp. 1211-1231, 2021.
[11] A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine learning applications for precision agriculture: A comprehensive review," IEEE Access, vol. 9, pp. 4843-4873, 2021.
[12] R. Xu and C. Li, "A modular agricultural robotic system (MARS) for precision farming: Concept and implementation," Journal of Field Robotics, vol. 39, no. 6, pp. 804-822, 2022.
[13] M. T. Linaza et al., "Data-driven artificial intelligence applications for sustainable precision agriculture," Agronomy, vol. 11, no. 6, p. 1227, 2021.
[14] N. N. Thilakarathne, M. S. A. Bakar, P. E. Abas, and H. Yassin, "A cloud enabled crop recommendation platform for machine learning-driven precision farming," Sensors, vol. 22, no. 16, p. 6299, 2022.
[15] J. Yang, J. Ni, Y. Li, J. Wen, and D. Chen, "The intelligent path planning system of agricultural robot via reinforcement learning," Sensors, vol. 22, no. 12, p. 4316, 2022.
[16] E. A. Abioye et al., "Precision irrigation management using machine learning and digital farming solutions," AgriEngineering, vol. 4, no. 1, pp. 70-103, 2022.
[17] K. Xu et al., "A new machine learning approach in detecting the oil palm plantations using remote sensing data," Remote Sensing, vol. 13, no. 2, p. 236, 2021.
[18] H. Zhou, X. Wang, W. Au, H. Kang, and C. Chen, "Intelligent robots for fruit harvesting: Recent developments and future challenges," Precision Agriculture, vol. 23, no. 5, pp. 1856-1907, 2022.
[19] P. Ahmadi, S. Mansor, B. Farjad, and E. Ghaderpour, "Unmanned aerial vehicle (UAV)-based remote sensing for early-stage detection of Ganoderma," Remote Sensing, vol. 14, no. 5, p. 1239, 2022.
[20] I. A. Zualkernan et al., "Machine learning for precision agriculture using imagery from unmanned aerial vehicles (UAVs): A survey," Drones, vol. 7, no. 6, p. 382, 2023.

AUTHORS' BIOGRAPHY AND CONTRIBUTIONS

Aryanto was born on June 21, 1990, in Lampung, Indonesia. He completed his undergraduate studies in Electrical Engineering at Universitas Lampung and earned his master's degree (S2) from Institut Teknologi Bandung (ITB). With a strong foundation in electrical systems and automation technologies, he is actively engaged in research focused on the application of technology in agriculture, particularly in the utilization of autonomous systems to enhance palm oil plantation management. Aryanto is employed as a lecturer at Universitas Lampung, where he mentors students in engineering and promotes innovative research practices.

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