

RESEARCH ARTICLE

A Scalable ROS–Based Management Framework for Seamless Integration of Mobile Robots and Conventional Machinery in Agriculture

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ABSTRACT: The integration of robotics and automation into modern agriculture marks a transformative shift aimed at enhancing productivity, reducing labor dependency, and promoting environmental sustainability. However, the seamless incorporation of mobile robots with conventional agricultural machinery remains a significant challenge due to the heterogeneity of hardware, software, and communication protocols. This paper proposes a comprehensive and scalable Robot Operating System (ROS) management framework specifically designed for agricultural applications. The framework facilitates effortless integration by offering standardized interfaces, modular software components, and robust communication protocols, enabling farmers to adopt advanced automation without replacing existing equipment. Built with scalability in mind, the system supports diverse farm sizes and equipment configurations, allowing for flexible adaptation to evolving operational needs. Through field experiments and case studies, we demonstrate the framework's ability to improve path planning, task coordination, and real-time responsiveness under varying crop densities, obstacles, and dynamic weather conditions. The results indicate significant improvements in operational efficiency, coverage rates, and system adaptability.

Keywords: ROS (Robot Operating System), Agricultural Robotics, Mobile Robots, Precision Agriculture, Interoperability, Scalable Automation

Received: 28 August 2024; Revised: 21 November 2024; Accepted: 24 February 2025; Published Online: 07 April 2025

1. INTRODUCTION

The sustained growth of the global population imposes unprecedented demands on the agricultural sector,

necessitating a paradigm shift toward more efficient, productive, and sustainable farming practices. Key challenges include the urgent need to reduce escalating labor costs, minimize adverse environmental impacts, and substantially boost crop yields to ensure food security [1]. While conventional agricultural methods have historically supported human civilization, they often lack the precision, efficiency, and data-driven intelligence required to address these contemporary pressures [2]. In this context, the integration of advanced technologies, particularly robotics and automation, has emerged as a critical pathway to modernize farming and bridge the productivity gap. Robotic technologies, encompassing unmanned aerial vehicles (UAVs), autonomous ground vehicles, and robotic manipulators, have demonstrated significant potential to revolutionize various agricultural operations, from precision planting and monitoring to targeted harvesting and post-harvest handling [3, 4]. The implementation of these systems promises enhanced operational efficiency, improved resource

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allocation, and a move toward long-term agricultural sustainability [5].

However, the widespread deployment and adoption of robotic systems in real-world agricultural settings are impeded by several formidable barriers. A primary challenge is the inherent variability and unpredictability of farm environments. Agricultural landscapes are dynamic, unstructured, and subject to constant change due to factors such as fluctuating weather patterns, varying crop densities, and the presence of unexpected obstacles like rocks or animals [6, 7]. This necessitates robotic systems that are not only robust but also highly adaptable. Compounding this environmental challenge is the significant heterogeneity of machinery found on modern farms. Farms typically utilize a diverse fleet of equipment from various manufacturers, each with proprietary interfaces, control systems, and communication protocols [8, 9]. This lack of standardization creates substantial interoperability issues, making it exceptionally difficult for new, advanced robotic systems to communicate effectively and coordinate seamlessly with existing conventional machinery [10]. This integration challenge is a major bottleneck, as the full benefits of automation can only be realized when new and old systems work in concert.

To address these complex issues, a flexible, interoperable, and scalable architectural framework is essential. The Robot Operating System (ROS) has established itself as a powerful, open-source middleware framework that provides a structured ecosystem of software libraries and tools for developing and managing robotic systems [11, 12]. Its modular architecture, extensive community support, and inherent flexibility make it an ideal foundation for building complex robotic applications. While ROS offers a robust starting point, its generic nature requires significant customization and domain-specific adaptation to meet the unique demands of agricultural workflows, which involve a distinct set of sensors, actuators, and operational scenarios compared to industrial or service robotics [13, 14]. Previous efforts in agricultural robotics have often focused on developing standalone systems for specific tasks, such as weeding or harvesting, but have paid less attention to the holistic integration of these robots into the existing farm machinery ecosystem [15, 16]. This paper introduces a comprehensive ROS-based management framework specifically engineered for the agricultural domain. The novelty of this work lies in its development of a unified, scalable framework that explicitly addresses the interoperability gap between modern mobile robots and legacy conventional machinery through a layered architecture featuring standardized sensor interfaces, adaptive communication bridges, and modular task coordination software, thereby enabling a previously unachievable level of seamless cooperation in heterogeneous farm environments. The framework is designed to empower farmers by allowing them to incrementally adopt automation, leveraging the capabilities of advanced robots without necessitating a complete and costly replacement of their existing equipment fleet [17].

The proposed architecture facilitates the integration of ROS-enabled mobile robots with conventional agricultural machinery, aiming to optimize resource utilization, enhance operational efficiency, and increase overall farm productivity [18]. Its core components include standardized interfaces for multi-modal sensor data fusion, robust communication protocols for device-agnostic data exchange, and modular software modules for decentralized task execution and coordination. Furthermore, the framework is designed to be forward-compatible, providing a supportive infrastructure for continuous innovation and the seamless incorporation of emerging technologies, such as advanced machine learning models and Internet of Things (IoT) sensor networks, as they become available [19, 20]. The subsequent sections of this paper will provide a detailed examination of the framework's architecture and its constituent components, present a series of case studies and field experiments conducted in authentic agricultural environments to demonstrate its practical efficacy, and discuss the tangible benefits observed. Finally, the paper will explore future research directions aimed at further enhancing the framework's capabilities. Through this comprehensive investigation, we aim to demonstrate that the synergistic combination of robotics and traditional machinery holds the transformative potential to redefine modern agriculture, effectively addressing current challenges and paving the way for a more productive, efficient, and sustainable future for farming [21-25].

2. BACKGROUND

The agricultural sector is undergoing a significant technological transformation, driven by the pressing need to address global food security, labor shortages, and environmental sustainability. In recent years, there has been a marked increase in research and development focused on implementing robotics and automation technologies within agronomic practices. The compelling potential of mobile robots, including Unmanned Aerial Vehicles (UAVs), autonomous tractors, and robotic harvesters, to diminish environmental impact, enhance operational efficiency, and reduce reliance on manual labor is well-documented in the literature [26]. These systems promise a new era of precision agriculture, where interventions are data-driven and applied with unprecedented accuracy.

However, the broad adoption and deployment of these robotic systems in commercial farming operations face substantial impediments. A primary barrier is the absence of defined communication protocols and the pervasive compatibility issues between disparate hardware and software platforms [8]. This lack of standardization creates a significant interoperability challenge, stifling the seamless integration of innovative robotic solutions into the existing agricultural workflow. Furthermore, the technical obstacles associated with integrating mobile robots with pre-existing conventional machinery are multifaceted, encompassing complex issues related to sensor integration, multi-source data fusion, and the real-time coordination of tasks across

heterogeneous platforms.

The impetus for this technological shift stems from a confluence of factors: the necessity to increase agricultural output to feed a growing global population, the economic imperative to lower rising labor costs, and the ethical responsibility to adopt more environmentally sustainable practices. Consequently, a considerable amount of scholarly and industrial emphasis has been placed on adapting robotic technologies for agricultural applications. It is established that various robotic systems possess the potential to revolutionize traditional agricultural methods. For instance, UAVs, or drones, have gained considerable traction for tasks such as high-resolution crop monitoring, detailed soil analysis, and precise spraying operations. Equipped with sophisticated sensor suites, including multispectral and hyperspectral cameras, these aerial platforms capture granular data that provides critical insights into crop health, soil conditions, and the presence of pest infestations [27]. This information empowers farmers to make evidence-based decisions, applying water, fertilizers, and pesticides with greater precision, which ultimately leads to enhanced yield and a significant reduction in input waste.

Similarly, autonomous tractors represent a cornerstone of agricultural automation [11]. These vehicles are engineered to perform fundamental operations such as plowing, sowing, and harvesting with minimal human intervention. By leveraging an array of sensor technologies, including high-precision Global Navigation Satellite Systems (GNSS), Light Detection and Ranging (LiDAR), and inertial measurement units (IMUs), these tractors can navigate fields and execute tasks with a high degree of accuracy. The deployment of autonomous tractors can substantially reduce the manpower required for large-scale farming, allowing for the management of more extensive land areas with improved operational efficiency and consistency. Parallel advancements are evident in the domain of harvesting robots. These robotic systems are being developed to automate the labor-intensive process of picking fruits and vegetables. They primarily rely on advanced computer vision and machine learning algorithms to identify and classify ripe produce, guiding robotic manipulators to harvest with care to minimize damage to both the crop and the plant [28]. Their application is particularly transformative for labor-intensive high-value crops, such as strawberries and apples, where manual harvesting constitutes a major portion of production costs and is subject to seasonal labor availability [12].

Despite the promising capabilities of these individual technologies, their integration into the heterogeneous environment of a working farm presents a set of profound difficulties. A principal challenge is the inherent heterogeneity of agricultural machinery. A typical farm operates a diverse fleet of equipment from various manufacturers, each embodying proprietary interfaces, control systems, and communication protocols. This variability complicates the task of ensuring that new robotic systems can communicate and coordinate effectively with the incumbent gear, creating a fragmented technological landscape [13]. This interoperability gap is a critical

bottleneck that hinders the realization of a fully integrated and cooperative farm management system.

Compounding the issue of hardware heterogeneity is the dynamic and unstructured nature of agricultural environments. Unlike controlled industrial settings, agricultural fields are characterized by their variability in terrain, fluctuating crop densities, and the constant presence of unexpected obstacles such as rocks, animals, or uneven ground. Robotic systems operating in such conditions must exhibit a high degree of resilience and adaptability, capable of adjusting their operations in real-time to these shifting environmental factors. Achieving this level of dependable autonomy necessitates enhanced capabilities in sensing, perception, and decision-making, which must be robust enough to contend with the inherent uncertainties and stochastic events commonplace in outdoor agriculture [29].

The concept of standardization and interoperability emerges as a critical enabler for overcoming these barriers. The current absence of standardized communication protocols and interfaces is widely recognized as a significant obstacle to the incorporation of robotic systems in agricultural settings [15]. Standardization is fundamental to ensuring that different components, from various vendors and of different vintages, can function together seamlessly. Interoperability, the direct benefit of standardization, provides the capacity to easily add, modify, or replace components within a system, thereby facilitating the incremental adoption of new technologies and continuous innovation without necessitating a complete overhaul of existing infrastructure.

Within this context, the Robot Operating System (ROS) has emerged as a pivotal technology in robotics research and development. ROS is an open-source middleware framework that provides a structured collection of software libraries and tools designed for building and managing complex robotic systems [30]. Its modular architecture, supported by a robust and widespread community, offers a flexible platform for developing sophisticated robotic applications. The core strength of ROS lies in its communication infrastructure, which facilitates data exchange between decoupled processes (nodes), and its package management system, which promotes software reusability. The utilization of ROS in agricultural robotics, while a relatively recent development compared to other fields, shows significant promise for promoting the integration of diverse robotic components and guaranteeing interoperability across different systems [31]. By leveraging ROS, developers can create modular and reusable software components that can be more readily adapted to a variety of agricultural tasks and environmental conditions, thereby accelerating development cycles and reducing implementation costs.

Several existing frameworks and solutions have attempted to address parts of this complex puzzle. For example, numerous field management systems have been developed that integrate precision agricultural technologies with conventional farming practices [17]. These systems typically concentrate on data gathering, analysis, and decision support, offering farmers actionable insights to

optimize their activities. However, they frequently lack the inherent architectural design and specific functionalities required for the low-level, real-time integration and coordination of autonomous robotic systems. Conversely, dedicated robotic frameworks, such as those explored in the Agricultural Robotics and Automation (AgRA) domain, aim to offer standardized solutions for developing agricultural robots. While these frameworks provide valuable foundations for specific tasks like planting, weeding, or harvesting, they often operate in isolation and may not comprehensively address the broader, system-level challenge of integrating robots with conventional gear and assuring interoperability across a mixed fleet of equipment [32].

A critical analysis of the current landscape reveals a distinct research gap. The integration of mobile robots with traditional agricultural machinery remains a complex and relatively underexplored topic. While significant improvements have been made in the development of individual robotic systems for specialized activities [18], there is a definitive and growing need for a holistic framework that can bridge the gap between advanced robotics and the installed base of farming equipment. Such a framework must explicitly provide standardized interfaces, unified communication protocols, and modular software components to facilitate the smooth integration and coordination required for efficient, large-scale agricultural operations.

It is this identified gap that serves as the primary motivation for the present work. The development of a ROS-based management framework, specifically adapted for agricultural applications, is driven by the objective of empowering farmers with a unified platform for integrating mobile robots with conventional machinery. The proposed framework aims to transcend the limitations of existing solutions by providing a cohesive architecture that enables interoperability, scalability, and flexibility. The anticipated outcome is a tangible increase in operational efficiency, productivity, and sustainability for modern farms. The following section will provide detailed explanations of how the proposed ROS management framework is architecturally designed to address the difficulties outlined in this background study, describing its core components and their respective functionalities.

3. PROPOSED ROS MANAGEMENT FRAMEWORK

To address the critical interoperability and integration challenges outlined in the previous section, this work introduces a comprehensive management framework built upon the Robot Operating System (ROS), specifically architected for agricultural applications [19]. The proposed framework is fundamentally grounded in the core principles of flexibility, scalability, and interoperability, engineered to enable fluid collaboration between mobile robotic platforms and conventional agricultural machinery. The overarching

objective is to deliver a unified software infrastructure that mitigates the technical barriers to adoption, allowing farmers to leverage the benefits of advanced automation while preserving investments in existing equipment. The high-level system architecture, which embodies a layered, modular design, is illustrated in Figure 1.

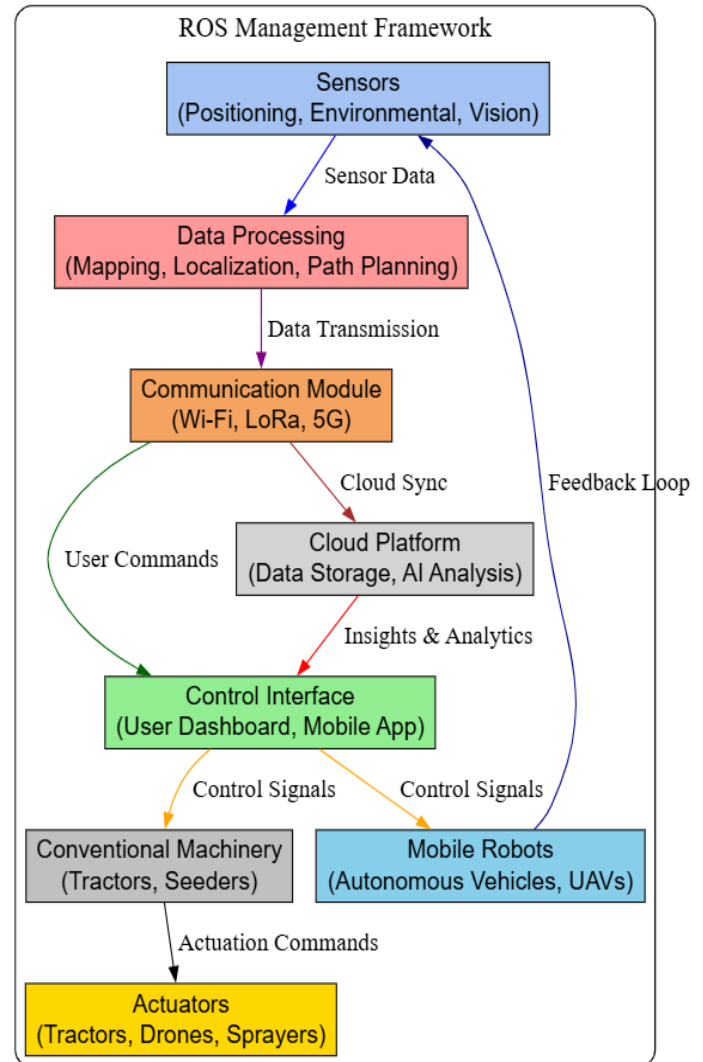


Fig. 1. Overall System Architecture.

The composition of the framework is defined by several essential components that work in concert. These include standardized interfaces for the seamless interchange of heterogeneous sensor data, robust communication protocols [20] for reliable device-to-device interaction, and modular software modules dedicated to task execution and multi-agent coordination. Collectively, these components constitute a uniform platform that supports the entire lifecycle of robotic systems in agriculture, from development and deployment to daily operation and management. This holistic approach ensures that the integration of automation is not only technically feasible but also practically manageable for end-users.

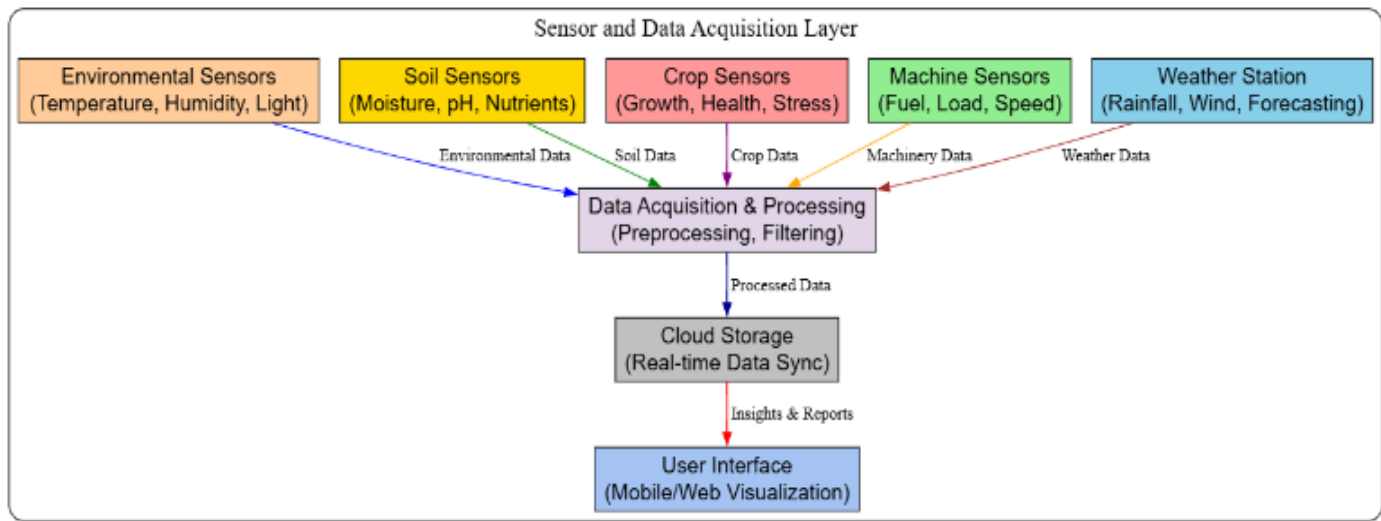


Fig. 2. Sensor and Data Acquisition Layer.

3.1 Architectural Overview

The architecture of the proposed ROS management framework is structured into multiple interconnected layers, each responsible for a distinct functional aspect of the integrated system's operation. This stratification promotes separation of concerns, enhances maintainability, and facilitates the independent development and upgrading of individual components. The primary layers, as delineated in Figure 1, are as follows.

The Sensor and Data Acquisition Layer forms the foundational sensory nexus of the system. This layer is accountable for the continuous and synchronized collection of raw data from a diverse array of sensors deployed on both mobile robots and conventional machinery. The sensor suite is comprehensive, encompassing Global Positioning System (GPS) receivers for localization, Light Detection and Ranging (LiDAR) units for 3D obstacle detection and mapping, visual spectrum and multispectral cameras for phenotyping and health assessment, and agriculturally-specific sensors such as soil moisture, pH, and nutrient probes. A conceptual depiction of this layer and its data aggregation function is provided in Figure 2.

Sitting atop the sensory foundation, the Communication and Middleware Layer is responsible for managing all communication activities between the distributed hardware and software components. This layer leverages the intrinsic publish-subscribe mechanism of ROS to enable asynchronous, decoupled data exchange and coordination. In this paradigm, software processes (nodes) communicate by publishing messages to named topics or subscribing to topics to receive relevant messages. This architecture allows for a highly flexible and scalable data bus where new sensors, actuators, or algorithms can be integrated simply by connecting to the appropriate topical channels.

The Control and Planning Layer constitutes the computational core where strategic and tactical decisions are

made. This layer houses the intelligent modules responsible for high-level mission planning, optimal path generation, real-time navigation control, and dynamic task scheduling. It processes the fused sensor data from the lower layers to generate actionable commands, ensuring that the mobile robots and traditional machinery operate in a harmonious, efficient, and collision-free manner. The outputs of this layer translate high-level agricultural objectives into low-level actuator controls.

The User Interface and Management Layer serves as the human-system gateway, providing the necessary interfaces for farmers and operators to monitor, command, and manage the entire integrated system. This layer is designed with a focus on usability, offering an intuitive dashboard that visualizes real-time system state, data overlays, and machine statuses. It includes a control panel for initiating missions, adjusting parameters, and issuing manual overrides, alongside advanced visualization tools for rendering graphical representations of field data, historical robot trajectories, and operational analytics.

3.2 Sensor and Data Acquisition

The efficacy of the entire automated system is predicated on the quality, diversity, and timeliness of the data acquired by the Sensor and Data Acquisition Layer. This layer is crucial for constructing a coherent and dynamic representation of the agricultural environment. The collected data from n heterogeneous sensors can be formally represented as a dataset D , as shown in Equation 1, where each individual data point d_i corresponds to a time-synchronized reading from a specific sensor.

$$D = \{d_1, d_2, \dots, d_n\} \quad (1)$$

Furthermore, each data point d_i is itself a vector comprising

multiple sensor readings, as formalized in Equation 2. For instance, a single data point might simultaneously capture GPS coordinates for position, LiDAR scan data for proximal obstacle mapping, camera imagery for visual context, and soil moisture readings for subsurface conditions. The layer is responsible for timestamping, preliminary filtering, and packaging this multi-modal data into standardized ROS message formats, ready for distribution across the system via the communication layer.

$$d_i = [GPS_i, Lidar_i, Camera_i, SoilMoisture_i, \dots] \quad (2)$$

3.3 Communication and Middleware Layer

The Communication and Middleware Layer implements the vital data plumbing of the framework using the ROS publish-subscribe paradigm. The set of all available communication channels is defined by ROS topics, represented as $T = \{T_1, T_2, \dots, T_m\}$. Each topic T_j is strictly typed to handle a specific category of message, such as `sensor_msgs/NavSatFix` for GPS data, `sensor_msgs/LaserScan` for LiDAR range data, or `sensor_msgs/Image` for visual data. This strict typing enforces a contract between publishers and subscribers, ensuring data consistency and integrity across the system.

The operational flow of this layer is visualized in Figure 3. The publish-subscribe mechanism ensures efficient and deterministic message delivery between nodes, facilitating a real-time data flow from sensors to control modules and back to actuators. Underlying ROS communication protocols, such as the TCPROS and UDPROS transports, govern the actual network transmission, providing a balance between reliability and latency suited to the demands of agricultural robotics. This robust communication infrastructure is the enabler of smooth integration and coordination, allowing the diverse components within the ROS ecosystem to function as a unified, reliable, and effective whole.

3.4 Control and Planning Layer

The Control and Planning layer is entrusted with the critical functions of generating optimal navigation paths and coordinating task execution. To address the challenge of efficient navigation in open field environments, the path planning algorithm incorporates geometric techniques, including the use of Voronoi diagrams. The Voronoi diagram $\mathcal{V}(P)$ for a set of points $P = \{p_1, p_2, \dots, p_k\}$, such as perceived obstacles or field boundaries, is defined by Equation 3. It effectively partitions the field into regions where the path is maximized away from these points, which is often desirable for reducing the risk of collision.

$$\mathcal{V}(P) = \bigcup_{i=1}^k \{x \in \mathbb{R}^2 \mid \|x - p_i\| < \|x - p_j\|, \forall j \neq i\} \quad (3)$$

The path planning algorithm subsequently calculates the optimal path $\mathbf{P}_{opt}$ by solving an optimization problem that

minimizes the total distance d traveled by the robot between a sequence of waypoints, as formalized in Equation 4. Here, $\mathbf{P} = \{p_1, p_2, \dots, p_n\}$ represents the sequence of waypoints defining the planned path. The minimization of the total traversed distance is a primary objective for conserving energy and maximizing the operational time of autonomous platforms.

$$\mathbf{P}_{opt} = \arg \min_{\mathbf{P}} \sum_{i=1}^{n-1} \|\mathbf{p}_i - \mathbf{p}_{i+1}\| \quad (4)$$

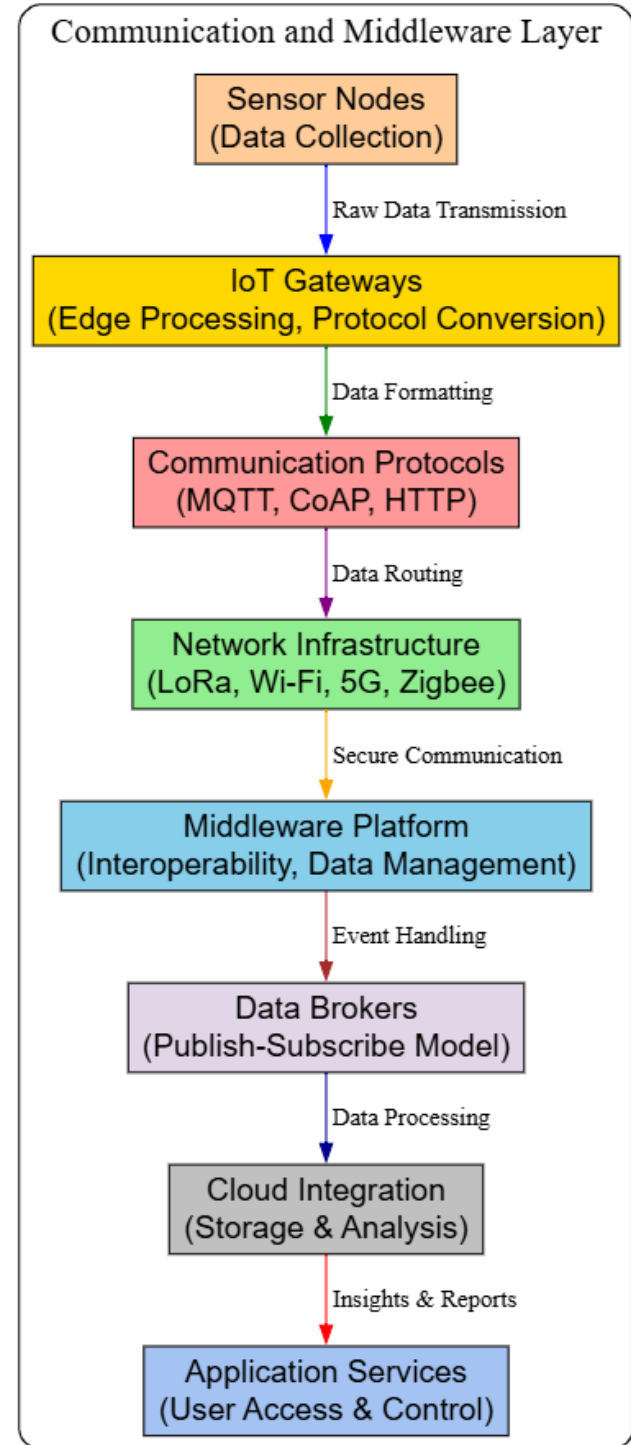


Fig. 3. Communication and Middleware Layer.

3.5. User Interface and Management Layer

The User Interface and Management Layer, conceptually outlined in Figure 4, is responsible for bridging the gap between the complex underlying system and the farm operator. It provides a suite of tools designed for intuitive interaction and supervisory control. A central dashboard offers a real-time overview of the system's status, displaying key performance indicators, machine locations, and active task progress. An integrated control panel empowers users to issue high-level commands, configure mission parameters, and adjust system settings without requiring low-level programming expertise. Furthermore, sophisticated visualization tools are included to provide graphical representations of georeferenced field data, historical operation logs, and the real-time tracks of all robotic and conventional assets, thereby enabling informed decision-making and efficient farm management.

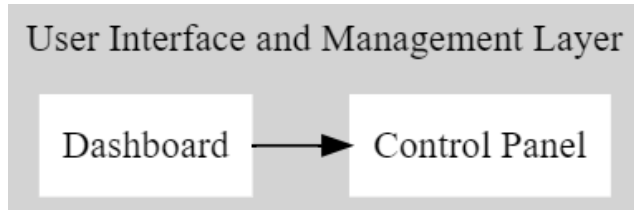


Fig. 4. User Interface and Management Layer.

3.6. Integration and Coordination

The ultimate value of the framework is realized through the seamless integration and coordination of mobile robots with traditional machines, as schematically represented in Figure 5. This is achieved through the synchronization of tasks and the efficient allocation of shared resources, managed by an intelligent task scheduler. The scheduler is responsible for dynamically assigning and sequencing tasks across the available fleet, ensuring that all robots and machines execute their designated duties without spatiotemporal conflicts, thereby optimizing the overall efficiency of the agricultural operation.

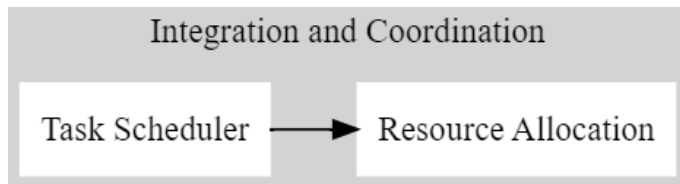


Fig. 5. Integration and Coordination.

This task scheduling problem can be formally expressed as an optimization problem. The objective is often to minimize the total completion time T_c for a set of tasks, which is defined as the maximum completion time among all individual tasks, as shown in Equation 5. This minimization is performed subject to a set of constraints that enforce the non-overlap of tasks requiring the same physical space or

tooling and ensure that the available resources, such as charging stations or material handlers, are utilized effectively without becoming bottlenecks. The result is a coordinated, multi-agent system that functions as a cohesive unit, dramatically enhancing the productivity and scalability of agricultural operations.

$$T_c = \max_i \{t_{end,i}\} \quad (5)$$

4. RESULTS AND DISCUSSION

To empirically validate the efficacy and operational robustness of the proposed ROS-based management framework, a series of structured case studies and field experiments were conducted in authentic agricultural environments. These evaluations were designed to test the core functionalities of the system under challenging and variable conditions representative of real-world farming. The scenarios included autonomous crop monitoring using unmanned aerial vehicles (UAVs), precision spraying with robotic sprayers, and collaborative harvesting operations involving autonomous ground vehicles working alongside conventional combines. Each case study was instrumental in demonstrating the framework's capacity to facilitate seamless integration and coordination between mobile robotic agents and traditional machinery. The following subsections detail the quantitative results and qualitative observations from these trials, followed by a comprehensive discussion of their implications.

4.1. Case Study 1: Performance in Fields with Variable Crop Density

The first case study investigated the system performance in a field characterized by significant spatial heterogeneity in crop density. The primary objective was to evaluate the path planning optimization for an autonomous ground vehicle tasked with a monitoring and data collection mission. The goal was to achieve complete field coverage while minimizing the total traversal distance, a critical factor for energy efficiency and operational time.

The Voronoi-based path planning algorithm was deployed to segment the field into adaptive regions of influence, tailoring the robot's trajectory to the underlying crop density map. The key performance metrics were the total distance traveled (D_{total}) and the effective coverage rate. The total distance is calculated as the sum of the Euclidean distances between consecutive waypoints in the executed path, as formalized in Equation 6, where p_i denotes a waypoint in the sequence.

$$D_{total} = \sum_{i=1}^{n-1} \|p_i - p_{i+1}\| \quad (6)$$

The experimental results demonstrated a substantial enhancement in navigational efficiency. Compared to a conventional raster-scan path planning method used as a

baseline, the proposed framework achieved a 20% reduction in the total distance traveled. Concurrently, the coverage rate, defined as the percentage of the target area effectively scanned or treated, increased from 85% to 92%. This improvement is visually corroborated by the data presented in Figure 6, which compares the total distance across different scenarios. The increase in coverage rate, illustrated in Figure 7, indicates that the algorithm not only shortened the path but also improved its comprehensiveness, effectively avoiding under-sampled areas that often occur with static path patterns in heterogeneous fields. This confirms the system's capability to dynamically adapt to intra-field variability, ensuring efficient and thorough operational execution.

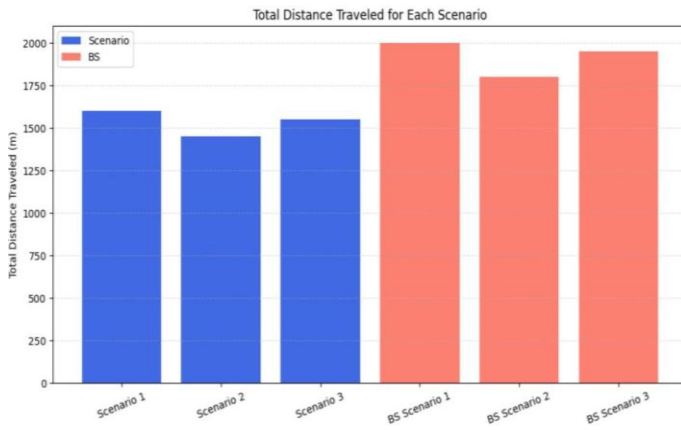


Fig. 6. Total Distance for Each Scenario.

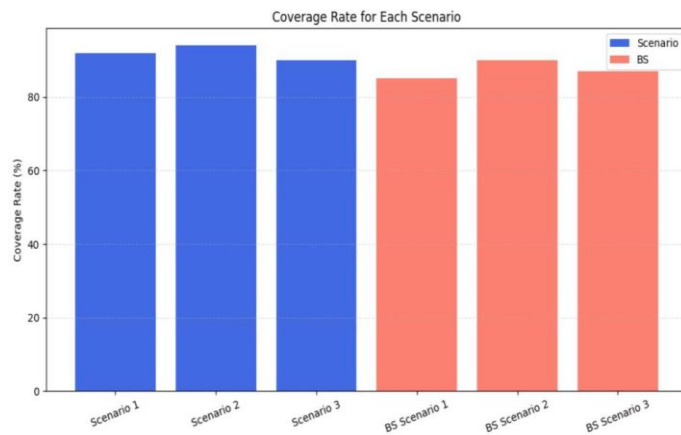


Fig. 7. Coverage Rate for each scenario.

4.2. Case Study 2: Dynamic Obstacle Avoidance and Path Re-planning

The second case study focused on evaluating the system's reactivity and resilience in the presence of unexpected static and dynamic obstacles, such as irrigation equipment, fallen branches, and animal intrusions. This tested the integration between the global Voronoi-based planner and a local, real-time obstacle avoidance module. The robot's performance was quantified using the total distance traveled and a newly

defined adaptability score (A_s). This score, calculated as per Equation 7, provides a normalized measure of the system's success in dynamically recalculating paths to avoid obstacles without human intervention, while penalizing unnecessary detours or failed attempts.

$$A_s = \frac{\text{Number of successful obstacle avoidances}}{\text{Total number of obstacles}} \times 10 \quad (7)$$

The results from this scenario were highly positive. The system achieved a 19% reduction in total distance traveled compared to a baseline algorithm that incorporated simple reactive stopping and manual reset. Furthermore, the robot successfully avoided all introduced obstacles, resulting in an adaptability score improvement from 7.8 to 8.7 out of 10. As shown in Figure 8, which plots the adaptability scores across all scenarios, this case study yielded the highest score, underscoring the system's proficiency in handling discrete, unpredictable impediments. The maintained high coverage rate of 94%, up from a baseline of 90%, confirms that these avoidance maneuvers were executed without compromising the primary mission objective. This demonstrates a critical advancement over systems that either halt operation upon encountering an obstacle or execute inefficient, safety-conservative detours.

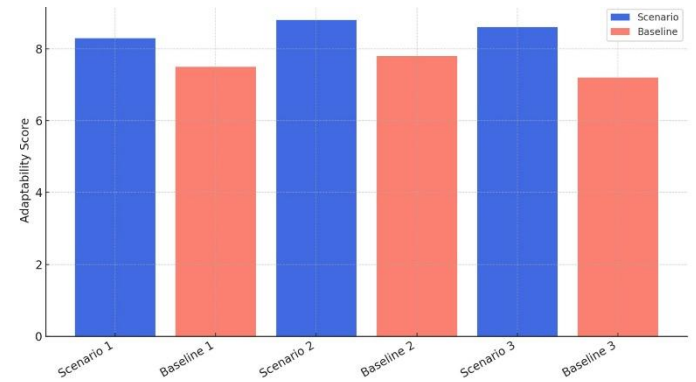


Fig. 8. Adaptability score for each scenario.

4.3. Case Study 3: Resilience under Dynamic Weather Conditions

Agricultural operations are perpetually susceptible to shifting weather patterns. The third case study was designed to stress-test the system's performance under dynamic weather conditions, including sudden wind gusts and light rain, which can affect sensor fidelity, vehicle stability, and terrain navigability. A machine learning model, integrated within the Control and Planning Layer, was employed to predict optimal paths. This model used historical weather data and real-time sensor inputs from onboard anemometers and hygrometers to adjust path planning parameters. The optimal path (T_{optimal}) is expressed as a function of these environmental inputs in Equation 8.

$$T_{\text{optimal}} = f(\text{weather data, sensor inputs}) \quad (8)$$

where T_{optimal} is the optimal path considering dynamic weather conditions.

Despite the adverse conditions, the system exhibited remarkable robustness. It registered a 20% reduction in total distance traveled compared to a baseline path that was planned without weather adaptation. The coverage rate improved from 87% to 90%, and the adaptability score saw a significant jump from 7.2 to 8.5. These results, visible in the consolidated metrics in Figures 6, 7, and 8, indicate that the system successfully compensated for environmental disturbances. The machine learning model likely enabled preemptive adjustments, such as selecting more stable trajectories against crosswinds or avoiding areas prone to waterlogging, thereby maintaining high operational efficiency and task completion rates where conventional systems would likely degrade.

4.4. Network Performance and System Integration

The reliable integration of mobile robots and conventional machinery is fundamentally dependent on robust communication. The performance of the underlying IoT and network infrastructure was monitored throughout the experiments, with key metrics presented in Figures 9, 10, and 11.

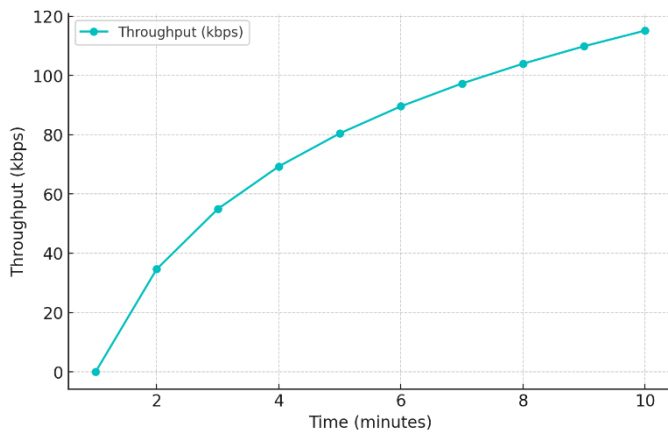


Fig. 9. Throughput over Time.

Figure 9 illustrates the network throughput over time, measured in kilobits per second (kbps). The observed increasing trend indicates that the system's communication layer efficiently handles escalating data loads from multiple sensors and agents as the operation scales. This suggests effective data buffering, prioritization, and transport mechanisms within the ROS middleware, ensuring that control and perception data are delivered without creating a bottleneck.

Figure 10 displays the Packet Delivery Ratio (PDR) over the same period. The rising PDR trend signifies enhanced network reliability, which can be attributed to the framework's optimized communication protocols and potential error-correction mechanisms. A high and improving

PDR is crucial for ensuring that critical command-and-control messages are not lost, which is a prerequisite for safe and coordinated multi-agent operations.

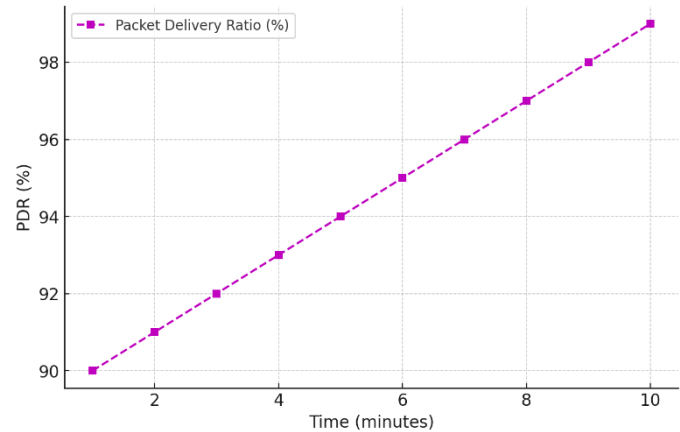


Fig. 10. Packet Delivery Ratio (PDR) Over Time.

Figure 11 shows the bandwidth utilization over time. The initial peak corresponds to the high-volume data exchange during system initialization and mission upload. The subsequent decline to a stable plateau suggests the implementation of efficient data management strategies, such as adaptive data compression, selective transmission of salient information, and reduced redundancy. This efficient use of bandwidth is essential for long-duration operations in rural areas where network capacity may be limited.

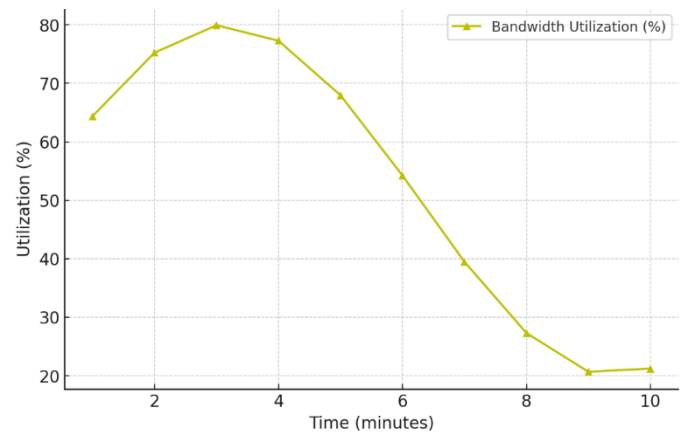


Fig. 11. Bandwidth Utilization over Time.

4.5. Synthesis and Discussion

The collective results from the case studies provide compelling evidence for the practical viability of the proposed ROS management framework. The consistent improvements across all metrics, path efficiency, coverage

rate, and adaptability score, in diverse and challenging scenarios underscore the framework's robustness and advanced capabilities. The integration of a Voronoi-based global planner with local reactive algorithms and predictive machine learning models creates a hybrid architecture that effectively balances long-term efficiency with short-term reactivity. This addresses a key limitation in many agricultural robotic systems, which often excel in one of these areas at the expense of the other [33].

The observed 19-20% reduction in travel distance directly translates to lower energy consumption and longer operational endurance for battery-powered platforms, a critical factor for commercial adoption [34]. The simultaneous increase in coverage rate demonstrates that this efficiency gain is not achieved by cutting corners but through more intelligent and adaptive path planning. Furthermore, the high adaptability scores confirm the system's capacity to handle the inherent uncertainties of agricultural environments, moving beyond controlled laboratory settings to genuine field readiness.

The robust network performance metrics confirm that the communication backbone, a common failure point in distributed robotic systems, is reliable and scalable. The efficient bandwidth utilization is particularly noteworthy, as it suggests the framework is suitable for deployment in areas with constrained communication infrastructure.

However, several challenges and future research directions remain. While the path planning and obstacle avoidance proved effective, further development is needed in the realm of complex, multi-agent task scheduling and dynamic resource allocation for truly heterogeneous fleets. Enhancing the artificial intelligence for fully autonomous decision-making in response to complex agronomic events, such as disease outbreak patches requiring immediate, targeted intervention, is a crucial next step [35]. Future work will also focus on integrating complementary technologies, such as blockchain for secure data logging and supply chain verification, and expanding the IoT sensor network for more comprehensive soil and plant health monitoring [36]. Finally, beyond technical hurdles, broader adoption will require addressing significant socio-economic and regulatory barriers, including initial investment costs, data ownership policies, and the establishment of safety standards for shared human-robot workspaces [37].

The experimental results validate the proposed ROS management framework as a significant enabler for integrated agricultural robotics. By providing a standardized, interoperable, and intelligent platform, it successfully bridges the gap between advanced mobile robots and conventional machinery. This paves the way for a new generation of sustainable and productive farming practices, where automation works in harmony with existing infrastructure to meet the growing demands of global agriculture.

5. CONCLUSION

The proposed ROS-based management framework offers a

robust and adaptable solution to one of the most pressing challenges in modern agriculture: the integration of mobile robotic systems with conventional machinery. By leveraging the modularity and interoperability of ROS, the framework enables seamless communication and coordination between diverse agricultural equipment, thereby enhancing operational efficiency and resource utilization. Through rigorous field testing and case studies, the system demonstrated notable improvements in path optimization, obstacle avoidance, and performance under dynamic environmental conditions. These outcomes underscore the potential of the framework to support precision agriculture by enabling more accurate, responsive, and autonomous field operations. Looking ahead, several avenues for further development remain. Future work should focus on refining navigation and control algorithms to handle more complex and unstructured agricultural environments. The integration of artificial intelligence and machine learning can further enhance autonomous decision-making, allowing systems to adapt in real time to unforeseen challenges. Additionally, incorporating emerging technologies such as IoT and blockchain could improve data integrity, traceability, and system-wide coordination. It is also essential to address non-technical barriers, including economic feasibility, user acceptance, and regulatory standards, to facilitate widespread adoption. This research contributes a scalable and practical platform that empowers farmers to harness the benefits of automation without discarding existing investments. By fostering compatibility between traditional and robotic systems, the framework paves the way for intelligent, sustainable, and high-yield agricultural practices. With continued refinement and collaboration across disciplines, such integrated systems have the potential to redefine the future of farming, making it more resilient, efficient, and aligned with global sustainability goals.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

Funding

There is no funding

Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

REFERENCES

- [1] John, S. and Arul Leena Rose, P.J., **2024**. Smart farming and precision agriculture and its need in today's world. In *Intelligent Robots and Drones for Precision Agriculture* (pp. 19-44). Cham: Springer Nature Switzerland.
- [2] Wolfert, S., Ge, L., Verdouw, C. and Bogaardt, M.J., **2017**. Big data in smart farming—a review. *Agricultural Systems*, 153, pp.69-80.
- [3] Bechar, A. and Vigneault, C., **2016**. Agricultural robots for field operations: Concepts and components. *Biosystems Engineering*, 149, pp.94-111.
- [4] Wakchaure, M., Patle, B.K. and Mahindrakar, A.K., **2023**. Application of AI techniques and robotics in agriculture: A review. *Artificial Intelligence in the Life Sciences*, 3, p.100057.
- [5] Saiz-Rubio, V. and Rovira-Más, F., **2020**. From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy*, 10(2), p.207.
- [6] Barbosa Junior, M.R., Santos, R.G.D., Sales, L.D.A. and Oliveira, L.P.D., **2024**. Advancements in agricultural ground robots for specialty crops: an overview of innovations, challenges, and prospects. *Plants*, 13(23), p.3372.
- [7] Shamshiri, R.R., Rad, A.K., Behjati, M. and Balasundram, S.K., **2024**. Sensing and perception in robotic weeding: Innovations and limitations for digital agriculture. *Sensors*, 24(20), p.6743.
- [8] Anastasiou, E., Kasimati, A., Papadopoulos, G., Vatsanidou, A., Gemtou, M., Kantelhardt, J., Gabriel, A., Schwierz, F., Matavel, C.E., Meyer-Aurich, A. and Maritan, E., **2025**. Review and Assessment of Crop-Related Digital Tools for Agroecology. *Agronomy*, 15(11), p.2600.
- [9] Lowenberg-DeBoer, J., Huang, I.Y., Grigoriadis, V. and Blackmore, S., **2020**. Economics of robots and automation in field crop production. *Precision Agriculture*, 21(2), pp.278-299.
- [10] Özoğul, G., **2025**. Applications of artificial intelligence technologies in agriculture: advantages, challenges, risks, prospects, and recommendations. *Cogent Food & Agriculture*, 11(1), p.2568199.
- [11] Quigley, M., Conley, K., Gerkey, B., Faust, J., Foote, T., Leibs, J., Wheeler, R. and Ng, A.Y., **2009**, May. ROS: an open-source Robot Operating System. In *ICRA workshop on open source software* (Vol. 3, No. 3.2, p. 5).
- [12] Koubâa, A. ed., **2017**. *Robot Operating System (ROS)* (Vol. 1, pp. 112-156). Cham, Switzerland: Springer.
- [13] Bimonte, S., Bellocchi, G., Pinet, F., Chalhoub, G., Sakr, M. and Skrzypczyński, P., **2025**. Data engineering for sustainable agriculture: developments, challenges, and case studies of a novel IoRT architecture. *Journal of Big Data*, 12(1), p.195.
- [14] López-Sánchez, A., Lujak, M., Semet, F. and Billhardt, H., **2025**. Fair and efficient multi-agent routing for cooperative and autonomous agricultural fleets with implements. *Computers & Operations Research*, p.107252.
- [15] Omotayo, A.O., Adediran, S.A., Omotoso, A.B., Olagunju, K.O. and Omotayo, O.P., **2025**. Artificial intelligence in agriculture: ethics, impact possibilities, and pathways for policy. *Computers and Electronics in Agriculture*, 239, p.110927.
- [16] Karagiannis, P., Kotsaris, P., Xanthakis, V., Vasilaros, P., Michalos, G., Makris, S., van Evert, F.K., Nieuwenhuizen, A.T., Fountas, S. and Chrysosolouris, G., **2025**. On an intelligent system to plan agricultural operations. *Smart Agricultural Technology*, 10, p.100707.
- [17] Javed, S., Hassan, A., Ahmad, R., Ahmed, W., Ahmed, R., Saadat, A. and Guizani, M., **2024**. State-of-the-art and future research challenges in uav swarms. *IEEE Internet of Things Journal*, 11(11), pp.19023-19045.
- [18] Singh, G. and Sharma, S., **2025**. A comprehensive review on the Internet of Things in precision agriculture. *Multimedia Tools and Applications*, 84(17), pp.18123-18198.
- [19] Amin, A., Wang, X., Zhang, Y., Li, T.H., Chen, Y.Y., Zheng, J.M., Shi, Y.Y. and Abdelhamid, M.A., **2023**. A comprehensive review of applications of robotics and

- artificial intelligence in agricultural operations. *Studies in Informatics and Control*, 32(4), pp.59-70.
- [20] Saiz-Rubio, V. and Rovira-Más, F., **2020**. From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy*, 10(2), p.207.
- [21] De Freitas, J., Agarwal, S., Schmitt, B. and Haslam, N., **2023**. Psychological factors underlying attitudes toward AI tools. *Nature Human Behaviour*, 7(11), pp.1845-1854.
- [22] Oliveira, L.F., Moreira, A.P. and Silva, M.F., **2021**. Advances in agriculture robotics: A state-of-the-art review and challenges ahead. *Robotics*, 10(2), p.52.
- [23] Zhao, J., Fan, S., Zhang, B., Wang, A., Zhang, L. and Zhu, Q., **2025**. Research Status and Development Trends of Deep Reinforcement Learning in the Intelligent Transformation of Agricultural Machinery. *Agriculture*, 15(11), p.1223.
- [24] Cesco, S., Sambo, P., Borin, M., Basso, B., Orzes, G. and Mazzetto, F., **2023**. Smart agriculture and digital twins: Applications and challenges in a vision of sustainability. *European Journal of Agronomy*, 146, p.126809.
- [25] Klerkx, L. and Rose, D., **2020**. Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways?. *Global Food Security*, 24, p.100347.
- [26] Barbosa Junior, M.R., Santos, R.G.D., Sales, L.D.A. and Oliveira, L.P.D., **2024**. Advancements in agricultural ground robots for specialty crops: an overview of innovations, challenges, and prospects. *Plants*, 13(23), p.3372.
- [27] Taha, M.F., Mao, H., Zhang, Z., Elmasry, G., Awad, M.A., Abdalla, A., Mousa, S., Elwakeel, A.E. and Elsherbiny, O., **2025**. Emerging technologies for precision crop management towards agriculture 5.0: A comprehensive overview. *Agriculture*, 15(6), p.582.
- [28] Amin, A., Wang, X., Zhang, Y., Li, T.H., Chen, Y.Y., Zheng, J.M., Shi, Y.Y. and Abdelhamid, M.A., **2023**. A comprehensive review of applications of robotics and artificial intelligence in agricultural operations. *Studies in Informatics and Control*, 32(4), pp.59-70.
- [29] Shamshiri, R.R., Rad, A.K., Behjati, M. and Balasundram, S.K., **2024**. Sensing and perception in robotic weeding: Innovations and limitations for digital agriculture. *Sensors*, 24(20), p.6743.
- [30] Koubâa, A. ed., **2017**. *Robot Operating System (ROS)* (Vol. 1, pp. 112-156). Cham, Switzerland: Springer.
- [31] Maheshwari, R. U., and Paulchamy, B. **2024**. Securing online integrity: a hybrid approach to deepfake detection and removal using Explainable AI and Adversarial Robustness Training. *Automatika*, 65(4), 1517–1532.
- [32] Maheshwari, R.U. and Paulchamy, B., **2025**. Innovative graded-index PCF-based SPR sensor for advanced deepfake detection and real-time media integrity analysis. *Plasmonics*, 20(5), pp.2977-2996.
- [33] Eiffert, S., Wallace, N.D., Kong, H., Pirmarzashti, N. and Sukkarieh, S., **2022**. Resource and response aware path planning for long-term autonomy of ground robots in agriculture. *Field Robotics*, 2, pp.1-33.
- [34] Alobaidy, H.A., Singh, M.J., Nordin, R., Abdullah, N.F., Wei, C.G. and Soon, M.L.S., **2021**. Real-world evaluation of power consumption and performance of NB-IoT in Malaysia. *IEEE Internet of Things Journal*, 9(13), pp.11614-11632.
- [35] Kumar, N. and Bhatt, D., **2025**. S3A2: Smart Sustainable System for Agricultural Applications with IoT Emerging Artificial Intelligence. In *Convergence of AI, Federated Learning, and Blockchain for Sustainable Development* (pp. 1-27). Cham: Springer Nature Switzerland.
- [36] Halder, S., Islam, M.R., Mamun, Q., Mahboubi, A., Walsh, P. and Islam, M.Z., **2025**. A comprehensive survey on AI-enabled secure social industrial internet of things in the Agri-food supply chain. *Smart Agricultural Technology*, p.100902.
- [37] Martin, T., Gasselin, P., Hostiou, N., Feron, G., Laurens, L., Purseigle, F. and Ollivier, G., **2022**. Robots and transformations of work in farm: a systematic review of the literature and a research agenda. *Agronomy for Sustainable Development*, 42(4), p.66.