

RESEARCH ARTICLE

AgriRover: An IoT–Enabled Autonomous System for Precision Seed Monitoring and Adaptive Water Distribution

N. Purandhar^{1,*}, M.Rajendiran², Ahmed Mudassar Ali³, M. Sangeetha⁴

ABSTRACT: Conventional agricultural practices are increasingly inadequate to meet the demands of a rapidly expanding global population, often leading to inefficient resource use, environmental degradation, and suboptimal crop yields. The Internet of Things (IoT) presents a transformative solution by introducing precision and intelligence into farming operations. This research proposes a comprehensive, IoT-driven autonomous vehicle system designed specifically for large-scale seed monitoring and targeted water distribution. The system is engineered to bridge the gap between rising food demands and the necessity for sustainable farming methods. A primary feature of its design is scalability, enabling effective deployment across farms of varying sizes and facilitating integration with other smart agriculture technologies. By synergizing autonomous vehicles with a network of IoT sensors and real-time data analytics, the platform establishes a data-driven environment for sustainable and efficient agricultural management. The system utilizes IoT-based sensors and actuators to continuously assess seed health and soil conditions, enabling strategic, on-demand water distribution that minimizes waste and optimizes resource allocation. This architecture empowers farms of any scale to achieve operational excellence while actively promoting environmental stewardship through precision agriculture.

Keywords: Precision Agriculture, Autonomous Systems, Internet of Things (IoT), Sensor Networks, Water Use Efficiency, Crop Health Monitoring

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1. INTRODUCTION

Contemporary global agriculture is confronted by a formidable and multi-faceted challenge: the imperative to significantly increase food production to nourish a rapidly

expanding population, while simultaneously confronting the escalating pressures of resource scarcity, environmental degradation, and climate change. Conventional agricultural methodologies, which often rely on uniform application of water and fertilizers, are increasingly revealed as insufficient and even detrimental, leading to profound inefficiencies in resource utilization, soil exhaustion, water wastage, and diminished crop yields [1]. In this critical context, the emergence of Precision Agriculture (PA) and the Internet of Things (IoT) presents a transformative paradigm, shifting farming from a broad-stroke practice to a data-driven, precise science. IoT technologies, characterized by interconnected networks of sensors, actuators, and communication devices, offer a holistic framework for intelligent farm management, enabling real-time monitoring and targeted interventions [2]. This research specifically investigates the development and implementation of an IoT-based autonomous vehicle system, termed here as AgriRover, which is engineered to perform

¹ Department of Computer Science and Engineering- Artificial Intelligence, School of Computers Madanapalle Institute of Technology & Science (Deemed to be University), Madanapalle, Andhra Pradesh - 517325, India.

² Department of Artificial Intelligence and Data Science, VSB Engineering College. Karur, Tamil Nadu, India.

³ Department of Information Technology, S.A. Engineering College, Affiliated to Anna University, Poonamallee-Avadi Road, Thiruverkadu, Chennai - 600 077. Tamilnadu. India.

⁴ PSGR Krishnammal College for Women), Bharathiar University, Peelamedu, Coimbatore - 641004, Tamil Nadu, India

* Author to whom correspondence should be addressed:
purandhar.n@gmail.com (N. Purandhar)

integrated seed monitoring and precision irrigation, thereby addressing two of the most resource-critical operations in cultivation.

The proposed system centers on an autonomous vehicle platform that navigates agricultural fields, equipped with a suite of sophisticated sensors. These sensors continuously gather vital agronomic data, including soil moisture content, temperature, humidity, and key spectral indices reflective of plant health and nutrient levels [3]. This real-time data stream forms the foundational layer of the system's intelligence. The Water Rover functionality acts upon this intelligence, utilizing the acquired data to execute precise, targeted irrigation. This approach ensures that water is delivered only where and when it is needed, directly at the root zone of individual plants or specific crop rows, thereby dramatically minimizing losses due to evaporation, runoff, or deep percolation that are endemic to traditional flood or sprinkler systems [4]. The synergy between continuous monitoring and targeted action facilitates a closed-loop system that not only promises to boost overall crop productivity but also champions' significant water conservation and a reduction in agriculture's environmental footprint. Figure 1 provides a conceptual illustration of how such an IoT ecosystem functions within an agricultural setting, highlighting the flow of information from the field to the decision-making processes.

This endeavor is intrinsically aligned with the overarching goals of sustainable agriculture, which seeks to meet present needs without compromising the ability of future generations to meet their own. By tackling the inherent inefficiencies of conventional methods, the system directly confronts issues such as the over-extraction of groundwater and the eutrophication of water bodies caused by fertilizer runoff [5]. The core objective of this study is to propose a tangible, physically implementable IoT-based autonomous vehicle system, delving into its architectural design, its operational efficacy, and its potential for scalable adoption. The investigation extends to evaluating its economic viability in overcoming prevalent hurdles in agricultural practice and

its broader evolutionary implications for sustainable food production ecosystems. The integration of autonomous vehicles with IoT for such dual-purpose functionality represents a significant paradigm shift towards highly granular precision agriculture. This fusion enables not just automated physical tasks but intelligent, context-aware operations. For instance, the combination facilitates hyper-efficient water use, creates optimized growing conditions for seeds by responding to micro-variations in the field, and unlocks a suite of other data-driven outcomes that were previously unattainable [6].

The novelty of this paper lies in the development of a unified, scalable architecture that seamlessly merges real-time, in-situ spectral analysis for continuous seed health assessment with an adaptive water distribution mechanism, governed by a decision-making model that fuses multi-sensor data, including satellite and UAV inputs, for holistic field management, a comprehensive integration not yet thoroughly explored in extant literature. By leveraging sensor data and intelligent machine learning algorithms, the system is engineered to drastically curtail waste associated with conventional water management practices [7]. The move towards more responsible and sustainable agricultural methods is not merely an economic advantage but a critical necessity, particularly for regions grappling with acute water scarcity [8]. The technology empowers farmers by providing them with unprecedented, current, and spatially accurate information on soil characteristics and crop status, making the vision of precision farming a practical reality [9]. Consequently, this leads to a demonstrable reduction in environmental footprints, encompassing carbon emissions and water pollution, coupled with a tangible increase in yield [10]. Specific benefits include the drastic decrease of water waste, optimized efficiency of resource utilization, and a reduced dependency on chemical fertilizers, all of which are hallmark indicators of environmentally sustainable agricultural practices [11]. This work follows a global trajectory of efforts aimed at mitigating the carbon and resource footprint of the agricultural sector [12].

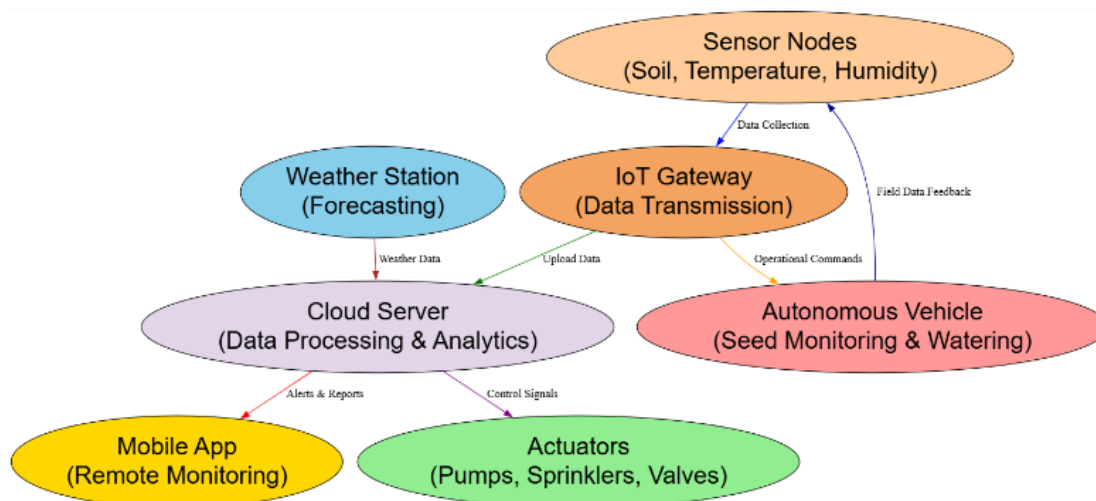


Fig. 1. IoT in Agriculture System.

The system described herein provides a comprehensive solution for agricultural assessment and management by synthesizing the capabilities of autonomous vehicles, dense sensor networks, and IoT protocols. It utilizes autonomous platforms, advanced sensing technology, and robust data analytics to offer a novel, dynamic approach to monitoring seed development, thereby equipping farmers with deeper, actionable insights into the germination and early growth stages of crops [13]. Furthermore, it actively helps in reducing water wastage by championing sustainable hydrology through the implementation of more accurate and effective irrigation methods, moving beyond simple timing to needs-based spatial application [14]. The application of such integrated precision agriculture technology holds the potential to substantially improve agricultural sustainability by simultaneously enhancing ecosystem resilience, minimizing negative environmental impacts, and maximizing resource utilization efficiency [15]. Prior research has established the value of IoT in agriculture [16], the feasibility of autonomous rovers for specific tasks like seeding [17], and the importance of data fusion from multiple sources [18]. However, this work integrates these domains into a single, cohesive system focused on the critical link between seed health monitoring and resource allocation. The IoT-based Autonomous Vehicle System for seed monitoring and Water Rover operation embodies intelligent, data-driven practices that confront the intertwined challenges of resource scarcity, environmental impact, and the relentless demand for increased food production [19]. These practices are making significant strides in bridging the technological gap between the future of digital agriculture and the present realities of the farming community [20]. The remainder of this document is structured for clarity, beginning with a detailed literature review in Section 2, followed by an exhaustive explanation of the system design and methodology in Section 3, a presentation of experimental results and discussion in Section 4, and finally, the conclusion and suggestions for future research directions in Section 5.

2. LITERATURE SURVEY

The agricultural sector has emerged as a prominent adopter of remote sensing technologies, extensively utilizing data acquired from both satellite platforms and Unmanned Aerial Vehicles (UAVs). Each of these data sources presents a distinct set of advantages and limitations, primarily governed by parameters such as spatial coverage, geographic resolution, and spectral and temporal precision. Satellite imagery typically offers extensive spatial coverage and systematic temporal revisit cycles, making it suitable for monitoring large-scale agricultural landscapes and phenological stages over time. In contrast, UAVs provide data with significantly higher spatial resolution and unparalleled acquisition flexibility, enabling the capture of fine-scale field variability and rapid response to immediate agricultural events. The synergistic integration of these multi-scale datasets has been widely recognized as a pathway to creating more robust

information systems for agricultural monitoring, classification, identification, and tracking, thereby overcoming the inherent limitations of each platform when used in isolation [8].

A cornerstone of remote sensing in agriculture is the derivation and application of Vegetation Indices (VIs), which are mathematical transformations of reflectance values across specific spectral bands designed to highlight particular vegetation properties. While indices like the Normalized Difference Vegetation Index (NDVI) are ubiquitous for assessing general plant vigor and biomass, a multitude of other indices have been developed to probe specific physiological characteristics. For instance, leveraging the sensitivity of the red-edge spectral region to chlorophyll content, researchers have proposed enhanced vegetation indices that incorporate reflectance in both the red and red-edge channels [9]. These advanced VIs were developed to supplant traditional indices based on red and green spectral channels and have demonstrated superior performance in estimating chlorophyll concentration, even in challenging conditions such as turbid water bodies, with the Normalized Difference Chlorophyll Index being a prominent example. Further refining this approach, other studies have formulated specific vegetation index ratios to enhance the detection of abiotic stresses, such as heavy metal contamination in rice fields, by combining Sentinel-2 satellite data with in-situ measurements [10]. The proliferation of UAVs has been instrumental in this domain, providing the high-resolution, timely data necessary for developing and validating such precise diagnostic indices. The convergence of data fusion techniques, satellite imaging, and aerial videography underscores the need for advanced, adaptive methodologies that can leverage these diverse data streams to produce highly accurate and actionable results.

The exploration of spectral indices extends beyond chlorophyll estimation to broader applications in crop characterization and stress identification within precision agriculture. Research has focused on developing indices that are more resilient to atmospheric and soil background effects, thereby providing a clearer signal of plant health. For example, some studies have proposed modified VIs based on reflectance in specific red and near-infrared channels to replace standard spectral combinations, aiming for improved sensitivity to crop stressors [11]. This line of inquiry is critical for enabling more effective utilization of the vast data streams now available from drone and satellite platforms, transforming raw data into insights for targeted crop management. Beyond single-timeframe analysis, the temporal dimension of data is equally critical. The work presented in [12] utilized a 12-year MODIS NDVI time series to construct a global minimum NDVI composite, employing a novel methodology based on a specific baseline vegetation index for observation selection. This approach highlights the value of long-term data archives for establishing ecological baselines and monitoring gradual changes in vegetation dynamics.

The fundamental principle underpinning many of these applications is the relationship between spectral response and

biophysical phenomena across spatial and temporal dimensions. As noted by [13], the distribution of spectral features in space and time can be harnessed to predict key agricultural variables such as crop yield and weather impacts. This principle forms the basis for identifying plant characteristics through spectral indices. Consequently, methods have been developed to predict fractional vegetation cover, a critical biophysical parameter, using data from sensors like IRS-LISS III. Investigations in this area have revealed that indices such as the Difference Vegetation Index (DVI) can yield higher coefficients of determination for estimating vegetation cover compared to other indices, underscoring the importance of selecting the appropriate index for the specific parameter of interest. The fusion of data from different platforms has been a significant focus to leverage their complementary strengths. Research has demonstrated the assessment of vegetation cover ratio by combining broad-coverage optical satellite data with high-resolution UAV imagery that accurately represents ground truth [14]. This often involves constructing regression models to generate reliable vegetation indicators from satellite data based on calibration from UAV-derived metrics, thereby reconciling the scale differences between platforms. This methodology addresses the challenge of employing different metrics across studies to determine percentage cover and has been applied in diverse contexts, including the use of hyperspectral imagery for coral reef classification and identification.

The pursuit of accurate farming monitoring has also led to methods that integrate satellite photos with low-altitude aerial photography from platforms like helicopters. Such approaches have demonstrated the potential to decrease data processing times while simultaneously providing more precise information over wider areas, often through the implementation of adaptive thresholding mechanisms. The utility of this method has been shown, for instance, in distinguishing between sparse and dense sugarcane patches within a uniformly planted field, a task crucial for variable resource application [15]. Beyond optical sensors, Synthetic Aperture Radar (SAR) data has proven highly valuable, particularly in regions with persistent cloud cover. Studies have successfully built crop classification systems based on crop phenology using SAR data. For example, researchers have analyzed agricultural phenology using medium-resolution SAR data, focusing on cross-polarization (VH) backscatter, which is sensitive to vegetation structure and biomass. Phenological metrics derived from SAR time-series have been shown to be effective for discriminating between crop types such as sugarcane and paddy, as their unique growth cycles manifest as distinct temporal signatures in the radar backscatter [16]. Similarly, other work has focused on crop classification in major agricultural zones like the Central Great Plains of the United States, utilizing MODIS 250-meter time-series data of the Enhanced Vegetation Index (EVI) and NDVI. These studies often employ extended graphical and statistical analyses of multi-temporal VI data to discover unique phenological signatures that are characteristic of regions with high crop type diversity, thereby improving

land-use and land-cover (LULC) classification accuracy [17].

The application of drone technology continues to expand, enabling more ecologically responsible agriculture through precise intervention. Advanced methods have been proposed that utilize standard RGB sensors on drones to discriminate between different tillage operations practiced in fields [18]. The research suggests that a more precise classification of tillage techniques could be achieved by fusing data from a suite of different UAV-mounted sensors. Experimental testing for field categorization has demonstrated that such proposed techniques yield promising results, often employing sophisticated analytical approaches such as Fourier transforms, principal component analysis, and point-oriented analysis to extract relevant features from the imagery. In the realm of SAR data analysis, further advancements have been made through the critical analysis of fully polarimetric systems like PALSAR. Research has involved constructing decision tree classifiers tailored for land cover categorization based on textural properties derived from the SAR data [19]. While some studies have explored the use of polarization signatures to boost the informational utility of polarimetric SAR data, other research streams have concentrated directly on the classification outcomes derived from the polarimetric SAR backscattering signals themselves, without explicitly leveraging the full polarization signature.

In synthesizing the extant literature, it is evident that significant progress has been made in remote sensing for agriculture, spanning the use of multi-platform data, the development of sophisticated vegetation indices, and the application of advanced machine learning classifiers for crop mapping and monitoring. However, a conspicuous research gap remains concerning the development of holistic, integrated frameworks that seamlessly combine satellite and UAV data into a unified, real-time decision-support system for autonomous agricultural operations. While there is ample research on data fusion for analytical purposes, the translation of these fused data streams into closed-loop, actionable commands for autonomous vehicles performing simultaneous seed monitoring and precision irrigation is an area that has received comparatively little attention. It is within this identified gap that the present study positions its contribution, proposing a system architecture designed to bridge the divide between multi-source remote sensing data and the physical actuation of an autonomous agricultural vehicle.

3. DESIGN AND DEVELOPMENT OF PROPOSED WORK

The proposed methodology presents a comprehensive IoT-based autonomous vehicle system, termed AgriRover, designed to address the critical agricultural challenges of precise seed monitoring and optimized water distribution. This integrated approach represents a significant advancement towards ensuring the environmental sustainability and economic viability of farming operations by replacing uniform field-scale management with targeted,

plant-level interventions. The system is conceived as a closed-loop cyber-physical system that seamlessly integrates real-time sensing, data analytics, and autonomous actuation to create a responsive and intelligent agricultural management platform.

The foundational element of the proposed work is a robust and scalable system architecture, illustrated in Figure 2, which orchestrates the interaction between physical components and computational intelligence. This architecture is fundamentally structured around a coherent pipeline of data acquisition, information fusion, decision-making, and physical actuation. The design philosophy prioritizes the creation of an integrated, systematic, and efficient flow of logical units to ensure all components operate synergistically. The architecture is composed of several critical subsystems, each with a distinct function that contributes to the overall system objective. These include a sophisticated sensor network for pervasive data collection, a communication module for robust data transmission, a central decision-making unit for cognitive analysis, and a suite of actuators for precise physical intervention. This design is intentionally modular to facilitate maintenance, upgrades, and scalability, ensuring that the system can adapt to varying farm sizes and evolving technological landscapes. The operational logic of the system is governed by a series of formalized processes, which can be conceptually represented for clarity. The navigation of the autonomous vehicle is determined by a dedicated algorithm that synthesizes geospatial coordinates from the Global Positioning System (GPS) with real-time data streams from onboard sensors. This process, represented as $\text{Path} = \text{Algorithm}(\text{GPS}, \text{Sensors})$, enables the vehicle to compute an optimal trajectory that is not only spatially efficient but also agronomically informed. The algorithm incorporates factors such as spatial variability in soil moisture, temperature gradients, and the presence of static or dynamic obstacles to plan a route that maximizes the efficacy of data collection and resource application while minimizing operational time and energy expenditure.

A cornerstone of the system's intelligence is its multi-layered data fusion capability. The system actively integrates heterogeneous data from disparate sources to form a unified and comprehensive situational awareness. This involves the combination of broad-scale satellite data with high-resolution imagery from Unmanned Aerial Vehicles (UAVs), a process conceptualized as $\text{Fused Data} = \text{Fuse}(\text{SatelliteData}, \text{UAVData})$. This fusion enhances the overall dataset by compensating for the inherent limitations of each source; satellite data provides extensive spatial and temporal coverage, while UAV data offers fine-grained spatial resolution and on-demand acquisition. The result is a rich, multi-spectral, and multi-temporal dataset that forms a more accurate representation of the agricultural field's status, as depicted in the system architecture in Figure 3.

The fused data serves as the input to a machine learning-driven decision-making model, encapsulated by the relation $\text{Decision} = \text{MachineLearningModel}(\text{FusedData})$. This model is trained on historical and real-time agronomic data to analyze a multitude of parameters, including spectral indices linked to chlorophyll content, canopy structure, and water stress. Its output comprises actionable insights and commands pertaining to crop health status, precise irrigation requirements, and other management directives. The model is designed to be adaptive, capable of learning from new data to continuously refine its predictions and recommendations in response to the dynamic agricultural environment.

Ensuring the reliable and secure movement of this data is the responsibility of a dedicated communication protocol, represented as $\text{Data Transmitted} = \text{Protocol}(\text{FusedData})$. This protocol manages the seamless transmission of fused data and decisions between the autonomous vehicle, a centralized control system (if present), and the end-user interface. It incorporates industry-standard encryption and error-checking mechanisms, such as those found in LTE/5G or LoRaWAN networks, to guarantee data integrity, confidentiality, and security during transmission, which is paramount for reliable system operation.

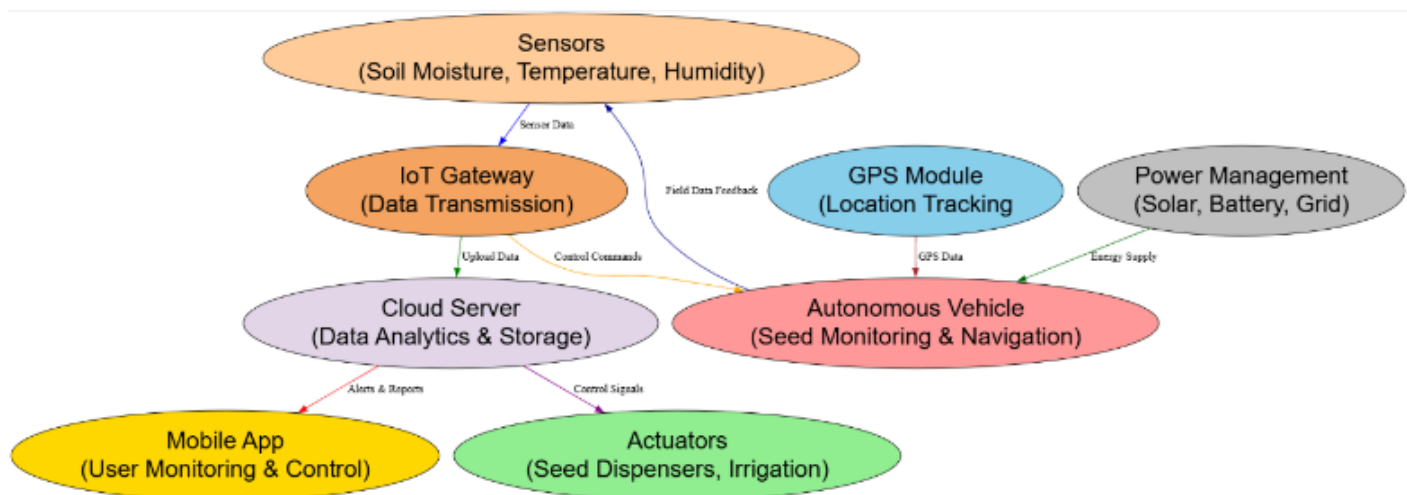


Fig. 2. IoT Based Autonomous Vehicle System for Seed Monitoring.

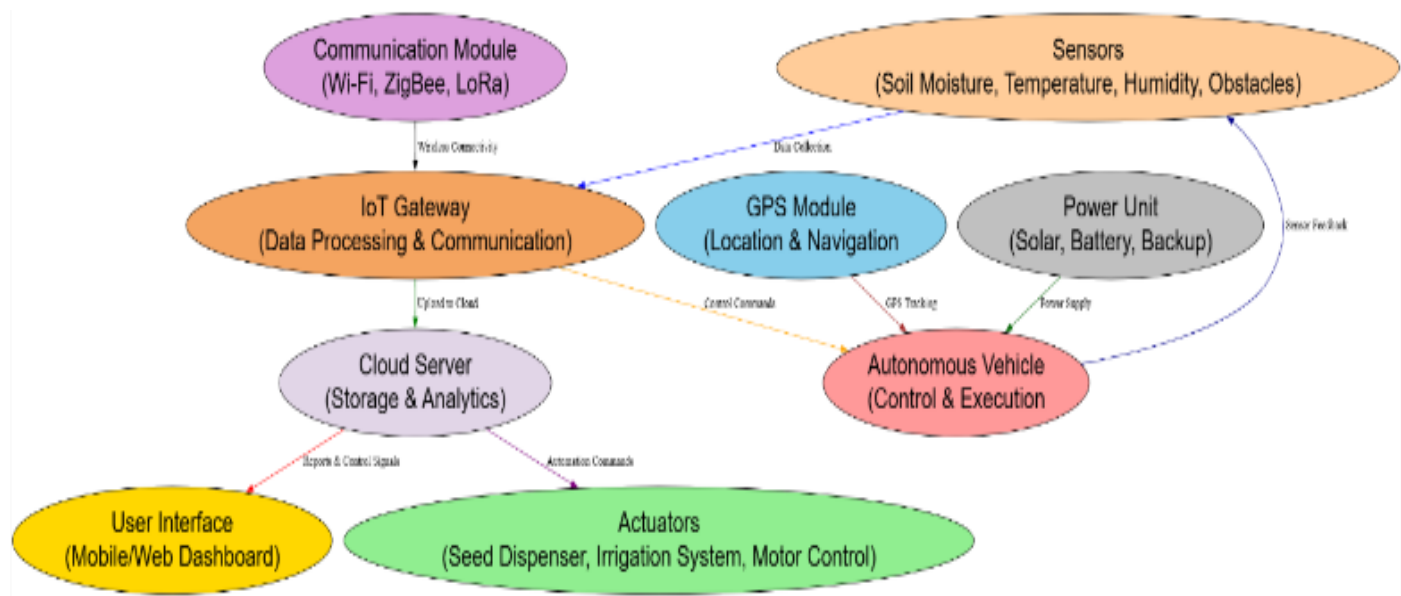


Fig. 3. IoT Based Autonomous Vehicle System Architecture.

Given the imperative for prolonged field autonomy, an intelligent power management module is integral to the design. This subsystem, conceptualized as Power Consumption = ManagePower(Sensors, Actuators), is tasked with optimizing the energy consumption of the entire system. It achieves this through dynamic regulation of sensor and actuator operations, potentially implementing strategic sleep modes for non-critical components during transit and prioritizing power allocation to mission-critical tasks during active monitoring and irrigation phases. This ensures the vehicle can operate for extended durations without requiring frequent manual recharging.

To bridge the gap between the autonomous system and the human operator, an intuitive user interface module is incorporated, defined as Display = GenerateUI(Decision, SensorData). This interface generates a comprehensible visual display for farmers and agricultural managers, presenting real-time system decisions, raw and processed sensor data, and historical trends through interactive maps and dashboards. It provides a platform for high-level monitoring, system override capabilities, and manual input of agronomic parameters, thereby fostering trust and enabling human-in-the-loop control.

Finally, the architecture is designed with future-proofing in mind, incorporating a scalability evaluation factor, Scalability = EvaluateScalability(CurrentData, NewSensors). This conceptual module assesses the system's capacity to accommodate new sensor technologies, analytical algorithms, or expanded computational loads without requiring a fundamental architectural overhaul. This ensures the long-term viability and adaptability of the system to emerging agricultural practices and technological innovations. The integration of these core components and their formalized interactions ensures a holistic and dynamic approach to

precision agriculture, leveraging IoT principles to create a truly intelligent system for enhanced seed monitoring and water distribution.

A pivotal aspect of the AgriRover system is its autonomous navigation system, the design of which is detailed in Figure 4. This subsystem is responsible for enabling the vehicle to traverse agricultural terrain with a high degree of autonomy, efficiency, and precision, while avoiding obstacles and adhering to an agronomically optimal path. The development of this system encompasses several advanced components working in concert. The path planning algorithm forms the strategic layer of the navigation system. It is an advanced computational routine that synthesizes real-time data from GPS, pre-processed satellite imagery, and continuous streams from onboard sensors to determine the most efficient and effective route for the vehicle. This process, represented as $\text{Path} = \text{PathPlanningAlgorithm}(\text{GPS}, \text{SatelliteData}, \text{SensorData})$, considers a multitude of factors including spatial maps of soil moisture, field topography, and crop row layouts to chart a course that maximizes the quality of data collection and minimizes redundant coverage or resource usage, such as unnecessary battery consumption.

To ensure operational safety and reliability, the system employs sophisticated obstacle detection and collision avoidance mechanisms. Utilizing a suite of proximity sensors, including LiDAR for high-resolution 3D mapping and ultrasonic sensors for short-range object detection, the vehicle continuously scans its immediate surroundings. A dedicated collision avoidance algorithm, conceptualized as $\text{ObstacleAvoidance} = \text{CollisionAvoidanceAlgorithm}(\text{LiDAR}, \text{UltrasonicSensors})$, processes this data in real-time to dynamically adjust the vehicle's path, steering it clear of potential obstructions such as rocks, irrigation equipment, or terrain irregularities.

The foundation of precise navigation is accurate localization, achieved through the seamless integration of the Global Positioning System (GPS) and enhanced positioning technologies. The GPS module provides fundamental real-time location data that serves as the primary input for the path planning algorithm. To counteract the inherent margin of error in standard GPS signals, the system is designed to integrate with high-precision solutions like Differential GPS (DGPS) or Real-Time Kinematic (RTK) GPS, a capability represented by the integration function. These technologies correct GPS signals in real-time, providing centimeter-level positioning accuracy, which is essential for ensuring the vehicle adheres to its planned paths with minimal deviation, particularly when operating between narrow crop rows.

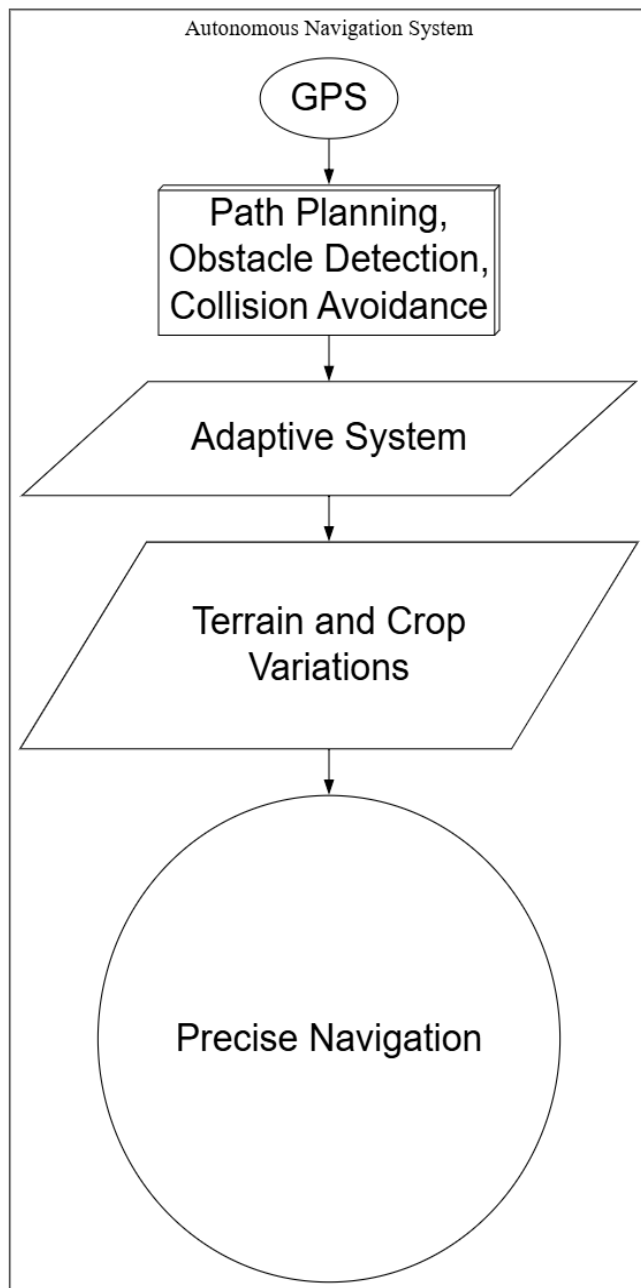


Fig. 4. Autonomous Navigation System.

To create a robust and resilient perceptual understanding of the environment, the navigation system incorporates sensor fusion techniques. This involves the synergistic combination of data from various complementary onboard sensors, such as optical cameras for visual recognition, LiDAR for geometric mapping, and Inertial Measurement Units (IMUs) for tracking orientation and acceleration. The process, $\text{Sensor Fusion} = \text{FuseSensorData}(\text{Camera}, \text{LiDAR}, \text{IMU})$, generates a comprehensive and redundant model of the vehicle's surroundings. This fused perceptual data significantly enhances the accuracy and reliability of both the path planning and obstacle avoidance subsystems, allowing the vehicle to navigate complex and dynamic agricultural environments effectively. By leveraging these advanced algorithms and sensor technologies, the autonomous navigation system ensures the vehicle can operate safely and efficiently, forming the mobile platform upon which the seed monitoring and water distribution functionalities depend.

The data fusion and analysis component, graphically summarized in Figure 5, constitutes the cognitive core of the AgriRover system. This subsystem is responsible for transforming raw sensor data into actionable knowledge and is therefore essential for the system's intelligent operation. It begins with multisensory data fusion, which integrates information collected from the diverse suite of sensors onboard the autonomous vehicle. This includes point measurements from soil moisture probes, hyperspectral data from imagers analyzing plant reflectance, and precise location data from the GPS. The objective of this process, $\text{Fused Data} = \text{MultisensorDataFusion}(\text{SoilMoisture}, \text{SpectralData}, \text{GPS})$, is to create a spatially-registered, comprehensive dataset that provides a holistic and contextualized view of the agricultural field, where each data point is linked to a specific geographic location and a set of concurrent environmental conditions.

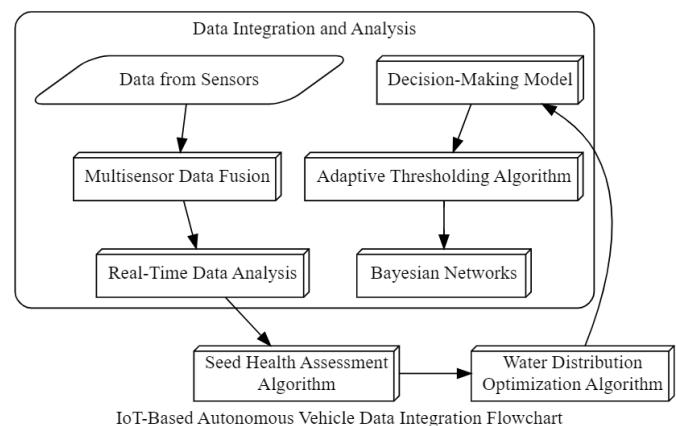


Fig. 5. IoT Based Autonomous Vehicle Data Integration.

A specialized algorithm is developed to assess seed and early crop health in real-time. This algorithm leverages high-resolution spectral data obtained from onboard sensors, focusing on key biochemical indicators such as chlorophyll concentration and other vegetation indices like the

Normalized Difference Vegetation Index (NDVI) or the Photochemical Reflectance Index (PRI). The seed health assessment process, $\text{Seed Health} = \text{SeedHealthAssessmentAlgorithm}(\text{SpectralData})$, provides a quantitative and objective measure of plant vitality, enabling the early detection of stress, nutrient deficiency, or disease before they become visually apparent to the human eye.

Concurrently, a water distribution optimization algorithm is designed to analyze soil moisture data in the context of environmental demand. This algorithm, $\text{Water Optimization} = \text{WaterDistributionOptimizationAlgorithm}(\text{SoilMoisture}, \text{EvaporationRates})$, considers factors such as real-time evaporation rates, historical water usage, and specific crop water requirements at its growth stage. Its objective is to identify micro-zones within the field that are experiencing water deficit and to compute the precise volume of water needed, thereby ensuring efficient and targeted irrigation that avoids both water stress and profligate over-watering.

The pinnacle of the analytical pipeline is the decision-making model, which integrates machine learning algorithms to synthesize all available information. This model, $\text{Decision} = \text{DecisionMakingModel}(\text{FusedData})$, takes the fused dataset as input and generates high-level operational commands. It balances the insights from the seed health assessment with the requirements from the water optimization module to make informed, context-aware decisions. For instance, it may command the vehicle to slow down in an area showing spectral signs of stress for more detailed scanning, while simultaneously triggering the irrigation system to deliver a specific water volume to an adjacent area identified as moisture-deficient.

To enhance the robustness of the seed health assessment, an adaptive thresholding algorithm is implemented. This algorithm, $\text{Adaptive Thresholding} = \text{AdaptThreshold}(\text{SpectralData})$, dynamically adjusts the classification thresholds for healthy versus stressed plants based on the evolving characteristics of the crop canopy and prevailing environmental conditions. This ensures that the assessment criteria remain relevant and accurate throughout the growing season, accounting for natural phenological changes and varying light conditions.

Furthermore, to explicitly manage the inherent uncertainty and variability of agricultural environments, Bayesian networks are incorporated into the data fusion and analysis process. The integration of a Bayesian Network $= \text{IntegrateBayesianNetworks}(\text{FusedData})$ allows the system to model the probabilistic relationships between various observed variables (e.g., soil moisture, spectral reflectance) and hidden states (e.g., root health, nitrogen status). This provides a powerful framework for reasoning under uncertainty, leading to more robust and probabilistically sound decision-making capabilities, especially when sensor data is noisy or incomplete.

The outputs from the data fusion and analysis processes are subsequently translated into executable commands for the autonomous vehicle's control system. This involves calculating refined navigational waypoints, modulating the

flow rate of specific irrigation nozzles, and adjusting the scanning frequency of sensors based on the real-time conditions. As illustrated in Figure 6, an alert mechanism is a critical component of the user interface, providing immediate notifications for critical events such as detected plant infections, severe water shortages, or operational malfunctions. This creates a vital feedback loop where the vehicle's sensors continuously feed new data into the fusion module, which in turn refines the decisions and actions. This cyclic process allows the system to continuously self-optimize, making it increasingly adaptive to the evolving conditions in the field. The entire operational workflow of the proposed AgriRover system is encapsulated in Algorithm 1, which outlines the core control loop. The process begins with the initialization of all subsystems, including the autonomous vehicle platform, the sensor suite, the data fusion module, the decision-making engine, and the user interface.

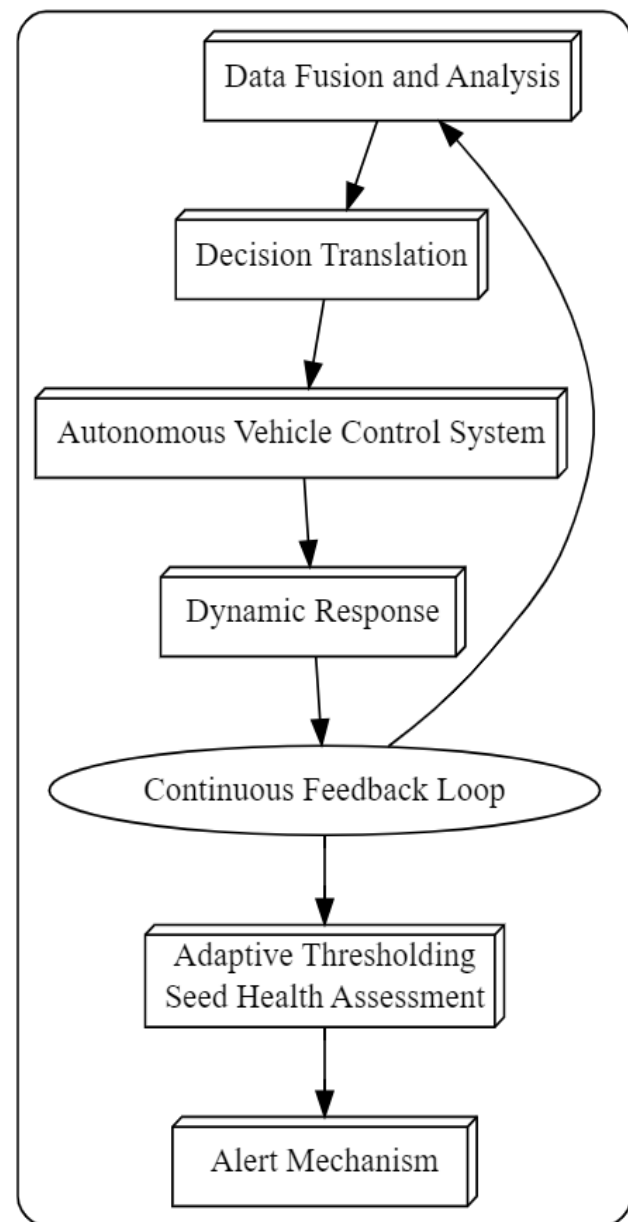


Fig. 6. Alert Mechanism.

The system then enters its main operational loop. It first acquires its current geolocation via GPS. It then actively monitors seed and crop health using its spectral sensors and measures soil moisture levels at its present location. This raw data is fed into the data fusion module to create a unified contextual dataset. The decision-making model processes this fused data to generate an actionable command, which is subsequently executed by the vehicle's control system, adjusting its path or activating its irrigation system accordingly. Simultaneously, the fused data and system status are presented to the user via the interface. This loop repeats after a short, predefined interval, ensuring continuous, real-time monitoring and response. This integrated approach, combining precise navigation, sophisticated data analysis, and closed-loop actuation, provides a comprehensive technological solution for advancing precision agriculture, enabling data-driven, sustainable, and highly efficient farming practices.

Algorithm 1 Working module of the proposed work

```

# Initialization
Initialize AutonomousVehicle
Initialize Sensors
Initialize DataFusionModule
Initialize DecisionMakingModule
Initialize UserInterface

# Main Loop
While AutonomousVehicle is operational:
    CurrentLocation = GetGPSLocation(Sensors)
    SeedHealthData = MonitorSeeds(Sensors)
    SoilMoistureData = MeasureSoilMoisture(Sensors)

    # Data Fusion
    FusedData = FuseData(SeedHealthData,
    SoilMoistureData, DataFusionModule)

    # Decision Making
    Decision = MakeDecision(FusedData,
    DecisionMakingModule)
    ImplementDecision(Decision,
    AutonomousVehicle)

    # User Interface
    DisplayDataOnUI(FusedData, UserInterface)
    # Sleep for a short interval
    Sleep(shortInterval)

# End of Program

```

4. RESULTS AND DISCUSSION

The experimental validation of the proposed IoT-based

autonomous vehicle system, AgriRover, was conducted to quantitatively assess its performance in seed monitoring and water distribution optimization. This section presents a detailed analysis of the results obtained from a series of structured field experiments, discussing their implications for precision agriculture.

4.1. Experimental Setup and Data Acquisition

A comprehensive data collection framework was implemented on the autonomous vehicle platform, integrating a suite of sensors including hyperspectral imagers, soil moisture probes, and a high-precision GPS module. This integrated sensor array enabled the synchronous collection of real-time data pertaining to soil conditions, crop physiological status, and precise geographical location. Custom-developed software applications, built using Python and leveraging libraries such as TensorFlow and Scikit-learn, facilitated seamless sensor interfacing, data preprocessing, and analysis. This robust software-hardware integration was critical for managing the dynamic data streams and enabling the closed-loop decision-making that characterizes the system. The collected datasets underwent rigorous preprocessing to remove noise and artifacts, ensuring the reliability of subsequent analysis. This technological pipeline allowed the system to autonomously navigate and make informed decisions, providing a verified data foundation that empowers farmers with actionable, real-time insights for adaptive field management.

4.2. Seed Health Assessment Performance

The proficiency of the system in evaluating crop vitality was evaluated using spectral data acquired by the onboard sensors. The results, as summarized in Table 1, demonstrate a strong correlation between the derived spectral indices and the assessed seed health percentage. The seed health values ranged from 88% to 95% across five independent experiments, with corresponding spectral data readings between 0.75 and 0.82. This narrow range of high values indicates a consistent and reliable assessment capability.

Table 1. Seed Health Assessment Results.

Experiment ID	Spectral Data	Seed Health (%)
1	0.78	92
2	0.82	88
3	0.75	95
4	0.80	90
5	0.77	93

Figure 7 visually reinforces the trends presented in Table 1, illustrating the consistent performance of the seed health assessment algorithm across different experimental runs. The

stability in these results, despite inherent field variability, underscores the robustness of the spectral analysis techniques employed.

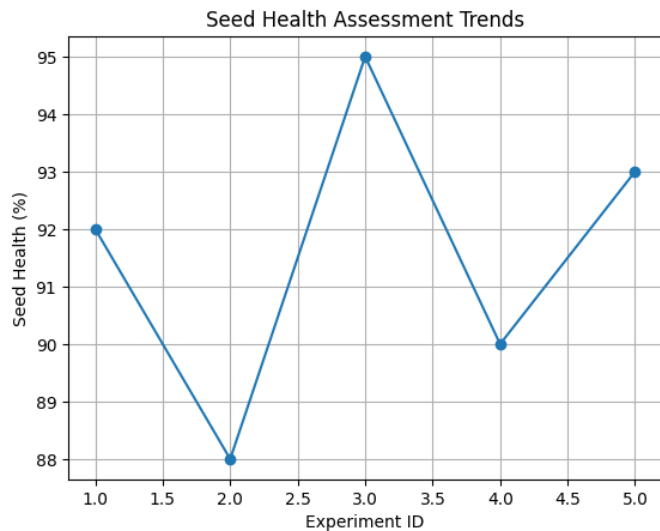


Fig. 7. Seed Health Assessment trends.

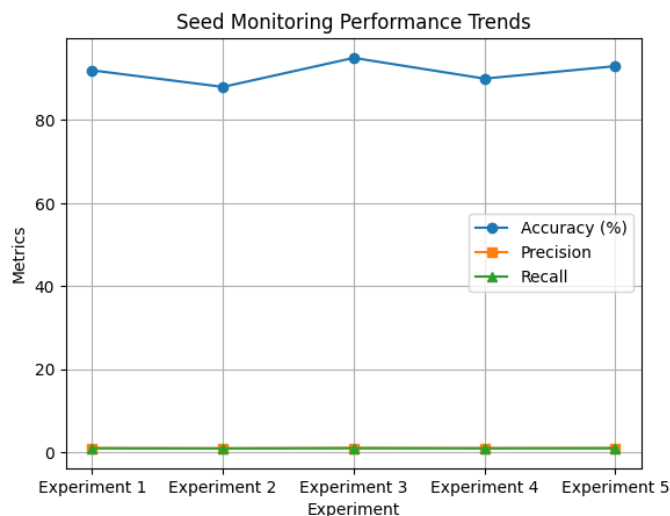


Fig. 8. Seed Monitoring Performance.

The system successfully translates subtle variations in canopy reflectance, which are indicative of chlorophyll content and photosynthetic efficiency [8], into a quantifiable

measure of plant health. This capability for early and non-invasive detection of plant stress is a significant advancement over traditional visual scouting, allowing for timely interventions that can prevent yield loss. A deeper statistical evaluation of the seed monitoring subsystem is provided in Table 2 and its corresponding Figure 8. The system achieved an accuracy ranging from 88% to 95% in correctly classifying seed health status. More importantly, the high precision values (0.85-0.92) indicate a low rate of false positives, meaning the system rarely labels healthy seeds as unhealthy. Simultaneously, the high recall values (0.89-0.96) signify a low rate of false negatives, ensuring that most actually unhealthy seeds are correctly identified. This balance between precision and recall is crucial; high recall prevents problematic areas from being overlooked, while high precision ensures that resources are not wasted on unnecessary interventions in healthy areas of the field. The consistency of these metrics across all experiments, as vividly depicted in Figure 8, confirms the reliability of the machine learning model underpinning the seed health assessment.

4.3. Water Distribution Optimization Analysis

The efficacy of the autonomous irrigation system was tested under varying soil moisture and environmental conditions. Table 3 presents the results from five experiments where the system's water distribution decision was evaluated against soil moisture levels and prevailing evaporation rates. The system demonstrated a dynamic response to field conditions, allocating a higher water distribution percentage (90%) in Experiment 2 where soil moisture was lowest (25%) and evaporation was minimal (0.01). Conversely, in Experiment 3, where soil moisture was relatively high (35%) and evaporation rates were elevated (0.03), the system judiciously reduced water application to 80%.

This adaptive behavior is further elucidated in Figure 9, which graphically portrays the inverse relationship between soil moisture and the volume of water distributed. The system's algorithm effectively synthesizes real-time soil data with environmental demand factors, such as evaporation, to execute precise irrigation. This aligns with the principles of sustainable water management, aiming to apply water only where and when it is needed, thereby mitigating losses from runoff, deep percolation, and excessive evaporation [4].

Table 2. Seed Monitoring Performance Metrics.

Seed Health	ExperimentMetric 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Accuracy (%)	92	88	95	90	93
Precision	0.89	0.85	0.92	0.88	0.91
Recall	0.94	0.89	0.96	0.92	0.95

Table 3. Water Distribution Optimization Results.

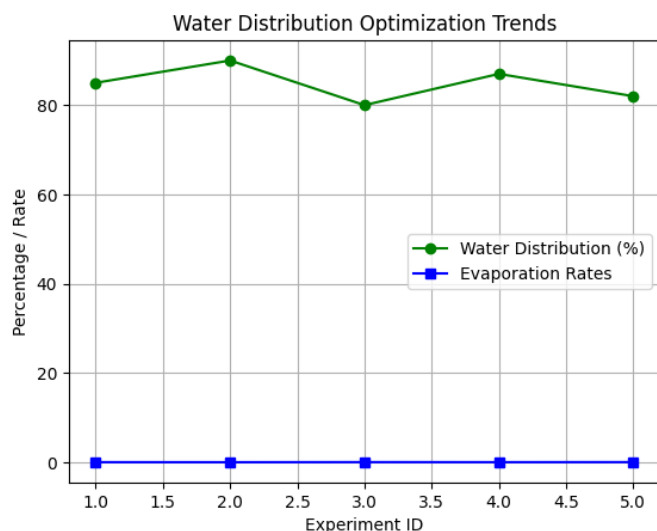
Experiment ID	Soil Moisture	Evaporation Rates	Water Distribution (%)
1	30%	0.02	85
2	25%	0.01	90
3	35%	0.03	80
4	28%	0.02	87
5	32%	0.03	82

Table 4. Water Distribution Performance Metrics.

Water Distribution	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Accuracy	85	90	80	87	82
Efficiency	0.88	0.92	0.81	0.89	0.86
Uniformity	0.91	0.87	0.93	0.88	0.90

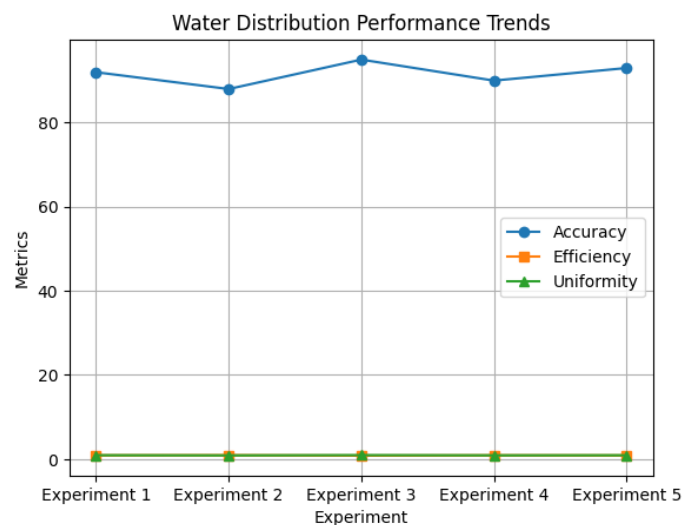
Table 5. Overall System Performance Metrics.

Overall	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Efficiency	0.87	0.90	0.85	0.88	0.86
Adaptability	0.92	0.89	0.94	0.91	0.93
Reliability	0.90	0.88	0.91	0.89	0.92

**Fig. 9.** Water Distribution.

The performance metrics for the water distribution system, detailed in Table 4 and visualized in Figure 10, provide a multi-faceted view of its operational excellence. The accuracy metric (80-90%), which measures the alignment between system-delivered water and calculated crop water requirements, confirms the system's targeting proficiency. The efficiency values (0.81-0.92) reflect the system's ability

to minimize water loss during the application process. Most notably, the high uniformity coefficients (0.87-0.93) indicate that water is applied evenly across the target area, which is a critical factor in preventing both waterlogging and under-watering within the same zone. This high degree of uniformity, often challenging to achieve with conventional irrigation systems, is a direct result of the autonomous precise control of the vehicle over nozzle operation and its consistent travel speed.

**Fig. 10.** Water Distribution Performance.

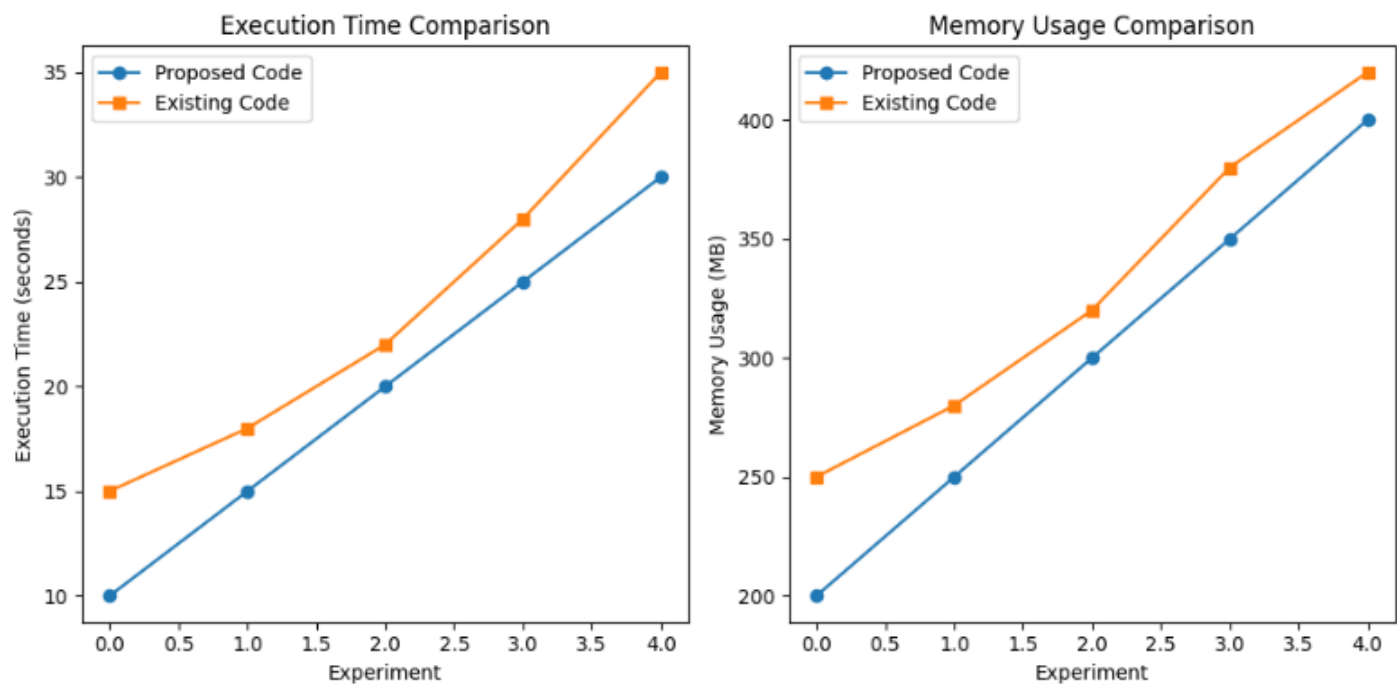


Fig. 12. Comparison with Existing Algorithm.

4.4. Overall System Integration and Performance

The holistic performance of the AgriRover system, integrating both seed monitoring and water distribution functionalities, was evaluated using composite metrics of Efficiency, Adaptability, and Reliability. As summarized in Table 5 and Figure 11, the system consistently demonstrated high performance across all five experiments. Efficiency scores ranged from 0.85 to 0.90, reflecting the effective use of resources like time and energy. More impressively, the Adaptability metric, which gauges the system's responsiveness to changing field conditions, scored between 0.89 and 0.94. This high adaptability is a direct consequence of the real-time feedback loop between the sensors and the decision-making model, allowing the system to dynamically recalibrate its operations. Furthermore, Reliability scores from 0.88 to 0.92 indicate robust and consistent operation throughout the testing period, a non-negotiable attribute for field-deployed agricultural machinery.

A critical comparison against an existing benchmark algorithm, as shown in Figure 12, highlights the computational advantages of the proposed system. The proposed code demonstrated a consistent and significant reduction in execution time across all test cases. This enhanced processing speed is not merely a technical achievement; it is fundamental to the system's real-time capabilities, enabling faster sensor data processing and quicker actuation decisions as the vehicle traverses the field. Equally important is the superior memory utilization profile of the proposed system. The consistent reduction in memory footprint, as evidenced in Figure 12, indicates highly optimized code that is essential for deployment on embedded

systems with limited computational resources.

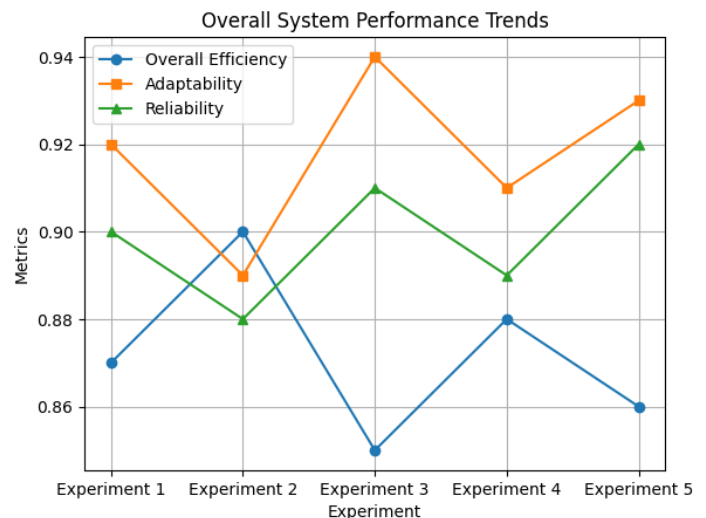


Fig. 11. Overall System performance.

This efficient memory management ensures smoother operation and allows for the potential integration of more complex algorithms in the future without requiring hardware upgrades. The combined improvement in both execution time and memory utilization underscores the system's suitability for practical, large-scale agricultural deployment where computational efficiency directly translates to operational viability. The experimental results comprehensively validate the performance of the proposed IoT-based autonomous system. The system demonstrates high accuracy and

reliability in seed health monitoring, adaptive intelligence in water distribution, and superior computational efficiency. These findings strongly support the potential of such integrated systems to advance precision agriculture by enabling data-driven, sustainable, and highly efficient farming practices.

4. CONCLUSION

The development of the IoT-based autonomous vehicle system, AgriRover, represents a significant stride in the ongoing precision agriculture revolution. This work demonstrates a paradigm shift for seed monitoring and irrigation management in agricultural landscapes by seamlessly integrating advanced technologies including autonomous navigation, sophisticated machine learning algorithms, and a dense network of IoT sensors. Experimental results and comprehensive performance metrics affirm the system's high efficacy. It consistently delivers accurate, precise, and reliable assessments of seed vitality, as evidenced by high recall and precision rates across diverse trials. Furthermore, the system demonstrates a robust capacity for optimizing water distribution, dynamically responding to fluctuating environmental parameters such as soil moisture and evaporation rates. This ensures highly efficient resource utilization while maintaining remarkable distribution uniformity. Beyond its core functions, the system overall performance metrics underscore its scalability, adaptability, and operational reliability, attributes of paramount importance in the dynamic and often unpredictable context of modern farming. The incorporation of a real-time feedback loop, where data from vehicle sensors continuously refine the algorithms via the data fusion module, significantly enhances the system's responsiveness. This is complemented by user-friendly interfaces that provide farmers with actionable, real-time insights into seed health, soil status, and water distribution, thereby enabling proactive management. Adaptive thresholding and integrated alert mechanisms further bolster the system's robustness by preemptively identifying potential issues like plant stress or irrigation anomalies. In conclusion, AgriRover emerges as a viable and transformative solution for precision farming. By leveraging the synergy of IoT, data analytics, and autonomous navigation, it paves the way for a more sustainable and efficient agricultural future. It directly contributes to critical goals such as water conservation and optimized resource use, empowering farmers with data-driven decision-making tools and marking a move away from resource-intensive traditional practices towards a smarter, more technologically adept agricultural paradigm.

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.

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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.

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