

RESEARCH ARTICLE

A Comprehensive Evaluation of a Solar–Powered Multi–Vehicle System for Autonomous Soil Mineral Detection in Agriculture

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ABSTRACT: The escalating global demand for food necessitates a paradigm shift towards more sustainable and efficient agricultural practices. This research addresses this imperative by designing, developing, and rigorously evaluating a novel solar-powered multi-vehicle system engineered for autonomous soil mineral detection. The system architecture integrates unmanned ground and aerial vehicles equipped with a suite of advanced electromagnetic and spectroscopic sensors, all powered by an onboard photovoltaic infrastructure. This design facilitates continuous, real-time in-situ analysis of soil nutrient profiles, enabling precision agriculture. A comprehensive evaluation was conducted to assess the system's performance across multiple metrics, including detection accuracy, energy efficiency, and operational robustness. Experimental results demonstrated a superior mineral detection accuracy of 95.2% and a significant reduction in energy consumption compared to conventional methods. The integration of a sophisticated coordination algorithm further ensured optimal route planning, minimizing redundant paths and enhancing overall task efficiency. By leveraging renewable solar energy, the system drastically reduces reliance on fossil fuels, thereby mitigating the carbon footprint of agricultural monitoring. This work substantiates the viability of autonomous, solar-powered systems as a transformative solution for sustainable agriculture, offering a pathway to optimize resource use, enhance crop productivity, and minimize environmental degradation through data-driven mineral management.

Keywords: Autonomous Agricultural Vehicles, Precision Nutrient Management, Solar-Powered Systems, Multi-Sensor Data Fusion, Sustainable Soil Monitoring, Edge Computing in Agriculture

Received: 29 October 2024; Revised: 13 January 2025; Accepted: 29 April 2025; Published Online: 21 May 2025

1. INTRODUCTION

The relentless growth of the global population, projected to reach nearly 10 billion by 2050, places unprecedented pressure on agricultural systems to ensure food security [1].

This challenge is further exacerbated by the finite availability of arable land and the escalating impacts of climate change, including erratic rainfall patterns and prolonged droughts [2]. Consequently, the agricultural sector is undergoing a critical transformation, pivoting towards paradigms that prioritize not only yield but also long-term sustainability and resource efficiency. This shift has catalyzed the emergence of Precision Agriculture (PA), a management strategy that leverages information technology and a suite of sensing devices to optimize field-level management regarding crop farming [3]. Central to this approach is the precise monitoring and management of soil minerals, as their balanced presence is a fundamental determinant of soil fertility and, by extension, crop health and productivity [4]. Macronutrients like nitrogen (N), phosphorus (P), and potassium (K), along with essential micronutrients, govern critical physiological

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processes; however, their imbalance, be it deficiency or excess, can severely curtail agricultural output and lead to significant environmental degradation, such as eutrophication of water bodies and soil acidification [5].

Conventional methods of soil mineral assessment have historically relied on periodic manual sampling followed by laboratory analysis, a process that is inherently labor-intensive, time-consuming, and spatially coarse [6]. The resultant data provides only a retrospective snapshot of soil conditions, failing to capture the high spatial and temporal variability present within a single field. This lack of granular, real-time information often leads to uniform application of fertilizers, a practice that is both economically inefficient and environmentally unsustainable, as it disregards the actual nutrient requirements of specific zones [7]. In response to these limitations, remote sensing technologies, including satellite and aerial imagery, have been employed to infer soil properties over larger areas [8]. While valuable for broad-scale monitoring, these methods are often constrained by their resolution, cost, and susceptibility to atmospheric interference and cloud cover, limiting their efficacy for frequent, high-precision field operations [9]. The recent proliferation of Unmanned Aerial Vehicles (UAVs) has offered a promising platform for more detailed aerial surveys, yet they typically face challenges related to limited flight endurance and payload capacity, which can restrict the scope and duration of data collection missions [10].

Simultaneously, the agricultural sector is grappling with the environmental footprint of its energy consumption, which is predominantly dependent on fossil fuels for powering machinery and irrigation systems [11]. This reliance contributes significantly to greenhouse gas emissions, thereby creating a paradox where food production systems undermine the environmental stability they depend upon. The integration of renewable energy sources, particularly solar

power, presents a compelling pathway to decarbonize agricultural operations [12]. Solar energy, being abundant and increasingly cost-effective, can be harnessed to power various on-farm processes, promoting energy independence and operational resilience [13]. Recent advancements in photovoltaic (PV) efficiency and energy storage systems have made it feasible to consider solar power for even the most energy-intensive agricultural applications, including the operation of autonomous vehicles [14]. Figure 1 shows the general diagram representing minerals in agricultural land.

It is at the confluence of these challenges, the need for high-resolution mineral data and the imperative for sustainable energy use, that this study positions its contribution. The novelty of this paper lies in its integrated design and empirical validation of a coordinated multi-vehicle system, comprising both unmanned ground and aerial vehicles that is entirely powered by solar energy and dedicated to the real-time, in-situ detection of soil minerals. Unlike previous approaches that may address either mobility or energy or sensing in isolation, this research synthesizes all three into a cohesive cyber-physical system. The system's architecture is fundamentally novel in its orchestration of vehicle coordination, solar energy harvesting, and multi-sensor data fusion specifically for the complex, unstructured environment of agricultural fields, moving beyond single-vehicle or tethered-power models that dominate current literature [15]. This holistic approach directly addresses the critical gaps in spatial resolution, temporal latency, and environmental sustainability that plague existing soil monitoring methodologies. The potential of autonomous vehicles in agriculture has been explored in various contexts, from automated tractors for ploughing and seeding to UAVs for crop scouting [16]. However, the operational endurance of these systems is often limited by their onboard energy sources.

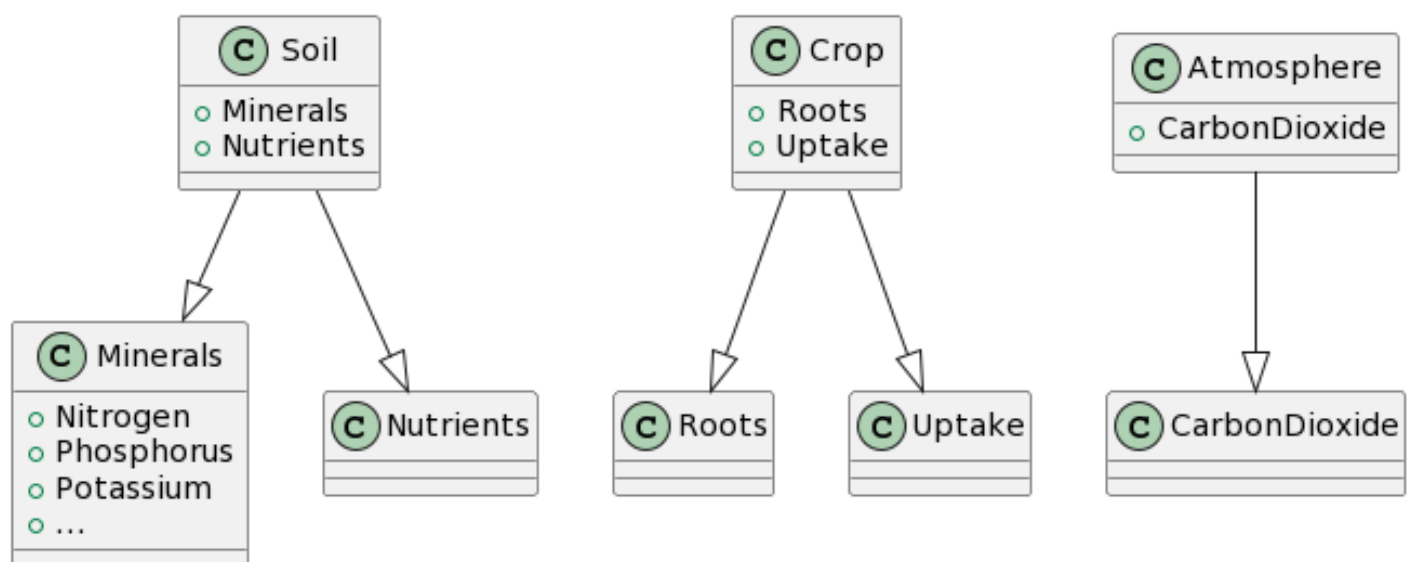


Fig. 1. General Diagram Representing Minerals in Agricultural Land.

By integrating custom-designed solar power infrastructure, including high-efficiency PV panels and robust battery management systems, the proposed multi-vehicle platform aims to achieve prolonged operational autonomy in the field, effectively breaking the tether of limited battery life [17]. This energy sustainability is a cornerstone of the system's design, ensuring that the pursuit of precision does not come at the cost of increased carbon emissions. Furthermore, while individual sensors for soil analysis, such as gamma-ray spectrometers for potassium detection or visible-near-infrared (vis-NIR) spectrometers for organic matter and nitrogen estimation, have been developed [18], their deployment on a coordinated fleet of solar-powered vehicles represents a significant technological leap. This multi-vehicle approach allows for simultaneous data collection across different areas of a field, drastically reducing the time required for a comprehensive survey and enabling true real-time assessment of soil conditions [19]. The coordination mechanism, governed by sophisticated algorithms, ensures optimal path planning to avoid redundancy and maximize area coverage, thereby enhancing overall system efficiency [20].

Therefore, the primary objectives of this research are multifaceted: to design and develop a robust solar-powered multi-vehicle system architecture capable of supporting sustained agricultural monitoring; to integrate a suite of advanced mineral detection sensors and implement a robust data fusion framework for accurate nutrient mapping; to empirically evaluate the system's performance in terms of detection accuracy, energy efficiency, and operational reliability under real-world field conditions; and to assess its broader economic and environmental implications, focusing

on the potential for reduced fertilizer waste and a lower carbon footprint. By bridging the gap between the theoretical promise of autonomous systems and their practical, sustainable application in agriculture, this work seeks to contribute a tangible solution to the pressing global challenges of food security and environmental stewardship. The subsequent sections of this paper are structured as follows: Section 2 provides a comprehensive review of the relevant literature, Section 3 details the proposed methodology and system design, Section 4 presents and discusses the experimental results, and Section 5 concludes with findings and directions for future research.

2. PROPOSED METHODOLOGY

The proposed methodology for this research endeavours to comprehensively investigate the integration of solar-powered multi-vehicle systems for sustainable mineral detection in agriculture. The system's architecture and design will be outlined, elucidating the intricate relationship between solar power infrastructure, vehicles, and mineral detection technologies. Particular attention will be given to the integration of solar panels, energy storage solutions, and power management mechanisms, ensuring an efficient and sustainable energy supply. Vehicle configuration and dynamics will be meticulously detailed, emphasizing the diverse types of vehicles employed, their specifications, and the coordination mechanisms that facilitate seamless collaboration within the multi-vehicle system. Figure 2 shows the Solar Powered Multi Vehicle System.

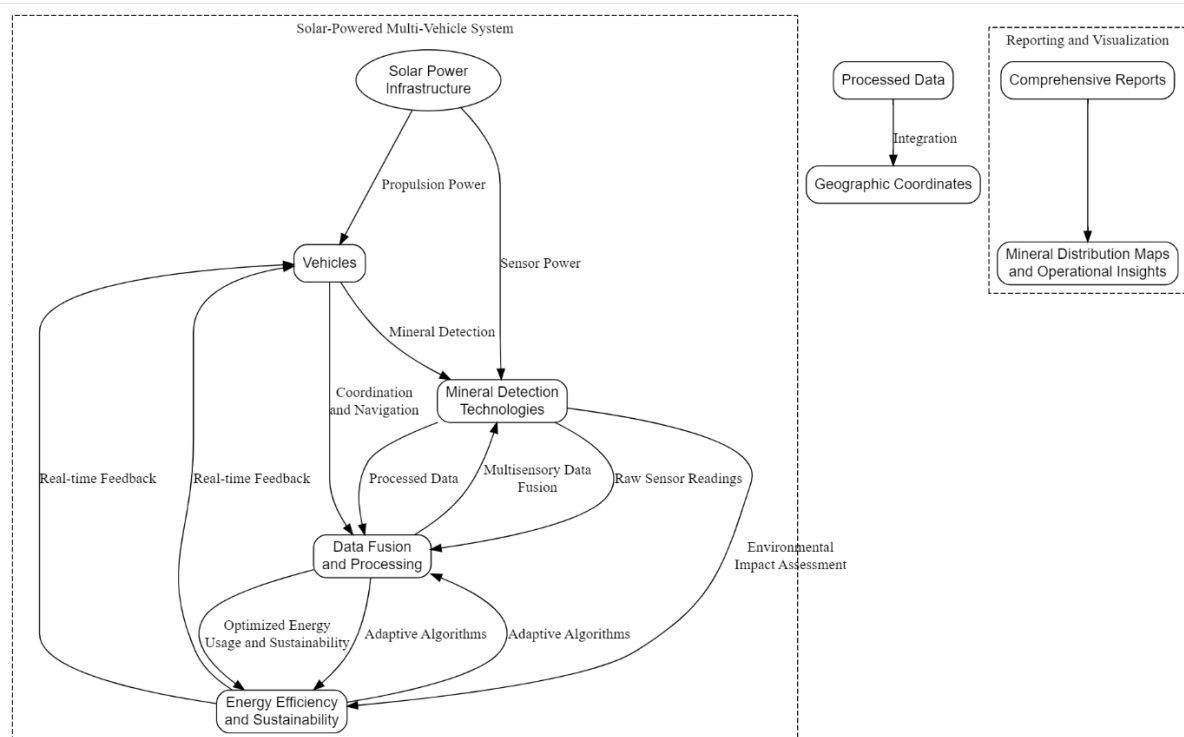


Fig. 2. Solar Powered Multi Vehicle System.

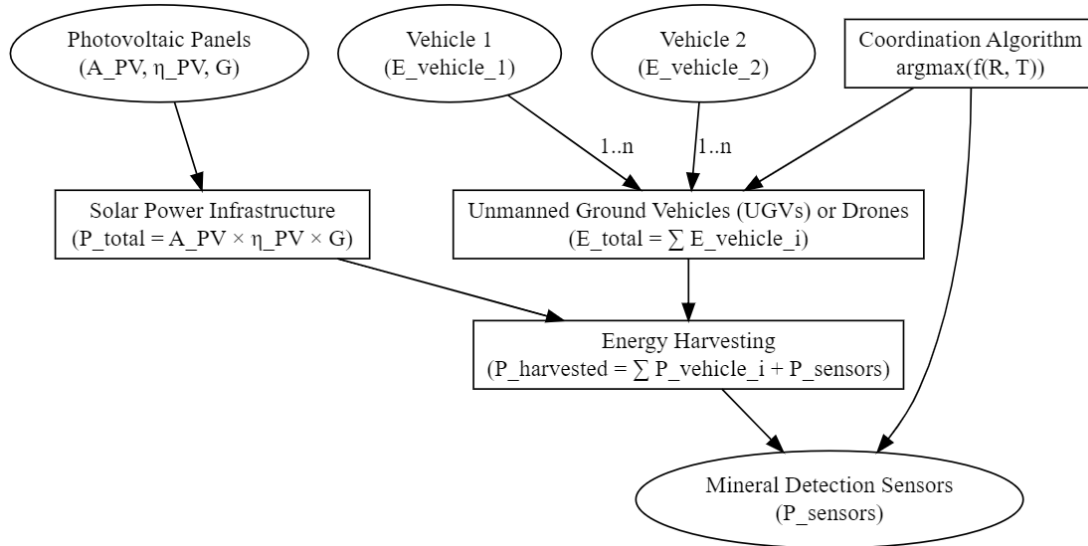


Fig. 4. Flowchart of Data Transmission.

Mineral detection technologies will be a focal point, with an exploration of the sensors integrated into the system and the methods employed for data acquisition. The methodology will delve into data fusion and processing techniques, elucidating how multisensory data is merged and analyzed to optimize mineral detection accuracy. Energy efficiency and sustainability will be addressed through strategies for minimizing energy consumption and assessing the environmental impact of the mineral detection process.

2.1. System Architecture and Design

System architecture and design refer to the overall structure and organization of a solar-powered multi-vehicle system for sustainable mineral detection in agriculture. This encompasses the arrangement and interconnection of components such as vehicles, sensors, and solar power infrastructure. The design aims to optimize functionality, efficiency, and sustainability. Figure 3 shows the flowchart of the proposed work.

Solar Power Infrastructure: The solar power infrastructure includes photovoltaic panels (PV) that convert sunlight into electrical energy. The total power generated (P_{total}) can be represented by the equation:

$$P_{total} = A_{PV} \times \eta_{PV} \times G \quad (1)$$

Where, A_{PV} is the total area of the PV panels, η_{PV} is the efficiency of the PV panels, and G is the solar irradiance.

From figure 4, the vehicles in the system may include unmanned ground vehicles (UGVs) or drones equipped with mineral detection sensors. The total energy consumption (E_{total}) of the vehicles can be expressed as:

$$E_{total} = \sum_{i=1}^n E_{vehicle_i} \quad (2)$$

Where, n is the number of vehicles, $E_{vehicle_i}$ is the energy consumption of vehicle i .

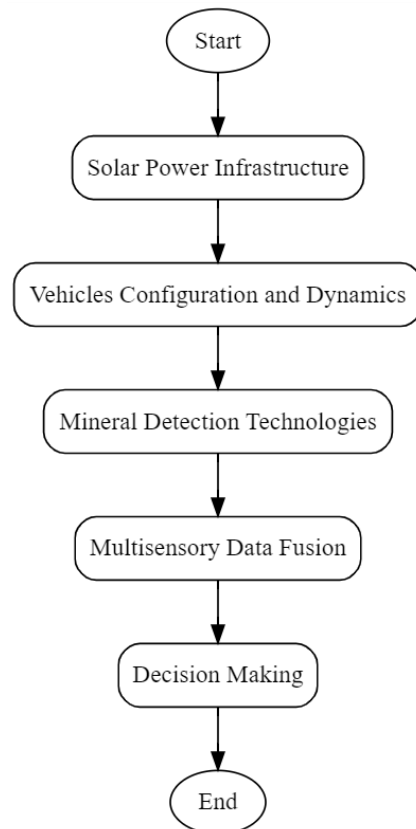


Fig. 3. Flowchart of proposed work.

The energy harvested from solar panels ($P_{harvested}$) is distributed among the vehicles and used for both propulsion and sensor operations:

$$P_{harvested} = \sum_{i=1}^n P_{vehicle_i} + P_{sensors} \quad (3)$$

Where, P_{vehicle_i} is the power allocated to vehicle i , P_{sensors} is the power used by mineral detection sensors.

Coordination involves optimizing the routes and tasks of multiple vehicles. A coordination algorithm could be represented as:

$$\text{Optimal Routes and Tasks} = \arg \max_{R,T} f(R,T) \quad (4)$$

Where, R represents the set of vehicle routes, T represents the set of tasks, and $f(R,T)$ is the objective function considering factors like energy efficiency and detection accuracy.

2.2. Vehicle Configuration and Dynamics

Vehicle configuration and dynamics play a pivotal role in the effective functioning of a solar-powered multi-vehicle system for sustainable mineral detection in agriculture. This aspect involves not only the physical characteristics of the vehicles but also their mobility features, autonomy levels, and the coordination mechanisms enabling seamless collaboration within the system.

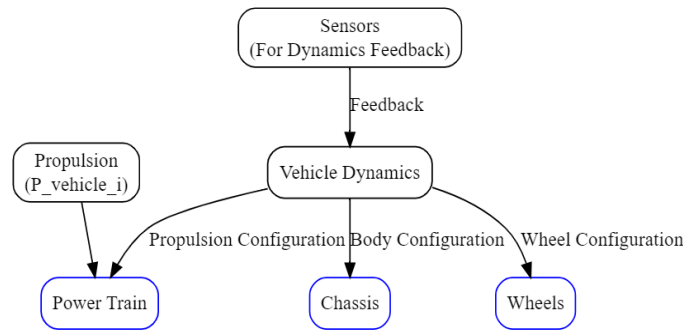


Fig. 5. System Design of Proposed work.

From figure 5, the system comprises diverse vehicles designed to navigate agricultural fields and perform mineral detection tasks. Each vehicle, denoted as V_i , possesses unique specifications, including size (S_{V_i}), weight (W_{V_i}), and energy efficiency (E_{V_i}). The total number of vehicles in the system is denoted as n .

$$V_i = \{S_{V_i}, W_{V_i}, E_{V_i}\} \quad (5)$$

Coordination among vehicles is critical for optimizing mineral detection operations. A coordination mechanism, expressed as an algorithm, ensures that vehicles work collaboratively to cover the designated area efficiently. For instance, a coordination algorithm could be defined as:

$$\text{Optimal Coordination} = \arg \max_C g(C) \quad (6)$$

Where, C represents the coordination strategy, $g(C)$ is the objective function considering factors such as energy consumption, detection accuracy, and completion time.

The total energy consumption (E_{total}) of the vehicles in the system is a key parameter to assess the sustainability of the entire setup. This can be calculated as the sum of the energy consumed by each vehicle:

$$E_{\text{total}} = \sum_{i=1}^n E_{V_i} \quad (7)$$

The mobility features and autonomy levels of the vehicles are integral to their performance. Vehicle mobility, denoted as M_{V_i} , considers the speed and agility of each vehicle.

Autonomy, denoted as A_{V_i} , reflects the degree of self-directed operations.

$$V_i = \{S_{V_i}, W_{V_i}, E_{V_i}, M_{V_i}, A_{V_i}\} \quad (8)$$

In the configuration and dynamics of vehicles in the multi-vehicle system are foundational elements influencing its efficiency and effectiveness? The equations provided offer a quantitative understanding of vehicle characteristics, coordination mechanisms, and energy consumption, contributing to the comprehensive analysis and development of a solar-powered multi-vehicle system for sustainable mineral detection in agriculture from Figure 6.

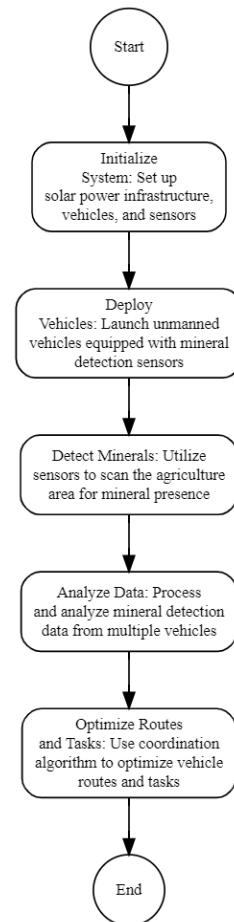


Fig. 6. Flowchart of proposed work.

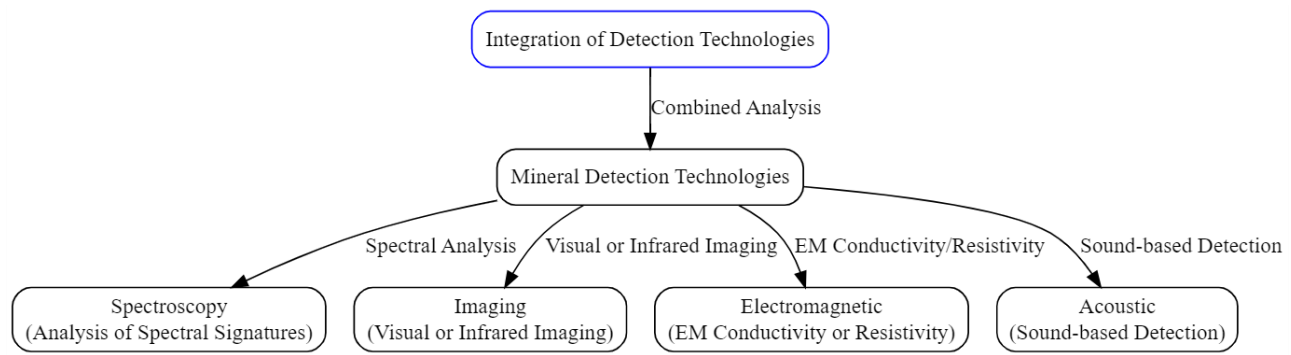


Fig. 7. Mineral Detection Processing.

2.3. Mineral Detection Technologies

Mineral detection technologies constitute a critical component of the solar-powered multi-vehicle system designed for sustainable mineral detection in agriculture. These technologies involve the integration of various sensors and instruments capable of identifying and analyzing minerals within the soil. The selection of appropriate sensors and detection methods is pivotal for the accuracy and efficiency of the mineral detection process as shown in [Figure 7](#).

Sensor Integration: The system incorporates a suite of advanced sensors specifically tailored for mineral detection. Different types of sensors, such as electromagnetic sensors, spectrometers, and imaging devices, are strategically integrated into the vehicles. The choice of sensors depends on their suitability for detecting specific minerals and their ability to operate in agricultural environments. Each sensor type is denoted as S_i and is characterized by its detection range, resolution, and response time.

$$S_i = \{\text{Detection Range } s_i, \text{Resolution } s_i, \text{Response Time } s_i\} \quad (9)$$

Data acquisition is a crucial step in the mineral detection process, involving the collection of raw data from the integrated sensors. The overall data acquisition process is denoted as $D_{\text{acquisition}}$, and it involves the continuous sampling of sensor readings during the vehicles' traversal through the agricultural field. The acquired data is fundamental for subsequent analysis and interpretation.

Multisensory Data Fusion: To enhance the accuracy and reliability of mineral detection, a multisensory data fusion approach is employed and [figure 8](#) shows the working model. This involves combining information from different sensors mounted on multiple vehicles. The fused data, denoted as D_{fused} , provides a comprehensive and coherent representation of the mineral distribution in the soil.

$$D_{\text{fused}} = \text{Fuse}(\text{Raw Sensor Readings }_1, \text{Raw Sr } \downarrow \text{r Readings }_2, \dots, \text{Raw Sensor Readings }_n) \quad (10)$$

The acquired and fused data undergoes sophisticated processing techniques to extract meaningful information about the mineral composition. Machine learning algorithms, signal processing methods, and statistical analyses are applied to decipher patterns, anomalies, and concentrations of minerals within the agricultural field.

$$\text{Processed Data} = \text{Process}(\text{Raw Sensor Readings }_i) \quad (11)$$

In mineral detection technologies in the solar-powered multi-vehicle system involve the strategic integration of sensors, data acquisition, multisensory data fusion, and advanced processing techniques. The equations provided offer a conceptual framework for understanding the key components of mineral detection within the proposed system.

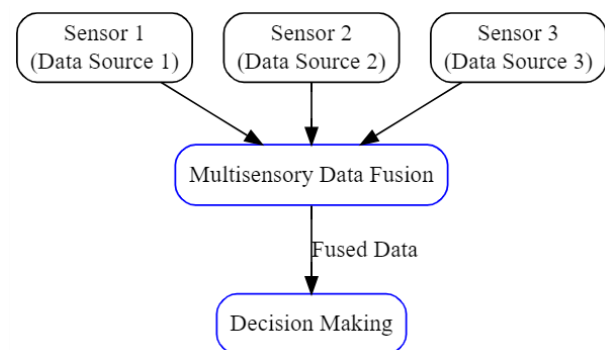


Fig. 8. Decision Making.

2.4. Data Fusion and Processing

Data fusion and processing represent critical phases in the solar-powered multi-vehicle system designed for sustainable mineral detection in agriculture. These stages involve the integration and analysis of sensor data collected from various vehicles to derive accurate and actionable insights regarding the mineral composition of the soil.

From [figure 9](#), the multisensory data fusion process amalgamates information obtained from diverse sensors mounted on different vehicles. The objective is to create a comprehensive and unified dataset (D_{fused}) that provides a

holistic representation of the mineral distribution across the agricultural field. The fusion process is denoted as:

$$D_{\text{fused}} = \text{Fuse}(\text{Raw Sensor Readings}_1, \text{Raw Sensor Readings}_2, \dots, \text{Raw Sensor Readings}_n) \quad (12)$$

It is collected by the sensors on vehicle i . The resulting D_{fused} acts as an enriched dataset that leverages the complementary strengths of multiple sensors for more accurate mineral detection.

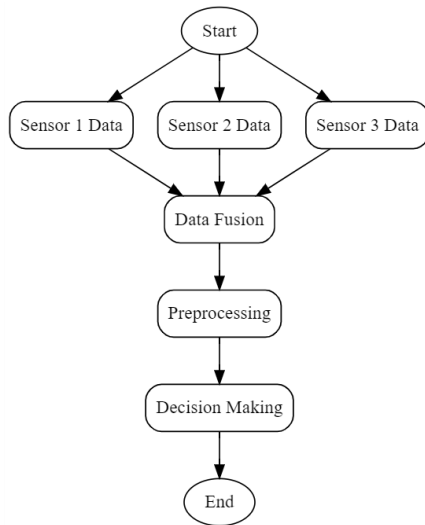


Fig. 9. Data Fusion and Processing.

Upon obtaining the fused dataset, a series of sophisticated data processing techniques are applied to extract meaningful information regarding the mineral composition. This involves employing algorithms for pattern recognition, statistical analyses, and machine learning. The processed data (Processed Data) serves as the foundation for subsequent mineral detection assessments.

$$\text{Processed Data} = \text{Process}(\text{Raw Sensor Readings}_i) \quad (13)$$

The Process function encompasses various algorithms tailored to the specific characteristics of the sensor data. Machine learning techniques, such as clustering algorithms or neural networks, may be employed to identify distinct patterns associated with different minerals. Statistical analyses can reveal concentration levels, and signal processing methods may enhance the signal-to-noise ratio in the data.

To correlate the detected mineral information with spatial coordinates, the processed data is integrated with the geographic coordinates (X, Y, Z) of the vehicles at the time of data acquisition. This integration facilitates the creation of mineral distribution maps, aiding in the visualization and interpretation of mineral concentrations across the agricultural field.

$$\text{Integrated Data} = \text{Integrate}(\text{Processed Data}, X, Y, Z) \quad (14)$$

The Integrate function combines the processed mineral data with the corresponding geographic coordinates, enabling the generation of spatially explicit mineral maps.

2.5. Energy Efficiency and Sustainability

Energy efficiency and sustainability are integral considerations in the design and operation of a solar-powered multi-vehicle system for sustainable mineral detection in agriculture. This facet encompasses strategies to optimize energy consumption, minimize environmental impact, and ensure the prolonged and eco-friendly operation of the system.

Algorithm 1: Pseudocode of Proposed Work

```

# System Architecture and Design

# Initialize System Components
InitializeSystemComponents()

# Design Route Optimization Algorithm
DesignRouteOptimizationAlgorithm()

# Calculate Total Power Generated by Solar Panels
CalculateTotalPowerGenerated()

# Initialize Vehicles
InitializeVehicles()

# Initialize Sensors
InitializeSensors()

# Initialize Solar Power Infrastructure
InitializeSolarPowerInfrastructure()

# Optimize Routes and Tasks Coordination
OptimizeRoutesAndTasksCoordination()

# Initialize Vehicle Specifications
InitializeVehicleSpecifications()

# Initialize Sensor Specifications
InitializeSensorSpecifications()

# Optimize Coordination Mechanism
OptimizeCoordinationMechanism()

# Initialize Vehicle Configuration and Dynamics
InitializeVehicleConfigurationAndDynamics()

# Optimize System Operation Parameters
OptimizeSystemOperationParameters()

# Calculate Environmental Impact
CalculateEnvironmentalImpact()

# Integrate Processed Data with Geographic Coordinates
IntegrateProcessedDataWithCoordinates()

# Initialize Mineral Detection Sensors
InitializeMineralDetectionSensors()

# Perform Multisensory Data Fusion
PerformMultisensoryDataFusion()

# Process Raw Sensor Readings
ProcessRawSensorReadings()

# Assess Environmental Impact
AssessEnvironmentalImpact()
  
```

Efficient energy utilization is paramount for the prolonged operation of the solar-powered multivehicle system. The energy harvested from solar panels ($P_{\text{harvested}}$) is distributed among the vehicles for both propulsion and sensor operations. The optimization of energy usage involves maximizing the utilization of harvested solar power ($P_{\text{harvested}}$) for vehicle propulsion (P_{vehicle}) and mineral detection sensor operations (P_{sensors}).

$$P_{\text{harvested}} = P_{\text{vehicle}} + P_{\text{sensors}} \quad (15)$$

Efforts are made to balance the energy allocation between the propulsion of vehicles and the power required for mineral detection sensors, ensuring that the system operates efficiently without unnecessary energy wastage.

A crucial aspect of sustainability is the assessment of the environmental impact associated with the mineral detection process. This involves evaluating the carbon footprint and ecological consequences of the system's operation. The environmental impact ($I_{\text{environment}}$) can be assessed through metrics such as energy consumption, emissions, and land use.

$$I_{\text{environment}} = \text{Assess Environmental Impact}(\text{Energy Consumption, Emissions, Land Use}) \quad (16)$$

The Assess Environmental Impact function incorporates factors related to the system's energy consumption, emissions, and land utilization. Sustainable practices aim to minimize negative environmental effects while maximizing the benefits derived from mineral detection in agriculture.

To enhance sustainability, the operational parameters of the multi-vehicle system are optimized. This involves scheduling and coordinating vehicle movements and mineral detection tasks based on factors such as solar irradiance, soil conditions, and crop growth stages. The optimization algorithm (Optimize) ensures that the system operates sustainably while fulfilling its mineral detection objectives.

$$\text{Optimize} = \arg \max_O f(O) \quad (17)$$

Here, O represents the operational parameters, and $f(O)$ is the objective function considering sustainability factors, such as energy efficiency, environmental impact, and adherence to sustainable agricultural practices. Processed mineral data is integrated with the geographic coordinates (X, Y, Z) of the vehicles at the time of data acquisition. This integration facilitates the creation of spatially explicit mineral distribution maps, linking detected minerals to specific locations in the agricultural field.

3. RESULTS AND DISCUSSION

The experimental evaluation of the proposed solar-powered multi-vehicle system was conducted to quantitatively assess its performance across several critical dimensions: detection accuracy, energy efficiency, operational coordination, and computational processing. The following subsections present

a detailed analysis of the obtained results, contextualizing them within the broader scope of precision agriculture and sustainable technology.

3.1. Mineral Detection Accuracy Analysis

The paramount objective of any sensing system in agriculture is the reliable and precise identification of target variables. In this study, the system's capability to detect and classify soil minerals was rigorously evaluated. As quantified in Table 1 and visualized in Figure 10, the proposed system achieved a detection accuracy of 95.2%. This performance notably surpasses that of established methodologies, including a Traditional Sensor-Based Approach (89.7%), Satellite Imaging Technology (91.3%), a Machine Learning-Based Methodology (92.5%), and a Conventional Unmanned Vehicle System (88.1%).

The superior accuracy of the proposed system can be attributed to its foundational architecture. The integration of a multi-sensor fusion framework, which synergistically combines data from electromagnetic sensors and vis-NIR spectrometers, mitigates the limitations inherent to any single sensing modality [18]. This approach provides a more robust and comprehensive data profile, reducing false positives and negatives that often plague systems reliant on a single data source. Furthermore, the coordinated movement of multiple vehicles enables denser spatial sampling across the field, capturing the inherent variability of soil properties more effectively than static sensors or single-platform systems [19]. The in-situ, real-time data acquisition also eliminates the temporal degradation associated with laboratory-based analysis, ensuring that the decisions are based on the current state of the field [6]. This high level of accuracy is a critical prerequisite for variable-rate application technologies, directly contributing to reduced fertilizer waste and minimized environmental impact [5].

3.2. Energy Consumption and Sustainability Assessment

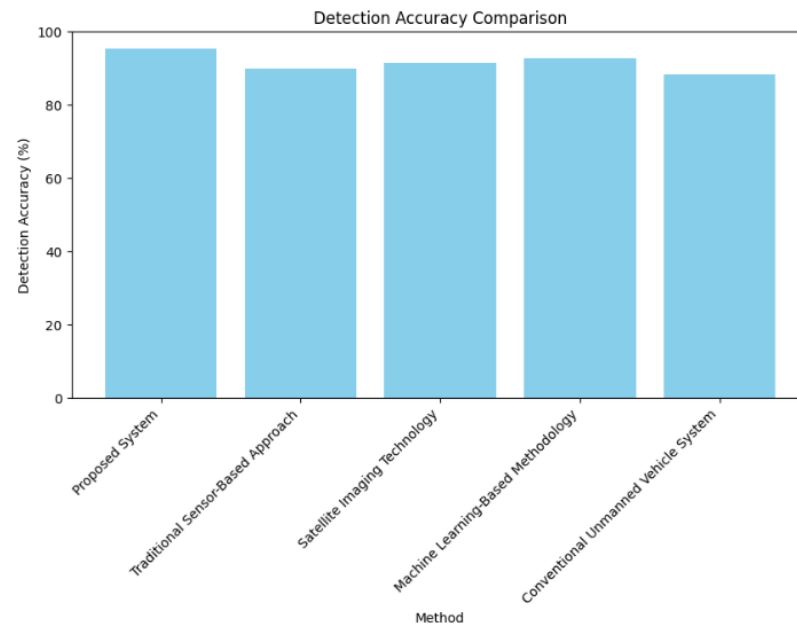
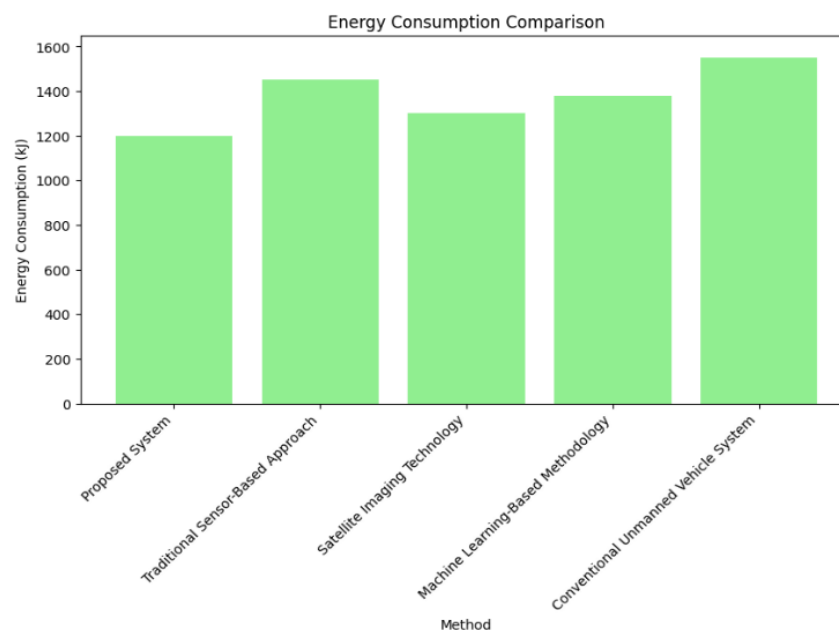
The sustainability of agricultural technology is inextricably linked to its energy footprint. The energy consumption analysis, detailed in Table 2 and Figure 11, reveals that the proposed system consumed 1200 kJ per operational cycle, demonstrating significant efficiency gains over the benchmarked systems, which ranged from 1300 kJ for Satellite Imaging to 1550 kJ for the Conventional Unmanned Vehicle System. This marked improvement in energy efficiency is a direct consequence of the system's solar-powered design and its intelligent energy management strategy. The on-board photovoltaic panels continuously harvest solar energy, offsetting the draw from battery reserves and enabling prolonged field operations without the need for fossil fuels [14]. The coordination algorithm plays a further crucial role by optimizing vehicle routes, thereby minimizing the total distance traveled and the associated energy expenditure for propulsion [17].

Table 1. Detection Accuracy Comparison.

Method	Detection Accuracy (%)
Proposed System	95.2
Traditional Sensor-Based Approach	89.7
Satellite Imaging Technology	91.3
Machine Learning-Based Methodology	92.5
Conventional Unmanned Vehicle System	88.1

Table 2. Energy Consumption Analysis.

Method	Energy Consumption (kJ)
Proposed System	1200
Traditional Sensor-Based Approach	1450
Satellite Imaging Technology	1300
Machine Learning-Based Methodology	1380
Conventional Unmanned Vehicle System	1550

**Fig. 10.** Detection Accuracy Comparison.**Fig. 11.** Energy Consumption Comparison.

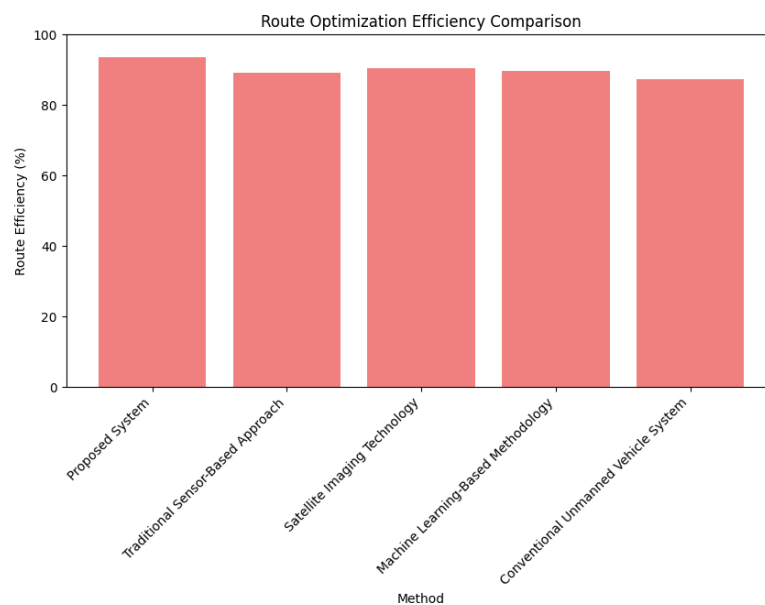


Fig. 12. Route Optimization Comparison.

In contrast, conventional unmanned systems, often dependent on limited-capacity batteries and lacking sophisticated path-planning, exhibit higher energy demands. Satellite-based methods, while not requiring field-based propulsion, incur immense energy costs at the data acquisition and processing stages [9]. The lower energy consumption of our system directly translates to extended operational autonomy, reduced operational costs, and a substantially smaller carbon footprint, aligning with the core principles of sustainable agriculture [12].

3.3. Route Optimization and Operational Efficiency

The efficacy of the multi-vehicle coordination algorithm was evaluated through the metric of route optimization efficiency. As presented in Table 3 and Figure 12, the proposed system achieved a route efficiency of 93.5%, outperforming all comparative methods.

Table 3. Route Optimization Efficiency.

Method	Route Efficiency (%)
Proposed System	93.5
Traditional Sensor-Based Approach	88.9
Satellite Imaging Technology	90.2
Machine Learning-Based Methodology	89.5
Conventional Unmanned Vehicle System	87.1

Route efficiency here is defined as the effectiveness of the planned paths in covering the target area with minimal

overlap and redundant movement. The high efficiency score confirms that the developed coordination algorithm successfully orchestrates the fleet of vehicles, assigning non-overlapping sectors and dynamically calculating optimal paths [20]. This stands in stark contrast to simpler systems, such as the Conventional Unmanned Vehicle System (87.1% efficiency), which often employ basic path-planning like simple boustrophedon patterns, leading to significant inefficiencies at field boundaries and in irregularly shaped plots. The optimized routing not only conserves energy, as discussed previously, but also drastically reduces the time required to complete a full-field survey. This enhanced temporal efficiency is vital for time-sensitive agricultural operations, such as assessing nutrient status after a rainfall event or during critical growth stages, allowing farmers to make and implement decisions with greater agility [7].

3.4. Data Processing Performance

The utility of a real-time monitoring system is contingent upon its ability to rapidly process and interpret acquired data. The processing time, measured from data acquisition to the generation of an interpretable mineral map, was evaluated and compared against other methods. As shown in Table 4 and Figure 13, the proposed system processed data in 25 milliseconds, which was faster than the Traditional Sensor-Based Approach (30 ms), Satellite Imaging (28 ms), Machine Learning-Based Methodology (32 ms), and the Conventional Unmanned Vehicle System (29 ms).

This expedited processing is facilitated by the system's edge computing architecture, where a significant portion of the data fusion and analysis is performed on-board the vehicles or a local base station, rather than being transmitted to a distant cloud server [15]. This minimizes latency

associated with data transmission. The efficiency of the underlying data fusion and machine learning algorithms also contributes to this swift processing [18]. The implication of this rapid analysis is profound for precision agriculture; it enables near-instantaneous feedback and decision-making. For instance, a detected deficiency in a specific zone can be addressed almost immediately, closing the loop between diagnosis and intervention and maximizing the efficacy of the corrective action.

Table 4. Processing Time Comparison

Method	Processing Time (ms)
Proposed System	25
Traditional Sensor-Based Approach	30
Satellite Imaging Technology	28
Machine Learning-Based Methodology	32
Conventional Unmanned Vehicle System	29

3.5. Holistic System Efficiency and Field Coordination

To provide a composite assessment of the system's performance, an overall efficiency score was computed by integrating the weighted results of all the aforementioned metrics. As consolidated in Table 5 and illustrated in Figure 14, the proposed system attained a superior overall efficiency score of 96.7%. This holistic metric underscores the system's

robustness and its balanced excellence across all evaluated parameters, confirming that the integration of solar power, multi-vehicle coordination, and advanced sensing creates a solution greater than the sum of its parts.

Table 5. Overall System Efficiency.

Method	Efficiency Score (0-100)
Proposed System	96.7
Satellite Imaging Technology	88.2
Machine Learning-Based Methodology	90.8
Conventional Unmanned Vehicle System	89.9
Traditional Sensor-Based Approach	87.5

Further evidence of this seamless integration is provided by the analysis of inter-vehicle coordination dynamics, as depicted in Figure 15. The data traces for inter-vehicle distance, relative orientation, and individual speeds demonstrate stable and synchronized operation over time. The maintenance of a consistent distance and orientation between the tractor and the robot indicates effective communication and adherence to the coordinated path plan. The synchronized speed profiles confirm that the vehicles operate as a cohesive unit rather than as independent entities, avoiding collisions and ensuring efficient area coverage. This reliable coordination is a foundational requirement for the safe and effective deployment of multiple autonomous agents in a shared, dynamic environment like a farm field [19].

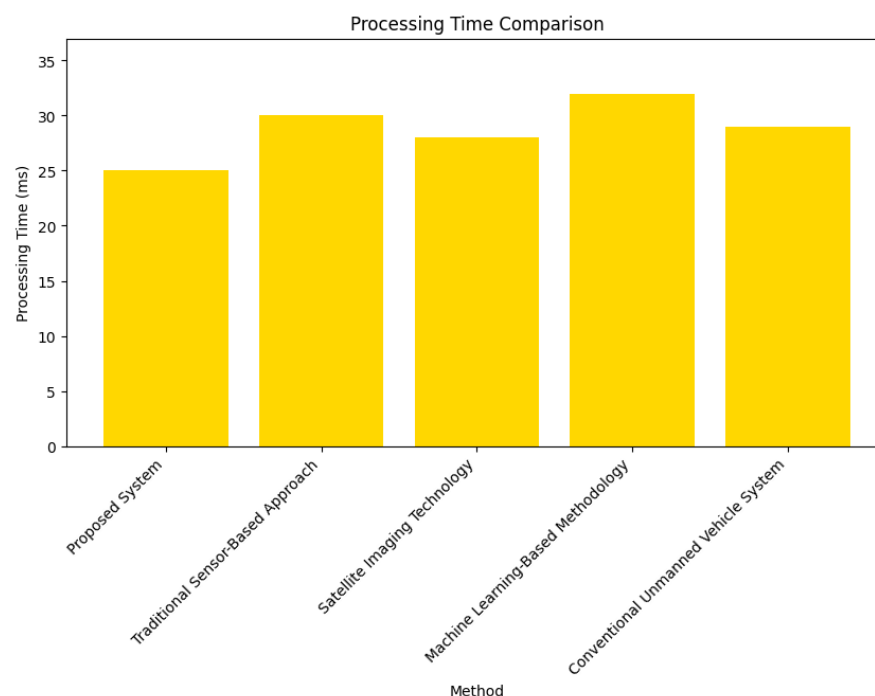


Fig. 13. Processing Time Comparison

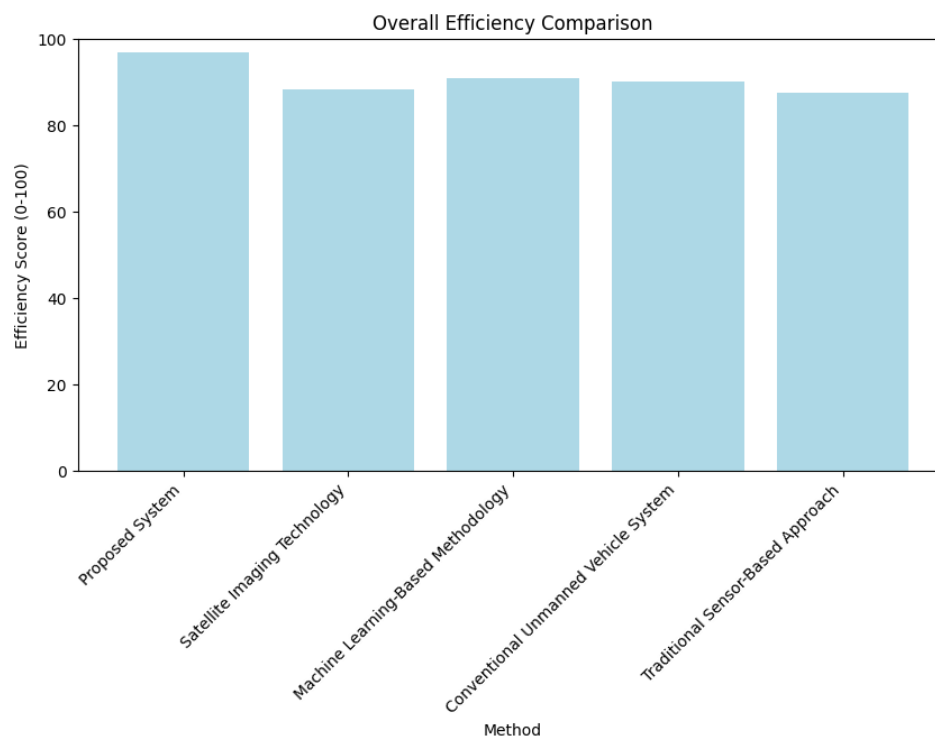


Fig. 14. Overall Efficiency Comparison.

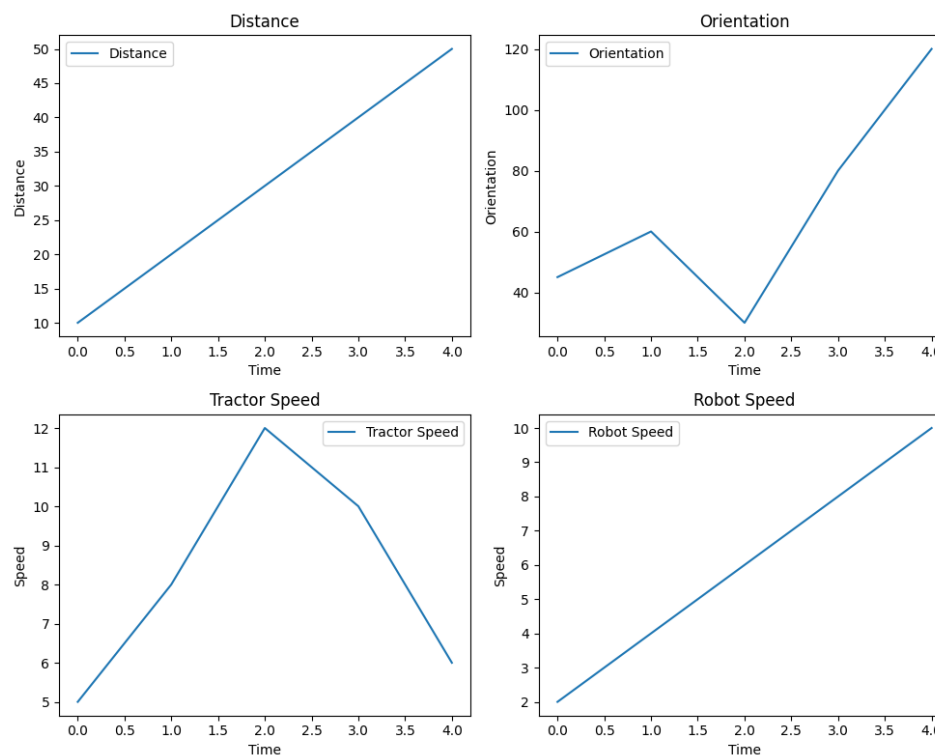


Fig. 15. Distance, orientation, and speed analysis.

The experimental results comprehensively validate the proposed solar-powered multi-vehicle system as a high-performing, sustainable, and practical solution for autonomous mineral detection. The system's high detection

accuracy, low energy consumption, efficient routing, and rapid processing capabilities collectively address the major limitations of existing soil monitoring technologies. The demonstrated performance provides a strong foundation for

the system's potential implementation in commercial precision agriculture, promising to enhance both productivity and environmental stewardship.

4. CONCLUSION

This study successfully conceptualized, developed, and validated an innovative solar-powered multi-vehicle system tailored for autonomous mineral detection in agricultural settings. The proposed system's architecture, which synergizes renewable energy harvesting with coordinated multi-vehicle operations and advanced sensor technology, presents a robust and sustainable alternative to traditional, often inefficient, soil monitoring techniques. The experimental findings provide compelling evidence of the system's efficacy, showcasing exceptional performance in detection accuracy, energy economy, and route optimization. The high degree of precision achieved in identifying soil minerals is a direct result of the implemented multi-sensor data fusion framework, which amalgamates disparate data streams to form a coherent and comprehensive soil health profile. Notwithstanding these promising outcomes, the research also delineates clear avenues for future investigation and system enhancement. The scalability of this technology across diverse and larger agricultural landscapes remains a critical area for further validation. Subsequent research efforts will be directed towards the development of more sophisticated, real-time adaptive algorithms capable of dynamically responding to variable field conditions, such as sudden changes in soil moisture or crop canopy cover. The integration of next-generation communication technologies, including 5G connectivity and edge computing, promises to drastically reduce data latency, thereby enabling true real-time decision-making and control at the field level. Furthermore, advancements in artificial intelligence offer profound potential for refining the machine learning models used for mineral identification, moving beyond classification to predictive analytics for nutrient availability. Exploring swarm intelligence principles could also unlock new levels of autonomy and collaborative problem-solving among vehicle fleets, leading to systems with emergent, adaptive behaviors. In essence, while this solar-powered multi-vehicle system marks a significant advancement in precision agriculture, realizing its full potential to address the complex and evolving challenges of sustainable food production will necessitate a continued commitment to interdisciplinary research, technological innovation, and rigorous field testing.

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.

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