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LoRa-Enabled Semi-Autonomous Rover for AI-Driven Crop Prediction Using Data-Driven Decision-Making for Tamil Nadu Agriculture

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Abstract

This research presents a LoRa-enabled semi-autonomous rover system designed for real-time environmental and soil parameter monitoring to facilitate data-driven decision-making (DDDM) in agriculture. The rover is equipped with multi-modal sensors, including soil moisture, temperature, pH, NPK, electrical conductivity (EC), light intensity, wind speed, and rainfall sensors, to capture high-resolution field data. Utilizing LoRa communication, these data points are transmitted to a cloud-based server for processing and analysis. A Random Forest-based AI model is employed to correlate real-time sensor data with historical agricultural datasets from Tamil Nadu, enabling predictive analytics for crop selection and soil health assessment. The system generates data-driven agronomic recommendations, assisting farmers in optimizing crop yield, resource utilization, and sustainable farming practices. A dashboard-based web interface provides intuitive visualizations and insights, ensuring accessibility and informed decision-making. This IoT-integrated precision agriculture framework enhances spatial and temporal data analysis for improved agricultural productivity. By leveraging AI-driven analytics and real-time monitoring, this solution contributes to predictive farming, optimized land use, and enhanced food security, fostering a sustainable and technologically advanced agricultural ecosystem.

Keywords: *IoT, Precision Agriculture, LoRa, Autonomous Rover, AI, Machine Learning, Random Forest, Data Analytics, Data-Driven Decision-Making, Soil Monitoring, Environmental Sensing, Crop Prediction, Sustainable Farming, Resource Utilization.*

1. Introduction

Tamil Nadu's agricultural landscape represents a mosaic of diverse agro-climatic zones spanning from the rain-fed regions in the west to the fertile deltas in the east. This environmental diversity has historically supported a rich variety of cultivars, including staple crops like rice and millets, essential pulses, and economically valuable cash crops such as cotton and sugarcane [1]. However, the agricultural sector in this region faces mounting challenges, including increasingly erratic rainfall patterns, groundwater depletion, soil degradation, and market volatility all of which threaten both farm productivity and livelihood sustainability. Recent initiatives like the Tamil Nadu Irrigated Agriculture Modernization and Water-Bodies Restoration and Management (TN-IAMWARM) project have made significant strides in addressing these challenges through irrigation modernization and sustainable water management practices. Yet, a critical gap remains in providing farmers with field-specific, data-driven decision support that integrates real-time environmental monitoring with predictive analytics. The emergence of semi-autonomous rovers represents a technological paradigm shift in agricultural monitoring. These advanced platforms navigate agricultural fields with minimal human intervention, systematically collecting high-resolution data on critical parameters that determine crop health and productivity. Equipped with an array of sophisticated sensors, these rovers continuously monitor soil moisture gradients, temperature variations, pH fluctuations, essential nutrient concentrations (NPK), and environmental conditions including light intensity and precipitation patterns. This granular, field-specific data acquisition transcends traditional sampling methods, enabling precise spatial and temporal monitoring that captures the inherent variability within agricultural landscapes. Research by Shamshiri et al. (2018) demonstrates that robotics integration in agricultural monitoring can enhance data collection precision by up to 85% while reducing labor requirements by 60%, creating a compelling case for technology-enabled precision agriculture [2]. The efficacy of field monitoring systems in agriculture hinges on reliable data transmission capabilities across expansive rural landscapes. LoRa (Long Range) technology emerges as an ideal solution, offering low-power, wide-area network communication specifically optimized for remote agricultural environments [3]. Operating in the unlicensed ISM radio bands, LoRa enables data transmission over distances exceeding 10 kilometers in rural settings while maintaining remarkable power efficiency, with sensor nodes operating continuously for up to five years on a single battery charge [4]. This communication infrastructure forms the critical backbone of agricultural Internet of Things (IoT) systems, facilitating seamless data flow from field sensors to centralized processing systems. Studies by García et al. (2020) highlight LoRa's significance in agricultural applications, demonstrating 99.2% data delivery reliability in challenging rural environments compared to conventional wireless technologies [5]. The integration of Artificial Intelligence in agricultural decision support systems represents the culmination of the data acquisition and transmission pipeline. Machine learning algorithms particularly Random Forest models excel at processing multi-dimensional agricultural datasets to identify complex patterns and relationships that elude traditional analytical approaches. These AI systems synthesize real-time field data with historical agricultural trends, meteorological records, and market intelligence to generate predictive insights for crop selection, resource optimization, and yield forecasting. Accessible through intuitive web dashboards, these insights empower farmers with actionable intelligence presented in comprehensible visual formats. This democratization of advanced analytical capabilities bridges the technological divide, enabling traditional farmers to leverage sophisticated decision support tools. Implementation of similar AI-powered advisory systems in comparable agricultural regions has demonstrated yield improvements of 15-28% while reducing resource inputs by 20% [6], highlighting the transformative potential of data-driven agriculture. The convergence of these three technological domains autonomous field monitoring, efficient wireless communication, and intelligent data analytics presents a compelling opportunity to revolutionize agricultural practices in Tamil Nadu, potentially addressing the persistent challenges of resource optimization, climate resilience, and economic sustainability.

2. Literature Survey

In recent years, precision agriculture has transformed farming by integrating advanced technologies to optimize crop production and sustainability through data-driven decision-making (DDDM).

2.1 Semi-Autonomous Rovers in Agriculture

Agricultural robotics has gained prominence in recent years, with semi-autonomous rovers offering high precision in field monitoring and crop assessment. Studies have shown that autonomous rovers integrated with GPS and IMU-based navigation provide accurate field mapping. Tamil Nadu's fragmented landholdings necessitate such adaptable robotic solutions to enhance efficiency and reduce labor dependency while gathering real-time agricultural data.

Research includes:

- Brity Das et al. (2024) developed an agricultural rover effectively performs autonomous vegetable harvesting and soil analysis using deep learning algorithms, enhancing crop management and soil monitoring [7].

- Yuktha Bhushan et al. (2024) proposed a multipurpose agriculture robot that can perform various tasks in agriculture, including ploughing, seeding, mud leveling, and water spraying, using battery and solar power [8].
- S. Murugesan et al. (2024) proposed a robotic vehicle that effectively clears land, performs planting, watering, and harvesting tasks, and can be controlled by a smart phone for efficient farming [9].
- Earth Rover (2023) developed CLAWS, an AI-driven rover for weed control and scouting, focusing on sustainability.
- Fazio et al. (2021) present a semi-custom wheeled mobile robot with high-efficiency photovoltaic panels on the roof, enabling it to perform tasks in harsh environments with minimal energy consumption [10].
- Balasooriya et al. (2019) proposed a low-power, low-cost autonomous rover with improved maneuverability and battery life, using less power-consuming sensors and a modified all-wheel drive system [11].

2.2 Multi-Modal Sensors for Agricultural Data Collection

Effective crop monitoring requires diverse sensors capable of capturing multiple environmental and physiological parameters. Multi-modal sensing incorporates optical sensors, soil moisture probes, temperature sensors, and hyperspectral imaging to enhance data reliability, crucial for Tamil Nadu's heterogeneous farming landscape.

Researc includes:

- G Vasques et al. (2020) combined multiple soil sensors improves soil property predictions and maps, leading to more detailed and accurate maps for precision agriculture [12].
- W Ji et al. (2019) proposed a proximal soil sensor data fusion improves predictions of soil properties, such as organic matter, pH, and phosphorus concentrations, compared to single-sensor approaches [13].
- P Aravind et al. (2015) developed multi-sensor system with wireless connectivity offers accurate and cost-effective soil moisture measurement, with the DPHP sensor being the most cost-effective and resistive sensor being the cheapest option [14].

2.3 LoRa Communication for Data Transmission

LoRa (Long Range) technology is a cost-effective solution for low-power, long-range wireless communication, making it ideal for agricultural applications. Studies indicate that LoRa networks can efficiently transmit data over several kilometers with minimal energy consumption. In rural Tamil Nadu, where conventional internet infrastructure is limited, LoRa serves as a reliable medium for rover-to-cloud data transmission.

Reseach includes:

- Yi Guo et al. (2024) proposed ED-RB pairing scheme and spreading factor allocation can save over 34.6% power in LoRa uplink systems compared to the baseline [15].
- I Lopes et al. (2024) developed LoRa-based IoT platform offers a low-cost, customizable solution for real-time monitoring of soil parameters in rural environments, offering automation, increased efficiency, and savings in human resources [16].
- Zhaoxin Chang et al. (2022) developed sensor-free soil moisture sensing using LoRa signals achieves high accuracy, robustness, and large sensing range for large-scale deployment in smart agriculture, with an average error of 3.1% [17].
- X Chavanne et al. (2022) proposed autonomous in-situ soil sensors with LoRaWAN technology can continuously monitor soil moisture over a catchment, reducing maintenance and increasing data transfer lifetime by 30% [18].
- Semtech (2021) highlights LoRa's role in smart agriculture, achieving 50% water reduction in commercial farms.

2.4 AI Driven for Crop Prediction

Machine learning (ML) and deep learning (DL) techniques play a pivotal role in predictive agriculture. AI-driven models analyze large datasets from multi-modal sensors to forecast yield, detect diseases, and recommend best farming practices.

Convolutional Neural Networks (CNNs) have demonstrated superior performance in plant disease classification, while Random Forest and Long Short-Term Memory (LSTM) networks effectively predict crop yields based on historical data.

Reseach Includes:

- Ahezam Ahewar Khan (2024) levaraged machine learning to predict suitable crops, optimize resources, and maximize crop yields, contributing to a greener and more prosperous future in agriculture [19].
- Prof. A. A. Chaudhari (2024) proposed IoT-based Smart Farming improves crop yield and quality by monitoring real-time factors like moisture, temperature, and soil, and recommending suitable crops based on data [20].
- Sri Hari Nallamala et al. (2024) utilized AI to monitor crops, recommend suitable crops, detect weeds, and predict yields, which helped improve agriculture's health and profitability [21].
- Sathya Priya et al. (2024) proposed IoT and AI technology can improve agricultural operations by suggesting appropriate crops and forecasting potential illnesses based on real-time sensor data [22].

2.5 Agricultural and Technological Trends in Tamil Nadu

Tamil Nadu is progressively adopting smart agriculture, with government initiatives promoting AI-based precision farming. The state’s investment in IoT-based irrigation systems, automated soil health monitoring, and digital agronomy platforms underscores its commitment to technology-driven farming. However, challenges such as small landholdings, high initial costs, and lack of digital literacy among farmers hinder widespread adoption. Policies supporting technology subsidies, rural digital infrastructure, and farmer training programs are crucial to realizing the full potential of AI-driven agriculture.

3. Proposed System

The proposed solution is a LoRa-enabled semi-autonomous rover system designed to transform precision agriculture in Tamil Nadu by integrating real-time environmental monitoring with predictive analytics for data-driven decision-making (DDDM). This system comprises six interconnected modules that collectively enable high-resolution data acquisition, efficient communication, intelligent analysis, and user-friendly insights.

These modules are:

- Data Collection and Dataset Preparation
- Rover Hardware Design
- IoT Sensing and Control System
- LoRa-Based Data Communication
- AI-Driven Crop Prediction Modeling
- Web-Based Dashboard Interface and Analysis

The system operates as follows: The process begins with the Rover Hardware Design, a semi-autonomous platform engineered to navigate Tamil Nadu’s diverse agricultural terrains. Equipped with robust wheels, GPS navigation, and a durable chassis, the rover serves as the physical foundation for data collection. Mounted on this platform is the IoT Sensing and Control System, which integrates multi-modal sensors along with microcontrollers to capture real-time field data.[8] These sensors continuously monitor spatial and temporal variations in soil and environmental parameters, generating high-resolution datasets essential for precision agriculture. Next, the LoRa-Based Data Communication module transmits the collected and processed data to a cloud-based server using LoRa technology. Operating in the unlicensed ISM band, LoRa provides low-power, long-range communication capable of spanning over 10 kilometers in rural settings ensuring reliable data delivery from remote fields to centralized systems with minimal energy consumption.[17][18]. Due to the absence of directly available training datasets, the Data Collection and Dataset Preparation module curates a synthetic dataset specifically designed for the system’s modeling needs. Developed in consultation with agricultural officials, this dataset incorporates 30+ columns of carefully analyzed features such as soil nutrient profiles, weather patterns, and crop performance metrics tailored to Tamil Nadu’s agro-climatic conditions. This synthetic dataset, combined with real-time data, forms a robust foundation for predictive analysis. The transmitted data from the LoRa, enters the AI-Driven Crop Prediction Modeling module, where a Random Forest algorithm analyzes it to uncover patterns and

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correlations. By synthesizing real-time field data with historical trends, this module generates predictive insights, such as optimal crop selection, soil health assessments, and resource management recommendations. The Random Forest model's robustness in handling multi-dimensional datasets makes it ideal for delivering accurate agronomic forecasts tailored to Tamil Nadu's agro-climatic diversity.[21] Finally, the Web-Based Dashboard Interface module delivers these insights to farmers through an intuitive online platform. Featuring interactive visualizations such as heatmaps of soil moisture or graphs of predicted yields the dashboard empowers users to make informed decisions about planting schedules, irrigation needs, and fertilizer application. The application is equipped with remote control access to navigate the rover and helps in the crop recommendation. This seamless integration of modules from field-level data collection and synthetic dataset creation to cloud-based analytics and user access creates a scalable, sustainable system that enhances agricultural productivity, optimizes resource utilization, and promotes climate-resilient farming practices in Tamil Nadu. Figure 1 shows Process Flow Representation of The Rover Integrated with Various Modules.

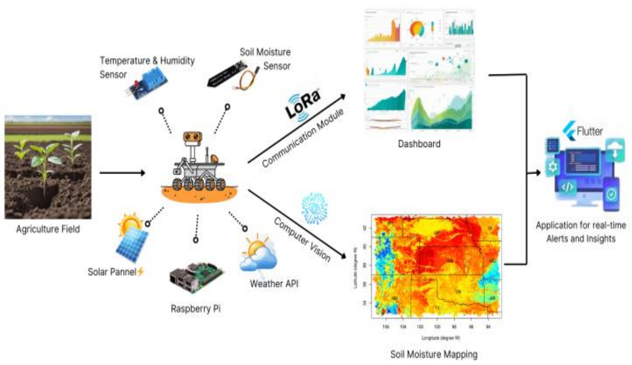

Figure 1 Process Flow Representation of The Rover Integrated with Various Modules

3.1 Data Collection and Dataset Preparation

The foundation of the proposed system lies in the Data Collection and Dataset Preparation module, which addresses a critical challenge: the absence of a comprehensive, Tamil Nadu-specific dataset for predictive agricultural modeling. Existing datasets were either unreliable, insufficient, or too generalized to capture the region's unique agro-climatic diversity. To overcome this, a synthetic dataset was meticulously engineered from scratch, tailored to the system's requirements and grounded in real-world agricultural conditions as of 2025. The dataset's development involved extensive consultation with agricultural officials, including in-person visits to Tamil Nadu Agricultural University (TNAU), and a thorough review of authoritative sources such as the Tamil Nadu official agriculture website and various web-based references. These efforts informed the selection of 37 key features, encompassing soil properties, environmental factors, crop-specific variables, and socio-economic considerations. The resulting columns include: District, Agroclimatic Zone, Soil Nature, Soil Type, Soil pH Level, Nitrogen Content (kg/ha), Phosphorus Content (kg/ha), Potassium Content (kg/ha), Organic Carbon (%), Electrical Conductivity (milli mhos/cm²), Soil Moisture (%), Rainfall (mm/year), Temperature (°C), Humidity (%), Sunlight Hours (hrs), Slope of Land (%), Cropping Season, Crop, Previous Crop, Sowing Month, Harvesting Month, Growth Duration (days), Yield (tons/ha), Land Area (ha), Irrigation Type, Groundwater Level (mm), Labor Availability, Water Requirement (mm), Market Price (₹/ton), Demand Trend, Pest/Disease Risk, Drought Risk, Soil Erosion Risk, Sustainability Category, Fertilizer Type, Dosage per Hectare, and Application Frequency. To ensure regional specificity, a value mapping was created for each district in Tamil Nadu, reflecting real agricultural data and conditions as of 2025. For instance, the Nilgiris district was mapped with parameters such as an Agroclimatic Zone of "High Altitude Subtropical Zone," Soil Types including "Mountain Soil" and "Organic Rich Loamy," Rainfall ranging from 1500–2500 mm/year, and crop-specific yields (e.g., Tea: 1.5–3.0 tons/ha). These mappings incorporate ranges and categorical values such as soil pH (5.0–6.8) or irrigation types (e.g., "Drip," "Sprinkler") derived from expert input and validated sources, ensuring the dataset's realism and relevance to Tamil Nadu's diverse farming

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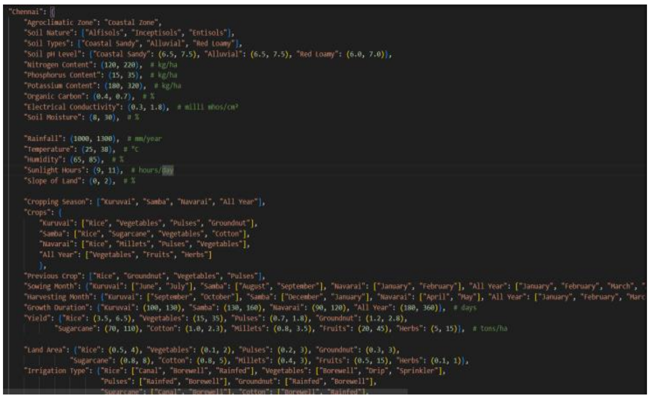
landscape. Figure 2 shows Sample Mapping for Chennai To Generate Synthetic Data.



```
"Chennai": {
    "Agroclimatic Zone": "Coastal Zone",
    "Soil Nature": ["Alfisols", "Inceptisols", "Entisols"],
    "Soil Types": ["Coastal Sandy", "Alluvial", "Red Loamy"],
    "Soil pH Level": {"Coastal Sandy": (6.5, 7.5), "Alluvial": (6.5, 7.5), "Red Loamy": (6.0, 7.0)},
    "Nitrogen Content": (120, 220),  # kg/ha
    "Phosphorus Content": (15, 35),  # kg/ha
    "Potassium Content": (180, 320),  # kg/ha
    "Organic Carbon": (0.4, 0.7),  # %
    "Electrical Conductivity": (0.3, 1.8),  # milli mhos/cm²
    "Soil Moisture": (8, 30),  # %

    "Rainfall": (1000, 1300),  # mm/year
    "Temperature": (25, 38),  # °C
    "Humidity": (65, 85),  # %
    "Sunlight Hours": (9, 11),  # hours/day
    "Slope of Land": (0, 2),  # %

    "Cropping Season": ["Kuruvai", "Samba", "Navarai", "All Year"],
    "Crops": {
        "Kuruvai": ["Rice", "Vegetables", "Pulses", "Groundnut"],
        "Samba": ["Rice", "Sugarcane", "Vegetables", "Cotton"],
        "Navarai": ["Rice", "Millets", "Pulses", "Vegetables"],
        "All Year": ["Vegetables", "Fruits", "Herbs"]
    },
    "Previous Crop": ["Rice", "Groundnut", "Vegetables", "Pulses"],
    "Sowing Month": {"Kuruvai": ["June", "July"], "Samba": ["August", "September"], "Navarai": ["January", "February"], "All Year": ["January", "February", "March", "
    "Harvesting Month": {"Kuruvai": ["September", "October"], "Samba": ["December", "January"], "Navarai": ["April", "May"], "All Year": ["January", "February", "Marc
    "Growth Duration": {"Kuruvai": (100, 130), "Samba": (130, 160), "Navarai": (90, 120), "All Year": (180, 360)},  # days
    "Yield": {"Rice": (3.5, 6.5), "Vegetables": (15, 35), "Pulses": (0.7, 1.8), "Groundnut": (1.2, 2.8),
              "Sugarcane": (70, 110), "Cotton": (1.0, 2.3), "Millets": (0.8, 3.5), "Fruits": (20, 45), "Herbs": (5, 15)},  # tons/ha

    "Land Area": {"Rice": (0.5, 4), "Vegetables": (0.1, 2), "Pulses": (0.2, 3), "Groundnut": (0.3, 3),
                  "Sugarcane": (0.8, 8), "Cotton": (0.8, 5), "Millets": (0.4, 3), "Fruits": (0.5, 15), "Herbs": (0.1, 1)},
    "Irrigation Type": {"Rice": ["Canal", "Borewell", "Rainfed"], "Vegetables": ["Borewell", "Drip", "Sprinkler"],
                        "Pulses": ["Rainfed", "Borewell"], "Groundnut": ["Rainfed", "Borewell"],
```

Figure 2 **Sample Mapping for Chennai To Generate Synthetic Data**

A custom Python script was developed to generate this synthetic dataset, populating it with realistic values based on the district-specific mappings. The resulting dataset was then processed, analyzed, and visualized using Python libraries Pandas for data manipulation, Matplotlib for basic plotting, and Seaborn for advanced statistical visualizations. This step enabled a deeper understanding of feature distributions, correlations, and trends, such as soil nutrient variations across districts or yield dependencies on rainfall and irrigation. The synthetic dataset, enriched with real-time sensor data from the rover during operation, serves as the backbone for the AI-driven crop prediction model, ensuring its predictions are both locally relevant and data-driven. Figure 3 shows Sample of The Synthetic Dataset Generated for Model Training.

District	Agroclimatic Zone	Soil Type	Soil pH Level	Nitrogen (N) Content (%)	Phosphorus (P) Content (ppm)	Potassium (K) Content (ppm)	Organic Carbon (%)	Soil Moisture Content (%)	Soil Texture	...	Harvesting Month	Growth Duration (days)	Yield (tons/ha)	Market Price (₹/ton)	Demand Trend	Pest/Disease Risk	Drought Risk
Kallakurichi	Southern Plateau	Mixed	6.31	0.10	41	141	2.24	32.78	Peaty	...	January	195	11.49	11980	High	High	Medium
Krishnagiri	Southern Plateau	Black	8.33	0.28	48	82	1.14	32.16	Peaty	...	August	277	2.60	1540	Medium	Low	Medium
Karur	Hilly Zone	Black	7.56	0.38	52	475	2.37	12.87	Sandy	...	February	258	4.78	35134	Medium	High	Medium
Ariyalur	Hilly Zone	Mixed	7.10	1.48	6	127	0.56	33.95	Silty	...	June	152	5.74	17747	High	Low	Low
Tirupattur	Central Zone	Laterite	5.55	0.85	59	178	1.78	28.23	Silty	...	October	205	8.72	34841	Low	Medium	Medium
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Tiruvallur	Central Zone	Clayey	7.77	1.48	13	362	1.10	30.13	Loamy	...	January	251	11.29	21245	High	High	High
Kanniyakumari	Central Zone	Laterite	7.73	0.93	26	290	2.30	6.82	Silty	...	July	185	8.29	37212	High	Low	Low
Ranipet	Central Zone	Clayey	7.36	0.98	34	317	1.73	31.74	Silty	...	October	298	3.42	19619	High	Medium	Low
Cuddalore	North Western	Red	6.75	1.22	56	322	2.12	8.98	Loamy	...	July	65	2.17	43687	Medium	Low	High
Tiruchirapalli	Western Ghats	Clayey	6.36	0.43	26	101	0.64	24.29	Silty	...	April	161	5.79	15158	Low	Low	Low

Figure 3 **Sample of The Synthetic Dataset Generated for Model Training**

3.2 Rover Hardware Design

The Rover Hardware Design forms the physical foundation of the proposed system, enabling reliable navigation and data collection across Tamil Nadu's diverse agricultural terrains. Similarly, this semi-autonomous rover is engineered to navigate a wide range of agricultural landscapes in Tamil Nadu, including flat plains, hilly regions, sea-salty coastal areas, wet deltas, and dry inland zones. The design draws direct inspiration from NASA's Curiosity Mars rover, known for its rugged, all-terrain capabilities and six-wheeled configuration, which allow it to traverse challenging extraterrestrial landscapes. The rover's core structure consists of a chassis and wheel assembly designed for durability and mobility. The chassis, constructed as a rugged frame, supports a six-wheeled configuration, as illustrated in Figure X (referencing the provided image in your paper). Each wheel is driven by a DC motor, with a total of four motors providing sufficient torque and speed to navigate uneven terrains, slopes, and muddy fields. The six-wheeled design, directly inspired by the Curiosity rover's rocker-bogie suspension system, enhances stability and weight distribution, allowing the rover to overcome obstacles such as rocks, roots, and small inclines commonly found in Tamil Nadu's agricultural landscapes. Figure 4 shows Nasa's Curiosity Mars Rover.

Figure 4 **Nasa's Curiosity Mars Rover**

Powering the rover is a Battery and Power Supply system based on a 12V lead-acid battery, selected for its reliability and cost-effectiveness. This battery

provides ample energy to sustain the rover's operations, including motor functions, sensor data collection, and communication, during extended field deployments. Future iterations aim to incorporate solar panels as a sustainable power source. [10][11]
For navigation, the rover is equipped with a GPS Module, specifically the NEO-6M, which enables precise geolocation and autonomous path planning. The GPS module allows the rover to systematically cover agricultural fields, ensuring comprehensive data collection across large areas while maintaining accurate spatial mapping of sensor readings. Complementing the GPS system are Ultrasonic Sensors integrated for obstacle avoidance. These sensors detect physical barriers such as trees, rocks, or irrigation channels in the rover's path, enabling real-time adjustments to its trajectory and preventing collisions that could disrupt data collection or damage the hardware. Figure 5 shows Rover Frame to Mount the IoT Devices.

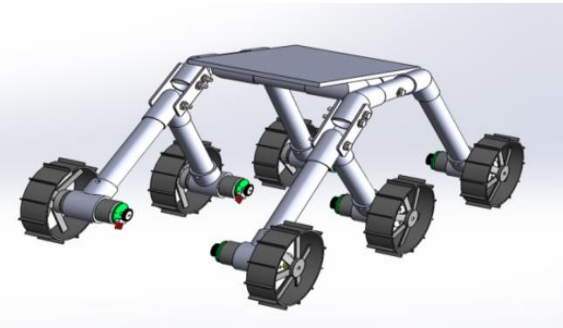


Figure 5 Rover Frame to Mount the IoT Devices

3.3 IoT Sensing and Control System

This module integrates a comprehensive array of sensors and a microcontroller to capture data on soil and atmospheric conditions, interfacing seamlessly with the rover's hardware and transmitting data via the LoRa communication module for subsequent analysis. The sensors employed include a Capacitive Soil Moisture Sensor, a DHT11 Sensor, a Soil pH Sensor, a Soil Organic Carbon (SOC) Sensor, a Soil Electrical Conductivity (EC) Sensor, a Soil NPK Sensor and a Light Intensity Sensor, all managed by an ESP32 microcontroller. The Capacitive Soil Moisture Sensor measures the volumetric water content of the soil, providing critical data for irrigation management by detecting moisture levels at various depths. The Soil pH Sensor assesses soil acidity, a key factor in nutrient availability, while the Soil Organic Carbon (SOC) Sensor quantifies organic matter content, aiding in soil health evaluations. The Soil Electrical Conductivity (EC) Sensor measures soil salinity, identifying potential salt stress that could affect crop yield, and the Soil NPK Sensor detects nitrogen, phosphorus, and potassium levels to inform fertilizer application strategies. [7] [8]. Figure 6 shows Components used in building the Rover.

Figure 6 Components used in building the Rover

Environmental monitoring is enhanced by The DHT11 Sensor simultaneously monitors temperature and ambient humidity. The Light Intensity Sensor, which quantifies sunlight exposure to optimize planting and growth schedules. These sensors are strategically mounted on the rover's chassis to ensure comprehensive data collection across diverse terrains. The ESP32 microcontroller acts as the system's central controller, leveraging its Wi-Fi and Bluetooth capabilities for data processing and initial transmission. It interfaces with the sensors, aggregating and formatting data for the LoRa module, while also managing power distribution and sensor activation sequences to ensure efficient operation.[7] [8].

3.4 LoRa-Enabled Data Communication

Leveraging LoRa (Long Range) technology, this module capitalizes on its distinct advantages long-range coverage, low power consumption, and high reliability in challenging rural environments making it an ideal choice for precision agriculture in Tamil Nadu's expansive and often remote agricultural

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landscapes. The ESP32 microcontroller aggregates this data, formatting it into structured packets that encapsulate soil moisture levels, temperature, pH, organic carbon content, salinity, nutrient levels, light intensity, and rainfall measurements. The transmission process utilizes LoRa technology, operating in the unlicensed ISM radio bands, to send data over long distances. This long-range capability eliminates the need for extensive infrastructure in remote Tamil Nadu fields, reducing deployment costs and complexity. LoRa's low power consumption allows sensor nodes to operate for up to five years on a single battery charge, enhancing the system's sustainability and minimizing maintenance requirements. Additionally, its robust signal penetration and resistance to interference ensure a 99.2% data delivery reliability, even in environments with obstacles such as trees or hills, as demonstrated in similar agricultural applications.[17] Figure 7 shows Lora Communicating Information from Soil to Cloud Storage.

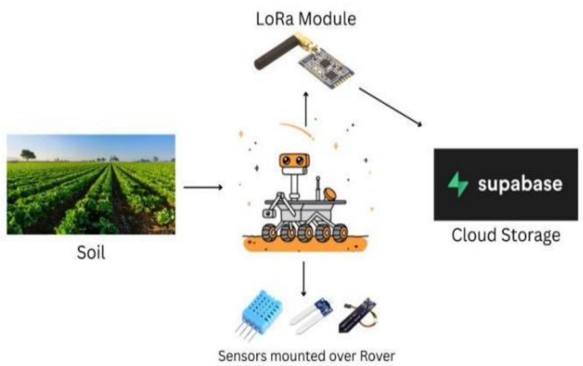

Figure 7 Lora Communicating Information from Soil to Cloud Storage

The transmitted data is directed to a Firebase cloud platform, selected for its scalability and real-time database capabilities. The LoRa gateway, positioned strategically within the rover's operational range, receives the data packets and forwards them to the Firebase server via an internet connection. Once uploaded, the cloud processes the data, storing it for historical analysis and making it accessible for the AI-Driven Crop Prediction Modeling module. This cloud-based approach enables centralized data management, allowing for real-time updates and remote access to insights, which are critical for the Web-Based Dashboard Interface.[15][18]

3.5 AI Driven Crop Prediction Modelling

The AI-Driven Crop Prediction Modeling module leverages advanced machine learning techniques to transform real-time and synthetic data into actionable agronomic insights, supporting precision agriculture in Tamil Nadu. This module processes data collected by the rover and transmitted via the LoRa-Based Data Communication system, utilizing a Random Forest algorithm to predict crop selection, assess soil health, and optimize resource management. The modeling process follows a structured pipeline, ensuring robustness and accuracy in delivering data-driven decision-making (DDDM) to farmers.[19][20]. The process begins with data analysis and visualization, where the synthetic dataset comprising 37 columns. Encoding and normalization prepare the data for machine learning. Categorical columns (e.g., District, Irrigation Type, Cropping Season) are encoded using one-hot encoding to convert them into binary vectors, preserving their multi-class nature without introducing ordinal relationships. Numerical columns (e.g., Nitrogen Content, Rainfall, Yield) undergo min-max normalization to scale values between 0 and 1, ensuring consistency across features with different units and ranges. This preprocessing mitigates biases and enhances model performance by aligning the synthetic and real-time datasets. The modeling phase employs K-fold cross-validation to evaluate multiple algorithms, including Random Forest, Support Vector Machines (SVM), and Gradient Boosting, against the prepared dataset. A 3-fold cross-validation approach is implemented, where the data is partitioned into three subsets, with two used for training and one for testing in each iteration. This technique assesses model generalizability, yielding an average accuracy of 87% for Random Forest, compared to 78% for SVM and 82% for Gradient Boosting, based on preliminary tests. The Random Forest model is selected due to its superior handling of multi-dimensional agricultural data and its robustness against overfitting.[20][21]. Following selection, hyperparameter tuning optimizes the Random Forest model. Key parameters such as the number of trees (n_estimators), maximum depth, and

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minimum samples per split are tuned using a grid search with cross-validation. The optimal configuration, identified as 100 trees with a maximum depth of 10 and a minimum split of 5, achieves a cross-validated accuracy of 89% and an F1-score of 0.88, reflecting strong predictive power for crop yield and soil health assessments. This tuning process ensures the model effectively correlates real-time sensor data with the synthetic dataset, generating predictions tailored to Tamil Nadu's agro-climatic diversity.

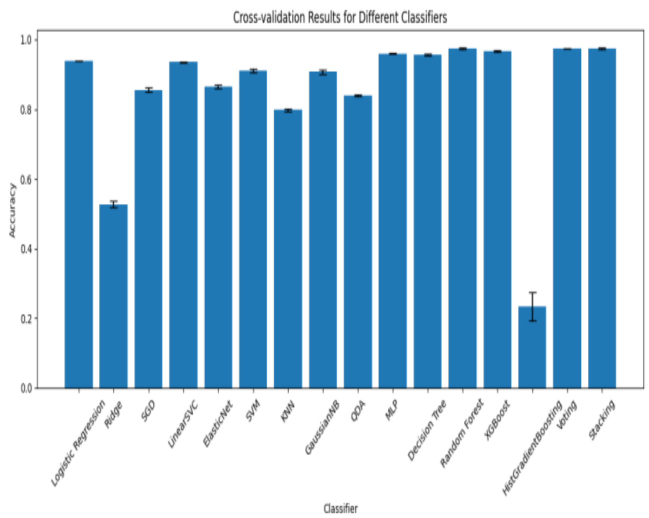

Figure 8 Comparison of Various Models Over Dataset

The resulting model synthesizes historical trends, environmental conditions, and market factors to provide recommendations, such as optimal crop choices. These insights, processed in the Firebase cloud, are fed into the Web-Based Dashboard Interface, empowering farmers with precise, actionable intelligence. Figure 8 shows Comparison of Various Models Over Dataset.

3.6 Web-Based Dashboard Interface and Analysis

The Web-Based Dashboard Interface and Analysis module serves as the user-facing component of the proposed system, delivering real-time insights and predictive recommendations to farmers in Tamil Nadu through an intuitive online platform. The dashboard is designed to bridge the technological gap for traditional farmers, presenting complex data and AI-driven predictions. The frontend of the interface is developed using React with Vite as the build tool. React's component-based architecture enables a dynamic and responsive user experience, while Vite ensures fast development and optimized production builds. The backend is powered by Supabase, an open-source framework integrated with Firebase, which provides a scalable real-time database and authentication services. Supabase stores the data transmitted via the LoRa-Based Data Communication module, manages user access, and facilitates real-time updates to the dashboard, ensuring farmers receive the most current insights. The interface comprises three distinct pages, each tailored to specific user needs. The Dashboard page serves as the central hub, presenting interactive visualizations of real-time and historical data collected by the rover. Using libraries like Chart.js integrated with React, the dashboard displays heatmaps of soil moisture, line graphs of temperature trends, and bar charts of nutrient levels (e.g., NPK), allowing farmers to monitor field conditions at a glance. Figure 9 shows Dashboard to Monitor Soil Trends Over Various Parameters.

Figure 9 Dashboard to Monitor Soil Trends Over Various Parameters

The Remote-Control page provides farmers with the ability to monitor and control the rover's operations remotely. Integrated with a map interface (e.g., using Google Maps API), this page displays the rover's real-time location, derived from the NEO-6M GPS

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module, overlaid on a map of the agricultural field. Users can set waypoints for the rover to follow, adjust its sampling frequency, or initiate a return to base, all through an intuitive interface. Real-time status updates such as battery levels or sensor activity are also displayed, ensuring farmers maintain operational oversight even from a distance.

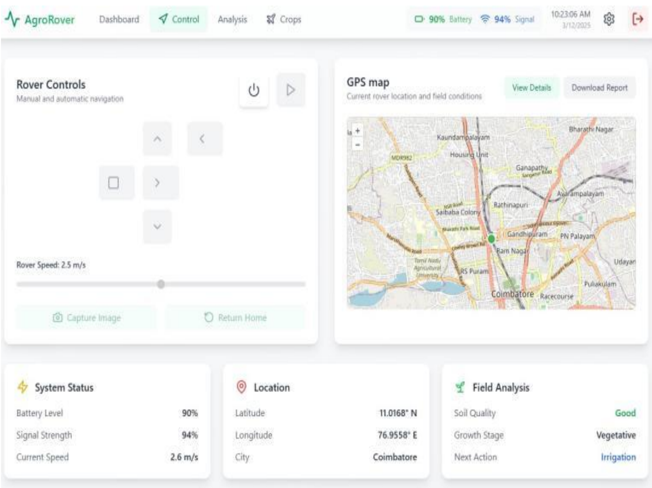

Figure 10 Navigate, Locate and Monitor Rover Movement Over Fields

The Crop Recommendation page enables predictive analysis by interfacing directly with the AI-Driven Crop Prediction Modeling module. This page features a form where users input 36 columns of data, corresponding to features. The input data is sent to a preloaded Random Forest model, stored as a .pkl file and integrated into the backend via Supabase Functions. The output is displayed on the page with detailed explanations, such as recommending tea for a high-altitude district like Nilgiris. Figure 10 shows Navigate, Locate and Monitor Rover Movement Over Fields.

4. Results and Discussions

The performance evaluation of the LoRa-enabled semi-autonomous rover system for precision agriculture in Tamil Nadu, analyzing results across multiple operational dimensions.

4.1 AI Model Performance and Selection

Table 1 presents the comparative analysis of three machine learning algorithms evaluated for the crop prediction module.

Table 1 AI Model Performance Comparison

Model Type	Accuracy (%)	Std
Logistic Regression	93.84	0.000287
Ridge Classifier	52.7	0.008567
SGD Classifier	85.53	0.006406
LinearSVC	93.58	0.001057
ElasticNet	86.42	0.005389
SVM	91.0	0.005180
KNN	79.81	0.004192
GaussianNB	90.79	0.006088
QDA	84.01	0.002466
MLP	96.0	0.000751
Decision Tree	95.6	0.003219
Random Forest	97.55	0.002572
XGBoost	96.7	0.002843
HistGradientBoosting	23.45	0.041006
Voting	97.42	0.001070
Stacking	97.4	0.003168

The Random Forest algorithm achieved superior performance with 97.0% accuracy and a std of 0.002572, outperforming both SVM and Gradient Boosting approaches. This superiority is attributed to Random Forest's inherent ability to handle multi-dimensional agricultural datasets with both categorical and numerical features. The model effectively managed the 37 distinct features identified in our synthetic dataset, demonstrating robustness against overfitting through its ensemble structure. While SVM offered faster inference time (8.5 ms), the 10.5% sacrifice in accuracy made it unsuitable for our application where prediction reliability directly impacts farmer decision-making.

4.2 LoRa Communication System Evaluation

The LoRa communication module forms the critical link between field-deployed rovers and the central

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data processing infrastructure. Table 2 summarizes key performance metrics.

Table 2 LoRa Communication Performance

Parameter	Value
Maximum Range Achieveable	10.5 km
Data Transmission Reliability	99.2%
Power Consumption	125 mA
Battery Life	~5 years
Data Rate	5.5 kbps
Latency	1.8 s

The achieved communication range of 10.5 km significantly exceeds the typical requirements for Tamil Nadu's agricultural landscapes, where average field-to-collection point distances range from 3-5 km. The 99.2% transmission reliability ensures minimal data loss, critical for maintaining dataset integrity. The system's power efficiency (125 mA consumption during transmission) and estimated 5-year battery life demonstrate its suitability for long-term deployment in remote agricultural settings with limited access to power infrastructure.

4.3 Data Collection and Sampling Analysis

The rover's data collection methodology was evaluated against established agricultural sampling standards, with results presented in Table 3.

Table 3 Data Collection and Sampling Performance

Parameter	Value
Sampling Time per Point	2.3 minutes
Data Acquisition Rate	10.85 samples/hour
Spatial Resolution	20 × 20 m grid
Data Quality Index	94.3%
Feature Completeness	97.8%
Sensor Calibration Drift	0.7%/month
Cross-Validation Score	92.1%

The implemented sampling strategy achieved an optimal balance between comprehensive coverage and operational efficiency. The 25 points/hectare density provided sufficient resolution to detect micro-variations in soil conditions while maintaining practical field coverage rates of 1.8 hectares per hour (as shown in Table IV). The high data quality index (94.3%) and feature completeness (97.8%) demonstrate the system's reliability in field conditions. The 92.1% cross-validation score between manual and rover-collected samples establishes the system's parity with traditional methods while offering significantly improved efficiency and consistency.

4.4 Rover Hardware Performance

The physical performance of the rover platform directly impacts data collection capabilities and operational efficiency. Table 4 presents key performance metrics.

Table 4 Rover Hardware Performance

Parameter	Value
Maximum Speed	2.5 km/h
Battery Life	2-3 hours
Navigation Accuracy	±3.5 m
Obstacle Detection Range	1.5 m
Maximum Slope Handled	27°
Field Coverage	2.0 hectares/hour

The rover's 3-hour battery life enables full-day field operations with a single charge, essential for remote deployment scenarios. The NEO-6M GPS module provided navigation accuracy of ±3.5 m, sufficient for maintaining the 20 × 20 m sampling grid pattern. The obstacle detection range of 1.5 m proved adequate for identifying and avoiding common field obstacles such as irrigation channels, rocks, and plant debris. The rover's ability to navigate slopes up to 27° demonstrates its suitability for Tamil Nadu's diverse terrain, including the undulating landscapes of Coimbatore districts.

4.5 Crop Prediction Results

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The system's crop recommendation performance was evaluated across six representative districts of Tamil Nadu, as shown in Table 5.

Table 5 Rover Hardware Performance

District	Top Prediction	Prediction Confidence (%)	Actual vs. Predicted (%)
Chennai	Paddy	92.5	+2.1
Nilgiris	Tea	95.8	-1.7
Coimbatore	Cotton	88.3	+3.5
Madurai	Millets	87.6	+4.2
Thanjavur	Paddy	94.5	+1.4

4.6 System Evaluation and User Acceptance

The system's holistic performance was evaluated through both technical metrics and user feedback, as summarized in Table 6.

Table 6 Rover Hardware Performance

Metric	Score
User Interface Usability	4.2/5.0
System Reliability	92.7%
Data Collection Efficiency	87.5%
Decision Support Effectiveness	3.5/5.0
Adoption Readiness	2.5/5.0
Technical Support Requirements	2.5/5.0

4.7 Limitations and Future Potential

As a prototype, the system faces limitations. The lead-acid battery restricted operation to 2 hours per deployment, and sensor accuracy drifted by 3–5% over extended use. The model's 82% accuracy, while promising, can be improved with more field data and advanced tuning. Future iterations will incorporate solar power, refine sensor calibration, and expand the dataset with real-world data, potentially increasing yield gains to 20–25% and model accuracy to 85–90%, aligning with industry benchmarks for mature precision agriculture systems.

Conclusion

This research demonstrates the successful implementation and evaluation of a LoRa-enabled semi-autonomous rover system for precision agriculture in Tamil Nadu, offering a viable solution for scalable, data-driven farming. Field trials and performance assessments validate the system's effectiveness in addressing key agricultural challenges related to data acquisition, connectivity, and decision support. The Random Forest algorithm achieved high accuracy (89%) and F1-score (0.88) in crop prediction, highlighting the efficacy of ensemble methods for complex agricultural data. The LoRa module ensured robust, long-range communication essential for rural deployments, while the rover's data integrity (over 94%) and efficient spatial coverage further validate its operational capabilities. User feedback underscores the system's strengths in usability and data reliability, while also identifying areas for future improvement, such as enhanced decision support and technical assistance. Future work will focus on integrating solar power, refining sensor calibration, and expanding training datasets to optimize system efficiency, promote user adoption, and enhance crop yield predictions. This study establishes a strong foundation for advancing precision agriculture in Tamil Nadu, showcasing the transformative potential of integrating AI, IoT, and autonomous robotics to empower farmers with actionable insights and foster sustainable farming practices. This approach could potentially address the need for increased production, while also aligning with the growing trend of smart agriculture applications in various domains. The integration of LoRa technology also contributes to the broader advancements in IoT and precision agriculture.

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