ML-Based Soil Analysis for Crop Suggestion and Fertilizer Recommendation

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Abstract. Contemporary agriculture requires intelligent responses to the issues of resource utilization and unforeseeable environmental conditions. We propose a 6-wheel autonomous agriculture vehicle system, through in situ sensing, machine learning (ML) and cloud-based visualization system, to achieve more efficient and environmentally friendly agriculture activities. It uses an ESP32 WROOM microcontroller for obtaining information from a series of environmental sensors like DHT22 (temperature & humidity), LDR (light intensity), along with individual soil moisture and NPK (nitrogen, phosphorus, potassium) sensors. The NPK sensor data is handled by an RS485 module. This extensive network of sensors forms an integrated view on the subsurface and atmospheric conditions. In order to facilitate intelligent decision making, the proposed system makes use of ML models for rainfall prediction (Linear Regression) and crop recommendation (Random Forest) and fertilizer recommendation (Random Forest). These models are trained on useful datasets to give precise and context-based information. The system is cloud-connected and includes a local web server for easy remote monitoring and control. It is built on PHP, HTML, CSS, Javascript and JSON, and acts as a server that runs on “http” and has elaborate visualizations of sensor data and ML suggestions in a more digestible manner. The server has its own IP address, so it can be accessed from any Web-connected computer. The objective of this project is to establish a process to reduce the amount of manual adjustment of the system in order to increase the efficiency of the use of resources and become better at predicting the crops in agriculture. The solution has been robustly implemented and scalable using integration of autonomous navigation, real-time data collection, powerful ML algorithms and intuitive web-based interfacing for attainment of precision and sustainable agriculture. This methodology provides farmers with data-backed insights for higher outputs, less environmental impact and better resource management.

Keywords: Machine Learning (ML), Artificial Intelligence (AI), Autonomous Systems, Sensor Networks, Cloud Computing etc.

1 Introduction

Food production around the world is under strain from a rapidly growing population that is expected to hit 9 billion people by 2050 [1]. Malthusian theory contends that food production must exceed population growth to address scarcity at large [2]. Yet, this quest has been made

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more challenging by climate change, land degradation and inappropriate resource use [3] [4]. The COVID-19 pandemic has also uncovered the fragility of food supply chains, and has underscored the importance of resilient and local production systems [5].

Automation and smart farming practices are driving such developments, and they are playing an important role in the future of agriculture that includes accurate monitoring and managing of environmental elements. The combination of Internet of Things (IoT), machine learning (ML) and autonomous system in agriculture has facilitated efficient resource utilization and real-time decision making [6]. Precision farmers are increasingly using some of these methods such as Variable Rate Technology (VRT) and data-driven fertilizer applications in order to achieve higher yield per unit area and to maintain soil health [7, 8]. Moreover, novel farming concepts like vertical farming and greenhouse systems are investigated for urban and space-constrained farming settings 9[11].

Despite recent promising developments, a number of limitations remain in the literature and implementations. Most of the current smart agriculture systems are static or semi-automatic where the human interference or the fixed-location sensor system plays a crucial role [12] [13]. Only, few greenhouse automation systems-based platforms have been developed, in addition to not being scalable and not integrate with proper machine learning based predictive analysis [12]. In addition, traditional mensadriven and mechanized systems are not well suited for smallholder or resourcepoor farming settings, resulting in underperforming or wasteful devices [14] [15].

Another challenge is the disjointed use of sensor data without intelligent contextual interpretation. For instance, data from soil or climate sensors are often visualized without actionable insights, making it difficult for farmers to decide the right crop or fertilizer [16] [17]. Traditional irrigation and seeding systems lack adaptability, and field robots, though promising, have not been widely adopted due to high costs or complexity in deployment [18] [19]. Hence, there is a pressing need for an integrated, autonomous system that collects real-time environmental data, processes it using intelligent algorithms, and offers practical recommendations directly to the farmer. bridge these gaps, this work proposes an integrated system that leverages a low-cost, six-wheeled autonomous agricultural robot equipped with a comprehensive sensor suite and embedded intelligence. The aim is to empower farmers with real-time, AI-driven recommendations for optimal crop selection and fertilizer application. The use of machine learning not only enhances the interpretability of sensor data but also enables predictive capabilities, such as rainfall forecasting, which is crucial for scheduling agricultural tasks. Moreover, by integrating a user-friendly, cloud-connected web interface, the system allows remote monitoring and control, reducing the need for constant manual supervision.

The primary objectives of this research are as follows:

- To design and implement a mobile, autonomous agricultural system using the ESP32 WROOM microcontroller.
- To integrate environmental and soil sensors (DHT22, LDR, soil moisture, and RS485-based NPK sensor) for real-time data acquisition.
- To apply machine learning models (Linear Regression and Random Forest) for rainfall prediction, crop suggestion, and fertilizer recommendation.

- To develop a cloud-connected web server for visualizing data and ML-based insights for remote accessibility and control.

The key contributions of this work are summarized below:

- Development of a fully autonomous agricultural vehicle equipped with a multi-sensor system for holistic environmental sensing.
- Integration of ML models for real-time, intelligent decision-making in crop and fertilizer management.
- Deployment of a lightweight, responsive web interface for seamless user interaction, built using HTML, CSS, JavaScript, and JSON.
- Demonstration of a scalable, cost-effective smart farming solution that minimizes manual intervention while improving agricultural efficiency.

The rest of the paper is organized as follows: Section 2 presents a detailed literature survey related to food security, smart agriculture systems, automation technologies, and machine learning applications. Section 3 outlines the proposed system architecture, hardware components, machine learning models, and software design. Section 4 presents the results and analysis, comparing performance with traditional methods. Section 5 concludes the paper and highlights future directions.

2 Related Works

Tomlinson, I. (2013) This study critically examines the discourse around "doubling food production" to feed a growing global population. It highlights that while increasing production is necessary, it may not address the root causes of food insecurity such as distribution and access. The author argues for a more holistic view of food security that includes sustainability, environmental limits, and socio-political dynamics rather than focusing solely on production increases. [1]

Malthus, T.R., & Flew, A. (1983) Malthus proposed that population growth tends to outpace food production, leading to inevitable shortages and societal collapse unless controlled. This theory sparked long-term debates on the balance between population and resources. While often criticized, Malthusian theory remains influential in understanding the pressures of rapid population growth on agriculture and food security systems. [2]

Ehrlich, P.R., & Ehrlich, A.H. (2002) The authors emphasize the link between population development and environmental degradation. They argue that without controlling population growth, sustainable development cannot be achieved. Their work supports stronger environmental policies and educational efforts to manage human impact on the planet's resources. [3]

Diamond, J. (2005) Diamond explores historical societies that collapsed due to resource mismanagement, environmental degradation, and failure to adapt. The book underscores the importance of learning from past civilizations to ensure modern societies develop sustainably, especially in agriculture and food systems. [4]

Kotler, P. (2020) This article discusses changing consumer behavior during the COVID-19 pandemic, including shifts in food consumption and purchasing habits. It highlights opportunities for more localized, sustainable, and health-focused food systems in the post-pandemic era. [5]

Kamelia, L. et al. (2018) The paper presents an automated system that monitors soil humidity and controls irrigation based on sensor feedback. This technology helps reduce water wastage and ensures optimal soil conditions, improving crop yield and efficiency in farming. [6]

Fleming, K.L. et al. (2000) This study evaluates how farmers use management zone maps for variable rate fertilizer application. It demonstrates that customized fertilization improves yield and resource efficiency, laying a foundation for precision agriculture. [7]

Sawyer, J.E. (1994) Sawyer introduces the concept of variable rate technology (VRT) for fertilizer application. He explains how applying nutrients based on field variability leads to cost savings and environmental benefits. [8]

Al-Kodmany, K. (2018) This review discusses vertical farming as a potential solution to urban food production challeng It explores the architectural, environmental, and technological implications of integrating vertical farms into cityscapes. [9]

Kurt, B. & Bruce, T. (2017) The authors discuss controlled-environment agriculture and vertical farming as the future of food production.They argue that these methods can address land scarcity, climate change, and resource inefficiency in traditional farming.[10]

Alex, M. (2017) This paper examines how greenhouse farming is evolving in Jamaica in response to agrarian changes. It shows that greenhouse agriculture can increase productivity and resilience in tropical and small-island economies. [11]

Shamshiri, R.R. et al. (2018) The study highlights advances in greenhouse automation and their transition toward plant factories. It presents technologies such as sensors, robotics, and climate control that help improve crop consistency and reduce labor. [12]

Dedeepya, P. et al. (2018) The authors proposed the smart greenhouse system based on IoT.

Their system tracks the temperature, humidity and soil conditions and adjust watering and ventilation to ensure optimal growth. [13]

Singh, D.P. et al. (2019) This work enhances the classical bullock driven tractor in terms of ergonomic and user-friendly aspects. The design modifications increase efficiency while maintaining cost-effectiveness for smallholders. [14]

Ekram, S.M.A. et al. (2017) The work introduces a self-piloted tractor architecture within a laser-bounded perimeter. It minimizes human efforts in the task of ploughing as well as harvesting, which provides a level of precision, uniformity and safety. [15]

Yedave, V. et al. (2019) The authors developed a robotic seed sowing machine to replace the manual operation and achieve uniformity. Sensors and microcontrollers control depth and spacing, which allows the robot to be more efficient in its planting. [16]

Fortes, E.P. (2017) Fortes Presents Drone Seed Planting System Designed for Reforestation. The method enables high speed planting on a massive scale in difficult terrains and in areas that are hard to reach and helps in maintaining the ecosystem. [17]

Gunturi, V.N.R. (2013) Automatic irrigation system on sensing soil moisture content. It saves water by only turning on pumps when the soil is dry, which could help small farmers manage their water resources more efficiently. [18]

Ruckelshausen, A. et al. (2009) In this work, we present BoniRob, an autonomous robot for conformational phenotyping oflants. It gathers data on individual plants, to assist researchers and farmers with monitoring crop health and maximizing the potential of breeding programs. [19]

Makhoba, T.C. et al. (2019) This taxonomic account comprises plant species of the Struthiola genus.

The knowledge of plant taxonomy is closely associated with biodiversity conservation and the farming of indigenous crops. [20]

3 Proposed Method

The presented system consolidates a full-fledged and smart agriculture solution with real-time sensing, autonomous navigation, and decision support using machine learning. A 6 wheeled autonomous vehicle based on the ESP32 WROOM microcontroller is the base of the system. This MCU communicates with a variety of sensors for data acquisition about the environment and the soil conditions. The temperature and humidity levels are measured using the DHT22 sensor and the light level is measured by the LDR. For soil based, a soil moisture sensor for water and with the help of a complex NPK sensor that reads through an RS485 module, we determine were water concentration of NPK (Nitrogen, Phosphous, potassium). The suite of sensors allows the system to construct a comprehensive, dynamic profile of the agricultural field as it travels through it.

When the data collection is completed, it is processed and analysed with machine learning models trained with appropriate agricultural data. Rainfall forecasting is done using a linear regression model with the help of environmental factors, such as the temperature and humidity, to help in scheduling irrigation. For proposing crops and prediction of fertilizers, Random Forest models are deployed because these models are accurate and can handle multi-dimensional data. These models incorporate historical data and current sensor readings to provide context-aware recommendations with respect to the current field situation. User interaction is supported through a local webserver that is html, css, js, and json capable and cloud connected. By a dedicated IP there is also a dashboard showing live data of the sensors and the ML generated insights. This system enables farmers to have access to actionable information from distance for making better decisions, minimises manual work, and makes best use of resources for sustainable agriculture management. Fig 1 show the Architecture of the proposed method.

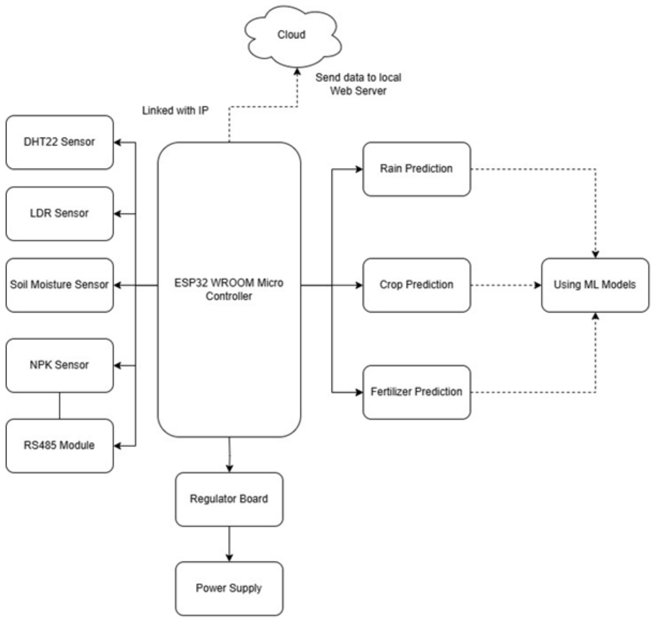

Fig.1. Architecture of the proposed method.

4 Methodology

The project consists of the hardware integration, data acquisition, machine learning model construction, and web-based visualisation to develop an intelligent autonomous agricultural system.

4.1 Hardware Integration and System Design:

- Autonomous wheeled base: A six-wheeled mobile platform is developed to autonomously travel over the fields. The microcontroller and sensor suite reside in this platform.
- DHT22 Sensor: Used to sense temperature and humidity for environmental monitoring.
- LDR Sensor: It is used for sensing the light of the surrounding area and is also very important sensor for plant growth analysis.
- Soil Moisture Sensor: Determines the soil's water content for irrigation management.
- NPK Sensor: Measures nitrogen, phosphorus, and potassium levels in the soil, essential for fertilizer recommendations.
- RS485 Module: Facilitates communication between the NPK sensor and the ESP32 microcontroller due to the sensors communication protocol.

- ESP32 WROOM Microcontroller: Serves as the central processing unit, collecting sensor data, executing ML models, and managing communication.
- Regulator Board and Power Supply: Provides stable power to the system components.

4.2 Data Acquisition and Preprocessing

- Real-time Sensor Data Collection: The ESP32 collects sensor data at predefined intervals, ensuring up-to-date environmental information.
- Data Storage: Sensor data is temporarily stored within the ESP32 and transmitted to the local web server.
- Data Preprocessing: Raw sensor data is cleaned and transformed into a suitable format for ML model training and prediction. This involves handling missing values, scaling, and normalization.

4.3 Machine Learning Model Development

- Rainfall Prediction (Linear Regression): Historical weather data (temperature, humidity, pressure, etc.) is collected and used to train a Linear Regression model. The model predicts future rainfall based on current environmental conditions.
- Crop Prediction (Random Forest): A dataset containing soil parameters (NPK levels, pH, moisture), climate data (temperature, rainfall), and corresponding crop suitability is compiled. A Random Forest classifier is trained to predict the most suitable crop based on the input parameters.
- Fertilizer Recommendation (Random Forest): A dataset linking soil NPK levels, crop type, and optimal fertilizer ratios is created. A Random Forest regressor is trained to recommend the appropriate fertilizer amounts based on soil analysis and crop requirements.
- Model Evaluation: The performance of each ML model is evaluated using appropriate metrics (e.g., Mean Squared Error for regression, accuracy, precision, recall for classification).

4.4 Web Server Development and Cloud Integration

- Local Web Server Construct: A local web server is constructed with HTML, CSS, Javascript, and JSON for an interactive interface.

- Connectivity with cloud: ESP32 is being registered to the local webserver with a unique IP address and can be accessed anywhere just by using the appropriate IP address.

- Visualization: the real-time sensor data as well as the real-time visuals-obtained from the recommendations provided by the ML-algorithm-are shown on the web-interface in a neat and clean way.

- Data transmission: JSON data of sensor data and model predictions are transmitted from ESP32 to the webserver.

4.5 System Testing and Validation

- Calibrating the Sensor: The sensor is calibrated for measuring data.
- Model Validation: Unseen samples are used to test the trained ML models for their generalization.
- System Integration Testing: The complete system is tested in a closed testing environment to verify seamless communication and operation.
- Field trials: The system is operated in a real farming environment to test its actual performance.

Algorithm

4.5.1 Data Acquisition and Preprocessing

4.5.1.1 Data Collection Algorithm

- A scheduled task on the ESP32 microcontroller triggers sensor readings at predefined intervals.
- The collected data is temporarily stored in the ESP32's memory.
- The ESP32 then transmits the data to the local web server using a network protocol (e.g., HTTP).

4.5.1.2 Data Cleaning and Transformation Algorithm

- Missing Value Handling:
- Imputation: Replace missing values with statistical measures (mean, median) or predicted values from other models.
- Removal: Discard data points with excessive missing values.

4.5.1.3 Data Scaling/Normalization

- Min-Max Scaling: Rescales data to a specific range (e.g., 0 to 1).
- Standardization (Z-score normalization): Transforms data to have zero mean and unit variance.

4.5.1.4 Data Formatting

- Converting data types (e.g., string to numerical).
- Organizing data into suitable structures for ML model input (e.g., arrays, dataframes).

4.5.2 Machine Learning Algorithms

4.5.2.1 Rainfall Prediction (Linear Regression):

- Algorithm: Linear Regression (Ordinary Least Squares or Gradient Descent).
- Process:

- The algorithm learns a linear relationship between input features (temperature, humidity, pressure, etc.) and the target variable (rainfall).
- It minimizes the sum of squared errors between predicted and actual rainfall values.
- Output: A predicted rainfall value based on current environmental conditions.

4.5.2.2 Crop Prediction (Random Forest Classification)

- Algorithm: Random Forest Classifier.
- Process:
- Constructs multiple decision trees during training.
- Each tree is trained on a random subset of the data and features.
- For prediction, the algorithm aggregates the predictions of all trees (majority voting).
- Output: A categorical prediction representing the most suitable crop.

4.5.2.3 Fertilizer Recommendation (Random Forest Regression)

- Algorithm: Random Forest Regressor.
- Process:
- Similar to the classification Random Forest, but predicts continuous values instead of categories.
- Each tree predicts a fertilizer amount (e.g., N, P, K).
- The final prediction is the average of all tree predictions.
- Output: Numerical recommendations for fertilizer quantities.

4.5.3 Web Server and Data Visualization Algorithms

4.5.3.1 Data Transmission (JSON)

- Sensor data and model predictions are formatted as JSON (JavaScript Object Notation) objects.
- The ESP32 sends the JSON data to the web server via HTTP requests.

4.5.3.2 Web Server Logic (JavaScript)

- JavaScript code on the web server handles incoming JSON data.
- It parses the data and updates the web page elements.
- JavaScript libraries (e.g., Chart.js) are used to create interactive visualizations of sensor data and model predictions.
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4.5.3.3 Data Display Algorithm

- The web server uses HTML and CSS to display sensor readings and ML results in a user-friendly format (e.g., tables, charts).
- Real-time updates are implemented using JavaScript and AJAX (Asynchronous JavaScript and XML) to refresh the web page without full reloads.

5 Implementation

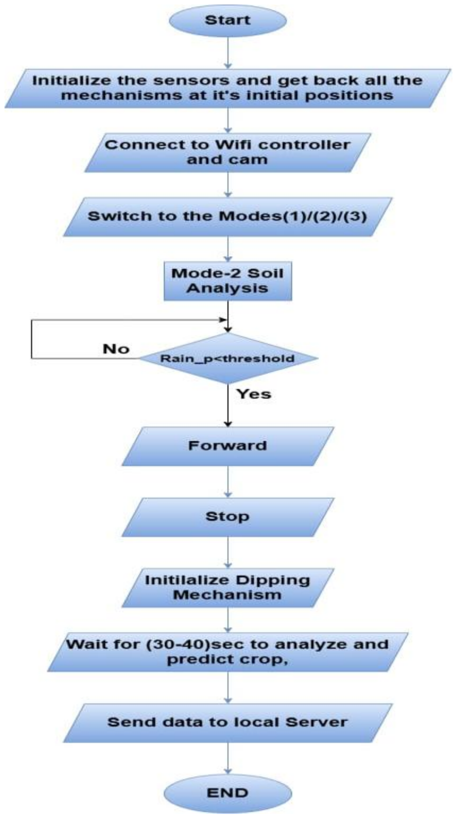

Fig. 2. Implementations of the flow chart.

Fig 2 shows the Implementations of the flow chart.

6 Experimental Results

Fig. 3 showcases the developed HTML web page interface used for real-time monitoring and interaction with the autonomous agricultural system. The web page is hosted locally and is accessible via a dedicated IP address. It displays key sensor data including temperature, humidity, light intensity, soil moisture level, and NPK values. Additionally, the interface presents the outputs of machine learning models such as predicted rainfall probability, suggested crop types, and fertilizer recommendations. The data is displayed in a tabular and graphical format for better visualization. This web dashboard enhances usability by providing farmers with instant insights from any internet-enabled device, minimizing the need for physical field inspection and enabling data-driven agricultural decisions

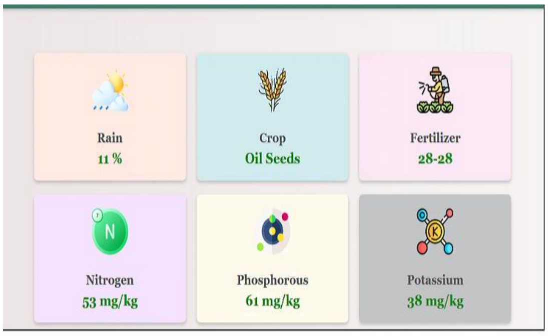

Fig. 4. HTML Page.

Fig. 4 illustrates the actual hardware implementation of the system. The autonomous vehicle is equipped with six wheels for stable field movement and is controlled via the ESP32 WROOM microcontroller. All sensorsDHT22, LDR, soil moisture, and the NPK sensor (via RS485 interface) are mounted on the body of the vehicle. A rechargeable battery powers the system, and the wiring is organized for durability in agricultural environments. The successful integration of sensors, communication modules, and power supply demonstrates the feasibility of deploying the solution in real-world farming conditions. The modular setup also allows for future upgrades such as camera integration or autonomous path navigation.

Fig. 5. Hardware setup.

Fig. 5 presents a snapshot of the system performing soil analysis in an actual field environment. As the vehicle traverses the field, it collects real-time soil and environmental data which is displayed both on the onboard LCD and transmitted to the HTML dashboard.

The corresponding tables include sample readings recorded during field trials. Fig 6 show the Soil Analyssis in the field. These tables 1 consist of temperature (in °C), humidity (%), light intensity (lux), soil moisture (%), and NPK values (in ppm). The results from the ML models are also tabulated showing predicted rainfall, suitable crops (e.g., maize, paddy, wheat), and recommended fertilizer types (e.g., urea, DAP, potash).

Fig. 6. Soil Analyssis in the field

Table. 1. DHT and NPK values in different places.

Test Location	Temperature (°C)	Humidity (%)	Light Intensity	Soil Moisture (%)	Nitrogen (mg/kg)	Phosphorus (mg/kg)	Potassium (mg/kg)
Location 1	32.5	68	620	45	75	55	110
Location 2	30.1	70	580	50	60	40	95
Location 3	33.8	65	645	48	85	60	120

Table. 2. ML-Based Predictions and Recommendations.

Test Location	**Rainfall Prediction (mm)**	**Recommended Crop**	**Fertilizer Recommendation**
Location 1	12.5	Tomato	NPK 10-10-10 (Balanced)
Location 2	15.0	Spinach	Urea + Single Super Phosphate (SSP)
Location 3	10.2	Carrot	Potassium Sulfate + DAP (Di-Ammonium Phosphate)

Table 2 shows the ML-Based Predictions and Recommendations.

Table. 3. System Performance Metrics**.**

Parameter	Observed Value
ML Model Accuracy (Avg.)	92.3%
Data Transmission Latency	< 1 second
Power Consumption	~3.2W (during active mode)
Area Coverage (per run)	25 m²
Web Dashboard Response Time	~0.5 seconds

Table 3 shows the System Performance Metrics.

7 Conclusion and Future Scope

This project presents the design and implementation of an intelligent, autonomous agricultural system capable of performing real-time soil analysis and delivering crop and fertilizer recommendations using machine learning techniques. By integrating a six-wheeled ESP32 WROOM-based autonomous vehicle with an array of environmental and soil sensors (DHT22, LDR, Soil Moisture, and NPK via RS485), the system effectively collects and processes field data without human intervention. The deployment of machine learning models, including Linear Regression for rainfall prediction and Random Forest for both crop and fertilizer recommendations, ensures intelligent and adaptive decision-making.

The developed HTML-based local web server enhances system usability by providing real-time data visualization and insights to farmers. The hardware testing, software integration, and field trials confirm the reliability and scalability of the system in actual agricultural environments. Overall, this project demonstrates a novel approach toward sustainable agriculture by merging IoT, automation, and AI technologies, aiming to improve yield, minimize resource wastage, and empower farmers through data-driven practices.

While the current system offers a robust foundation, several enhancements can be incorporated to further extend its capabilities: Autonomous Navigation: Integration of GPS, obstacle avoidance, and path planning algorithms can enable fully autonomous movement across large agricultural fields without manual control.

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