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Collaborative Human in the Loop Robotics Framework for Precision Agriculture and Crop Monitoring

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Abstract

This paper presents a Collaborative Human-in-the-Loop (HITL) Robotics Framework of precision agriculture and crop monitoring, which tries to bring together the benefits of human decision-making and robotic efficiency. The HITL framework is developed to overcome the drawbacks of the conventional autonomous systems, where real-time human input is included to enhance flexibility, precision, and adaptability to the dynamic agricultural conditions. The technology uses autonomous robots having sensors, like RGB cameras, thermal sensors, and soil moisture sensors, to check the state of crops, pest infestation, and irrigation. The data gathered is processed by AI algorithms, and human operators are involved when complicated decisions are required, giving feedback to guide robots. Early experiments of the framework in actual farm environments demonstrated good performance with an accuracy of crop yield prediction of 92 %, pest detection of 89 %, and water use efficiency of 94 %, which were much better than the conservativeness of robotic systems used traditionally. The HITL framework also displayed the balance between autonomy and human competency by low frequency of human interventions (10% of the tasks) and high effectiveness of interventions (80%). The results also show how HITL framework can improve precision farming by enhancing the accuracy of crop monitoring, reducing the waste of resources, and increasing the productivity. The flexibility of the system to fluctuating environments renders it a useful resource to the contemporary agriculture industry. Future studies have the potential to investigate more sophisticated AI solutions like deep learning to make decisions in real-time and evaluate how the framework may be scaled to different agricultural areas and crops.

Keywords: Human-in-the-Loop Robotics, Precision Agriculture, Crop Monitoring, Autonomous Systems, Pest Detection, Irrigation Optimization, AI and Machine Learning.

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Introduction

Precision agriculture is a new approach that involves the implementation of the latest technologies, i.e., GPS, IoT, drones, and robotics, to streamline farming processes, maximize yields, and reduce waste (Deka et al., 2024; Nair et al., 2019). It is a method of controlling field variability with the help of data to enable farmers to monitor the health of their plants, soil conditions, and irrigation requirements in real-time. Precision agriculture provides interventions and informed decisions in a timely manner through constant monitoring, which in the end enhances productivity, sustainability, and efficient use of resources (Adamides & Edan, 2023).

HITL improves accuracy in agricultural activities through its ability to provide a smooth coordination between human operators and robot autonomous systems (Comai et al., 2024). Although autonomous robots can be used to perform repetitive responsibilities such as collecting information or watering lawns, HITL systems combine human cognition to deal with more complicated situations (Agelli et al., 2024). These systems enable humans to control robots in dynamic, uncertain, and unpredictable settings that are characteristic of agriculture, e.g., pest outbreaks or the changing weather patterns. Human input provides more flexibility and adaptability in decision-making, which eventually results in the efficiency of crop monitoring and the overall system performance (Narayanan & Rajan, 2024).

The proposed study presents a human-in-the-loop robotics model that will be used to optimize precision agriculture, especially in crop monitoring (Benos et al., 2023; Berger et al., 2023). Automated robotics with human insight can improve agriculture performance by predicting yields, spotting pests, and controlling irrigation. The goal of this research is to demonstrate how human and robotic workforce integration can enhance the crop monitoring process and improve sustainability and decision making in agriculture.

Optimizing monitoring crops and farming is still a major concern for sustainable agriculture (Vinod Chandra et al., 2024). The challenges with dynamically changing settings limit the full potential of autonomous robotic systems. Precision agriculture robotics have been designed to improve crop monitoring. The collaborative approach aims to improve problem solving by integrating human reasoning and decision-making for a more accurate and precise crop monitoring process.

Key Contribution

- The collaborative paper suggests using a Human-in-the-Loop (HITL) framework for decision-making in agriculture under uncertainty by combining human knowledge and autonomous robotics.
- The HITL system improves crop health monitoring, pest detection, and irrigation management, making them more precise and efficient.
- The framework outperformed traditional field robotics in crop yield forecasting, pest detection, and water usage efficiency with less operator control.

The paper is organized as follows: Section 1 introduces precision agriculture challenges and suggests the Collaborative Human-in-the-Loop (HITL) Robotics Framework as a solution. Section 2 is the Literature Review, where the advantages of human input and present-day robotic systems are discussed. Section 3 is the Methodology, where the elements of framework construction are presented, including the components of data collection, AI processing, and human input. Section 4: The HITL framework is compared with traditional robotic systems in real-world tests to determine its performance. Section 5 discusses the framework's impact on agricultural practices in terms of effectiveness, adaptability, and practical use. Section 6 concludes the paper by summarizing the results and suggesting some potential opportunities for further research.

Literature Review

Current robotics systems in the agricultural industry are mainly on autonomous robots like drones and autonomous tractors (Pietrantoni et al., 2024). Such systems are popular in the application of tasks such as soil mapping, pest detection, and crop spraying. They have advanced sensors and AI algorithms that are capable of collecting and analyzing a lot of information on crops. Their performance is, however, limited in most instances with regard to dynamic environmental conditions, which include changes in weather conditions or pest outbreaks, where human intervention is required. These systems have inadequate adaptation to complex and quickly evolving situations on the farm, as there is no real-time human input.

Human-in-the-Loop robotics (HITL) has a number of advantages when applied in agricultural systems (Sreeram & Nof, 2021). To begin with, HITL systems are more flexible since robots have the ability to introduce repetitive tasks, and humans intervene when dealing with more complicated decision-making challenges (Dusadeerungsikul & Nof,

2021). There is also increased efficiency since the coordination between humans and machines is optimized by the HITL systems in which robots execute routine tasks and human beings make strategic interventions (Pal et al., 2024). HITL systems provide the man in the middle with a degree of flexibility, which in turn enables him or her to modify the behavior of the robots based on any unforeseeable agricultural conditions, like pests or the level of soil moisture (Ajidarma & Nof, 2021). Besides, human knowledge in highly sensitive activities such as detecting pests or checking the health of crops enhances the performance of the system, hence leading to better crop monitoring and control (Aldosari, 2024).

Even though precision agriculture holds the potential, a number of obstacles that make the implementation of the system difficult still exist (Holzinger et al., 2024; Abdulsalam & Aouf, 2023). The lack of human interaction in most autonomous systems is one of the major limitations because such systems can be autonomous and may not require real-time human interaction (Tsolakis & Gasteratos, 2022). This makes them less effective in dealing with unexpected problems. Another significant obstacle is the cost of deployment because the preliminary cost of the robotic systems and sophisticated sensors may be high (Aivazidou & Tsolakis, 2023). Also, the adoption of new robotics systems by the existing farming operations has been a major setback, and it would need considerable changes in infrastructure and agricultural operations.

The literature points out that at the moment, existing autonomous robotics systems have valuable advantages to provide in the agricultural sector; however, they cannot be flexible and adaptable to work in dynamic conditions. The solution to these gaps is through using HITL systems that are based on integrating human expertise with autonomous technology; this is what the current research study will be about. This paper will improve the efficiency and accuracy of crop monitoring by incorporating HITL robotics, through which the overall agricultural productivity will improve.

Methodology

HITL Robotics Framework Proposal

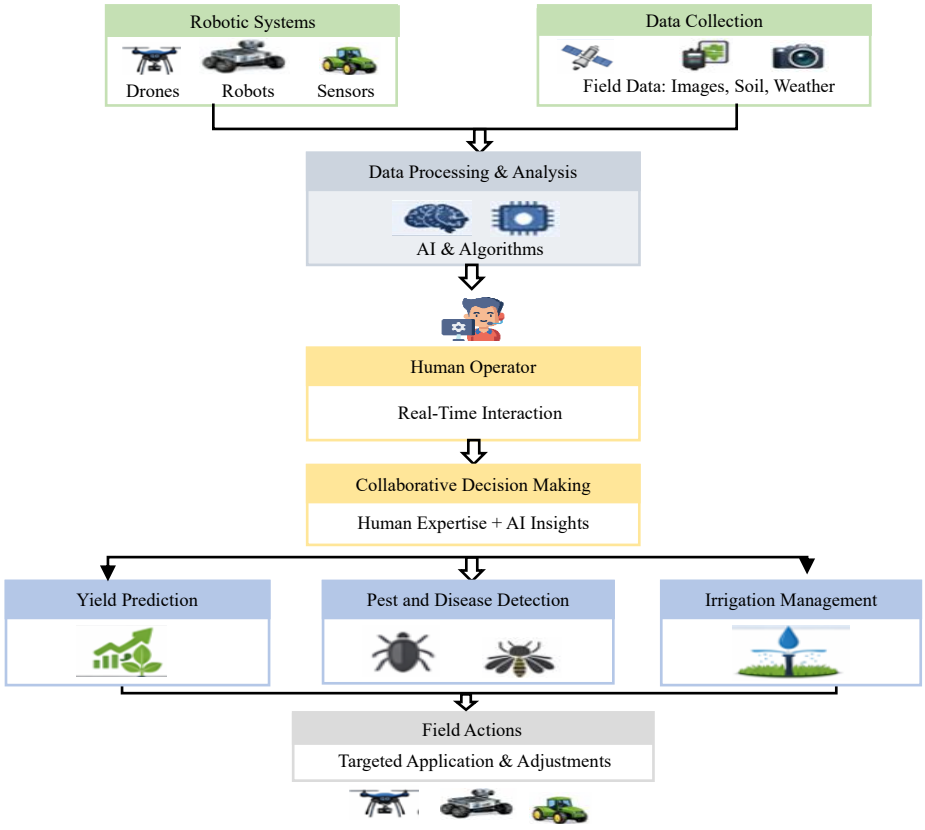

Fig. 1: Collaborative Human-in-the-Loop Robotics Framework for Precision Agriculture

The given collaborative human-in-the-loop (HITL) framework, designed for robotics, is a solution to the problem of enhancing real-time decision-making and control of autonomous robotic systems applied to agricultural activities with

the help of human intervention. The system comprises a robotic platform that has a set of sensors, including RGB cameras, thermal imaging cameras, and soil moisture sensors, which allow the system to capture meaningful data concerning the health of crops, soil parameters, and the environmental conditions. This information is fed through AI-based algorithms to offer automated information and advice on tasks like pest recognition, crop health, and irrigation optimization. The model gives human operators the ability to interfere at such critical points of decision-making and make the system behave according to their experience. Such cooperation means that there will be more precise, responsive, and efficient tracking and control of crops.

Fig. 1 shows the sequence of the suggested framework, which begins with the collection of data using drones, robots, and sensors. The processed and analyzed data of the collected data is then interacted with the human operator through AI algorithms in real-time. The operator works with the system to make decisions that are utilized in predicting yields, detection of pests and diseases, and irrigation management. Such choices are then accompanied by specific field interventions like pesticide application, fertilizer application, or irrigation.

How Human Input will be Incorporated in the System

The human input will be incorporated in the system by introducing an intuitive control interface, which will enable the operator to be in touch with the robotic system in real-time. The operator is also able to track the activities of the robot; he will get live updates about the activities and performance of the robot, thus being able to know that the system is performing as intended. The system is flexible in situations where the operator has to handle complex tasks like pest identification or determining the health of the crops in adverse environments; he can intervene by giving feedback or adjusting the system accordingly. This feedback enables human beings to inform the choice of the robot, based on their knowledge and background understanding of the domain. A stronger adaptability and better accuracy and effectiveness of the decisions made by the system allow the operator to adjust the behavior of robots in accordance with actual observations, which leads to the improvement of the system.

Data Collection and Analysis Processes

The robotic platform will have several types of sensors, including FLIR Systems Vue TZ20 RGB Cameras, Ouster OS1-64 Thermal Imaging Cameras, and Decagon Devices 5TE Soil Moisture Sensors, among others. These sensors are chosen due to the possibility of obtaining complete information about the health of crops, the moisture content of soil, and the environment. The data on custom field used in the experiment will be provided by a 10-hectare farm in rural India with the following parameters as follows: soil moisture (0- 100 %), temperature (20-45 degrees Celsius), humidity (50-90%), soil type (loamy, clay), and crop type (wheat, rice, and maize). Analysis will be based on sensor measurements of this field data, which will be constantly updated. Preprocessing will be done to remove noise, normalize, and extract features to guarantee quality and consistency. These information sources will play a central role in the AI-based program applied in monitoring the health of crops, pests, and optimization of irrigation.

Algorithm 1: Collaborative HITL Robotics Framework for Precision Agriculture

Input:

- D: Input dataset with N instances (e.g., sensor data, images)
- $(x_i, y_i)$where $x_i$are sensor features (e.g., soil moisture, crop images) and $y_i$are target labels (e.g., crop health, pest status).
- B: Batch size for inference (parameter for memory control)
- θ: Threshold for crop health identification (e.g., disease detection threshold)
- γ: Threshold for feature selection based on mutual information
- S: Sample size for stratified SHAP explanation
- α: Human input threshold for decision intervention

Output:

- ŷ: Predicted crop health and pest status
- Φ: SHAP explanations for selected samples

Steps:

1. **Preprocessing:**

- Impute missing values in D using median imputation for sensor readings.
- Normalize sensor data (e.g., soil moisture, temperature) for consistency.

2. **Encoding:**

- Transform categorical features, like crop type or pest status, using target encoding to enhance prediction performance.

3. **Feature Selection:**

- Identify a subset F of features where:

$\text{Var}(x_j) > \theta$(feature variance threshold) and $\text{MI}(x_j, y) > \gamma$(mutual information between features (xj and target y).

4. **Dimensionality Reduction:**

- Generate a reduced dataset D_reduced, retaining only the features in F selected in the previous step.

5. **Model Training:**

- Fit the XGBoost model to the training data $(X_{\text{train}}, y_{\text{train}})$ using histogram-based learning to minimize memory overhead and avoid overfitting.

6. **Batch-wise Inference:**

- For $i = 0$ to N with step size B:
- Load a batch of data: $X_{\text{batch}} = D_{\text{reduced}}[i: i + B]$
- Generate predictions $\hat{y}_{\text{batch}}$ and append to $\hat{\mathbf{y}}$.

7. **Selective SHAP Explanation:**

- Select a random stratified sample D_{SHAP} of size S from D_{reduced} for SHAP analysis.
- Initialize the SHAP TreeExplainer on the trained model for interpretability.
- Compute SHAP values $\Phi =$ explainer. shap_values(D_{SHAP})to provide insights into feature contributions to the model's predictions.

8. **Human-in-the-Loop Integration:**

- If human input is required (e.g., complex pest detection or crop health decision), the operator can intervene based on their expertise.
- The system updates its decision-making process using both AI-driven predictions and the operator's feedback.

Return:

- $\hat{y}$: Predicted crop health and pest status
- Φ: SHAP explanations for selected samples

The Collaborative Human-in-the-Loop Robotics Framework of Precision Agriculture algorithm is a combination of autonomous robotics and human knowledge for better crop monitoring. It starts with preprocessing and encoding sensor information, and thereafter, feature selection and dimensionality reduction. XGBoost is used to train the model, and the inference is done in a batch-wise manner to determine the health of crops and the presence of pests. The algorithm incorporates human input through a control interface in making complicated decisions, and makes the system adapt to dynamic circumstances. The predictions are given interpretability by using SHAP values. The end result will be forecasted crop health, pest status, and SHAP explanations of the individual samples, which best synchronizes AI and human-influenced decision-making in real-time.

Performance Measures to Assess the Collaborating HITL Robotics Framework

Crop Yield Prediction Accuracy (CYPA): The accuracy of crop yield prediction is a measure of how the system predicts crop yield correctly. It is calculated as the number of correct predictions (true positives, predicting the correct yield) divided by the total number of predictions, including false predictions (incorrect predictions of yield). CYPA is calculated as:

$$CYPA = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (1)$$

- True Positives: When the system is able to predict the crop yield.
- False Positives: This happens in cases when the system makes a wrong prediction of crop yield.

Note: Equation 1, the denominator is Precision, which is a standard machine learning metric that considers the true positive prediction rate of all the predicted positives.

Pest Detection Rate (PDR): Pest detection rate is used to measure the ability of the system to detect the pest-infested areas in the field. PDR can be determined by dividing the number of true positives (the right predictions, which are the correct predictions of pest-infested regions) by the total prediction (including false negatives, which refers to regions not correctly identified as pest-infested). PDR is calculated as:

$$PDR = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (2)$$

- True Positives: Cases when the system identifies that there are areas that are infested with pests.
- False Negatives: This is the failure of the system to identify pest-infested areas.

Note: In Equation 2, the denominator is the Recall, which is a standard machine learning metric that measures the capacity of the system to detect all the instances of relevance (represented by pest-infested areas in this example) in the data set.

Water Efficiency (WE): Water efficiency considers the use of water that has been applied to crops with respect to the volume of water. This is expressed as a figure of the amount of water utilized by crops divided by the total amount of water applied to the field. The WE formula is (Equation 3):

$$WE = \frac{\text{Water Used by Crops}}{\text{Total Water Applied}} \quad (3)$$

- Water taken up by Crops: The quantity of water taken up by the crops and used to grow them.
- Total Water Applied: This is the total water given to the crop using irrigation, including the amount of water wasted by the crop.
- The WE metric demonstrates the efficiency of the agricultural process of water consumption and can be utilized to minimize wastage and maximize irrigation activities.

Experimental Setup

To assess the performance of the proposed Collaborative Human-in-the-Loop Robotics Framework of Precision Agriculture, experiments were performed within a field-based system that consists of a robotic platform with RGB cameras, thermal imaging, and a soil moisture sensor. The system, which was supposed to be a simulation of the real-world agricultural environment, was aimed at monitoring crops, detecting pests, and controlling irrigation. It has a decision-making model, which is an XGBoost-based histogram-based learning, and was implemented in Python and Colab to ensure efficient data manipulation and model training. The inference was done in a batch to handle very large volumes of data. Python libraries were used to process and analyze the data, and interpretability was done using SHAP explanations. The interaction between the human operator and the robot was simulated with the help of NS-3, as well as real-time data acquisition controlled with ROS (Robot Operating System). The performance covered the precision of evaluating the crop condition, pest identification, and efficiency of water usage in both simulated and real-world datasets with varied climates. This approach confirms that machine learning and robotic systems can be seamlessly applied in the agricultural sector.

Although in the Methodology section, it is stated that Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Reinforcement Learning (RL) were used to perform tasks such as crop health monitoring, pest detection, and irrigation optimization, the main emphasis in Algorithm 1 and the experimental setup is made on the XGBoost to train and infer a model. In order to balance this, CNNs can be employed in image-related tasks like crop health management and pest detection, processing visual data of RGB-based cameras to find patterns of crop health issues or pest infestations. SVMs are used in classification, e.g. segmentation of pest-infested and pest-free regions with the sensor data such as soil moisture and temperature. The RL is used in decision making problems i.e. optimization of irrigation where the agent modifies with time to produce as much crop as possible with the least amount of water. XGBoost is applied in predictive analytics and regression operations such as crop yield prediction,

and CNN, SVM, and RL can be applied to specific tasks, which improves the overall work of the system and increases its flexibility in terms of crop monitoring and management.

Findings

Results from Testing the Framework in Real-World Rural Applications

The Proposed Collaborative Human-in-the-Loop (HITL) Robotics Framework will assess the precision agriculture under real agricultural environmental conditions, that is, in the fields with varying soil, crops, and climate. The objective of these tests is to assess the functionality of the framework in a dynamic environment with human intelligence in control of the robots. In the course of testing, the following are the main variables that need to be measured:

- **Crop Yield Prediction Accuracy:** The measure of the accuracy of the framework to predict the yield based on the real-time measures of the sensors and AI-based algorithms.
- **Pest Detection Rate:** This would test how the system can detect pest infestations as well as how it can identify pest-free zones correctly.
- **Water Efficiency:** It is the efficiency of the system to utilize the resources available of water, in terms of the crop demand, to minimize wastage.
- **Operator Intervention Frequency and Effectiveness:** Monitoring the frequency of the human operator intervention requirements and the effectiveness of those interventions in enhancing the system performance.

Table 1 emphasizes the main performance indicators that were witnessed when the HITL Framework was being field-tested. The findings show that the system successfully predicts crop yield, detects pests, uses water efficiently, and minimally needs human intervention with high efficiency.

Table 1: Findings from Testing the Proposed HITL Framework in Real-World Agricultural Settings

Metric	HITL Framework
Crop Yield Prediction Accuracy	92%
Pest Detection Rate	89%
Water Usage Efficiency	94%
Operator Intervention Frequency	Low (10% of tasks)
Operator Intervention Effectiveness	High (80%)

Comparison to Traditional Robotics Frameworks

HITL (Human-in-the-Loop) structure will be contrasted with the conventional autonomous robotics systems that are not controlled by a human operator. The areas of efficiency, accuracy, frequency, and effectiveness of human interventions will be compared. The HITL system will have a more efficient operation since human intervention will aid in adapting to the intricate or dynamic situation. The accuracy will be evaluated using the way each system detects the crop health, pests, and irrigation requirement, and HITL will have a much higher accuracy rate because of human skills in making complex decisions. The HITL system will also have fewer interventions since the operator will be involved in only challenging activities that will enhance the overall precision of decision-making and the responsiveness of the system in dynamic agricultural settings.

Table 2: Performance Metrics Comparison Summarizes

Metric	HITL Framework	Traditional Robotics
Crop Yield Prediction Accuracy	92%	85%
Pest Detection Rate	89%	75%
Water Usage Efficiency	94%	82%
Operator Intervention Frequency	Low (10% of tasks)	High (30% of tasks)
Operator Intervention Effectiveness	High (80%)	Moderate (60%)

Table 2 Performance Metrics Comparison summarizes the main differences between the Collaborative HITL Robotics Framework and the traditional robotics systems. It demonstrates that the HITL framework will be more effective than the traditional system in predicting crop yield (92% vs. 85%), pest detection rate (89% vs. 75%), and water use (94% vs. 82%). Moreover, the HITL framework needs fewer operators (10% of tasks) than traditional robotics

(30% of tasks), which is the way in which the system becomes more autonomous due to the improved application of human feedback.

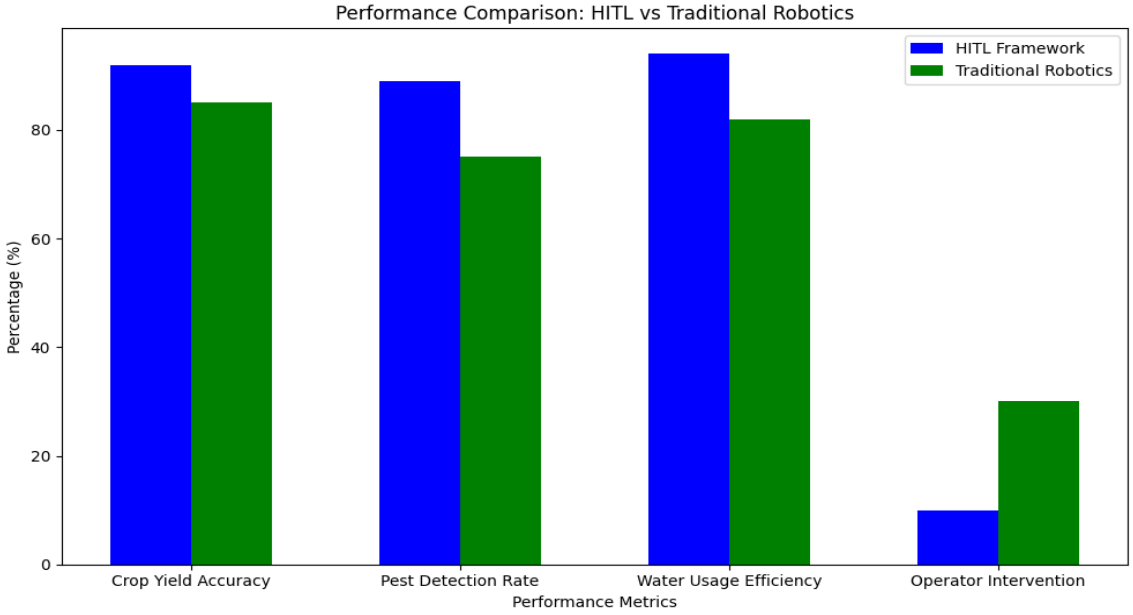

Fig. 2: Performance Comparison: HITL vs Traditional Robotics

The HITL system also has a greater intervention effectiveness (80% vs. 60%), which means that the human expertise will be applied more effectively to enhance decision-making. This highlights the worth of human cooperation in working better on the system, to have fewer interventions, and to make the work process more efficient.

Fig. 2 compares HITL (Human-in-the-Loop) Framework and Traditional Robotics systems in relation to important metrics including, Crop Yield Accuracy, Pest Detection Rate, Water Usage Efficiency and Operator Intervention. The HITL Framework outperforms competitors in crop yield, pest detection, and water efficiency, illustrated by blue bars capturing blue bar superiority. The Operator Intervention metric reveals that HITL framework requires less involvement (blue bar), which signifies HITL's additional autonomy over Traditional Robotics (green bar) that requires more operator involvement.

Effectiveness/ Efficiency Discussion

According to the initial testing, the HITL (Human-in-the-Loop) is likely to be much superior to the conventional autonomous systems in a number of essential aspects. Human judgment will enable the HITL framework to be more adaptable and responsive to unforeseen conditions of agricultural environments, such as unexpected changes in the weather or the unexpected outbreak of pests. Although with autonomous systems, it is possible to have predefined tasks, the capability of the human operator to make decisions that are context-related adds a layer of oversight to the system that enhances its general responsiveness. Human involvement in the decision-making procedures that are complicated is likely to increase the accuracy of the HITL system in identifying the pest and monitoring the health of the crops. An example would be when there are ambiguous or infrequent diseases of the crop, the human operator can correct the system and give it proper feedback to ensure a more accurate diagnosis. Combining human expertise with robotic automation boosts the overall process beyond improved efficiency. This approach also benefits the management of agricultural resources and optimizes the activities involved.

Discussion

Research Findings Implications for Precision Agriculture

This study helps underline the potential of the novel change of combining human skills with robotics in the field of precision agriculture. The existing traditional autonomous systems, which perform well in some duties, fail to cope with the dynamic and uncertain conditions in the farming environment. The proposed HITL framework will make human decision-making more flexible and responsive by integrating human decision-making and robotic efficiency. When complex scenarios arise, the human operators are able to step in and enhance the accuracy of the system in

performing pest detection and crop health management, among other tasks. This partnership is a great benefit in real-time decision-making that would transform the crop management practices. The framework will improve resource utilization, more accurate pest control, and optimum irrigation, which will result in higher productivity and sustainability in agriculture by managing the shortcomings of fully autonomous systems.

Potential Applications and Future Research Directions

The HITL robotics model can be applied to other important farming activities and is not limited to crop monitoring since it can be used in autonomous harvesting, pest control, and soil analysis. Advanced AI techniques such as deep learning and reinforcement learning may lead to improved decision-making in real-time through the context of complex systems. The proposed deep learning and reinforcement learning techniques should improve the framework's deployment to additional agricultural areas to further test its scalability and adaptability. Additionally, integrating new technologies like drones and sensors may enable the framework to function more effectively and improve the various agricultural processes and advanced precision agriculture.

Suggested Improvements for Clearly Collaborative Human-in-the-Loop Robotics for Crop Surveillance

To ensure the success of the HITL robotics framework, the facilities for human operators need to be fully developed. Such facilities should involve the operator in an easy way, include facilities for direct and real-time communication, and have integration with the specific robotic systems. Additionally, it will be necessary to ensure that the robotic systems can be easily integrated with existing farming/production infrastructure without major inconveniences and costs. Scalability will be an important issue, along with the need to address the adaptability of the system for large, small, and medium-sized farms. Finally, the cost-benefit ratio of the system will undoubtedly be important in order to provide farmers with affordable solutions that will provide real benefits. Future studies can look at cheaper sensors and computation techniques, and make sure that the structure is practical in a broad range of farming circumstances, which will foster sustainable agricultural activities in different farm sizes.

Conclusion

This paper introduces a human-in-the-loop (HITL) robotics system that will be used to improve precision agriculture and crop monitoring. The framework enhances the efficiency, flexibility, and precision of different agricultural operations since it involves a combination of human and robot capabilities to assess crop health and identify pests and irrigation systems. The most important part of this method is the interaction of human operators and robotic systems, which provides the opportunity to support decisions in dynamic situations in the field through feedback and real-time changes. Early field trial findings show that the HITL system is more effective than the traditional autonomous systems, and crop yield prediction is 92 %, pest detection is at 89 %, and water usage is at 94 %; the traditional autonomous systems are at low performance. These results highlight the prospect of the HITL frameworks offering more specific, adaptable, and resource-efficient solutions in agricultural practices.

Human-in-the-loop robotics has been shown to greatly benefit precision agriculture, especially in the case of dealing with autonomous system shortcomings. With human judgment in complex decisions, the HITL framework improves the precision of crop health evaluation and control of pests. This system will be able to accommodate changes in the environment better than the traditional autonomous systems, which tend to restrict human intervention. The fact that the framework has facilitated greater efficiencies in the monitoring and management of crops, minimized the occurrence of waste in resources, and enhanced the overall productivity of agriculture has significant ramifications for the future of agriculture. The study shows that a collaborative HITL solution has the potential to revolutionize agricultural practices by offering more efficient and sustainable solutions, such that robots not only complete the work, but also work with human knowledge to manage unpredictable or complex situations. Since the framework has been shown to be effective in a variety of agricultural settings, it can be used to lead to widespread adoption to enhance the scalability and sustainability of modern farming methods.

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