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AgriBot: Virtual Robotics Using ROS2

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Abstract: Agriculture faces few challenges, especially since there are many tasks that require great physical effort. Inefficiencies ultimately lead to more expenditure, wastage of resources, and decreased productivity. While India is among the highest agricultural producers, it consumes far more than it produces. This gap highlights the need for some creative and effective farming techniques. To address these problems, AgriBot is developed as a virtual robotic system. It automates three important farming tasks: seeding, irrigation, and weed control. The design basis of AgriBot is the combination of ROS2 (Robot Operating System 2) with simulation using Gazebo. The seed planting module automates the sowing procedure. The irrigation system uses soil moisture sensors to irrigate the crops only when needed to minimize wastage. The weed detection module utilizes a Random Forest algorithm to detect weeds and is removed by a laser-burn-based system. AgriBot reduces the amount of manual labor, conserves resources, and increases the efficacy of farming. Simulation tools such as Gazebo allow for the testing and refinement of a system before it is deployed in the real world. This project aims to make farming modern, efficient, cost-effective, and environmentally sustainable.

Index Terms **- Agricultural virtual robotics, Irrigation, Machine learning, Precision farming, ROS2, RViz, URDF, Weed detection.**

I. Introduction

Agriculture is important for feeding the growing population, but farmers face many challenges that affect productivity and efficiency. Traditional farming depends heavily on manual labor, which is time-consuming and physically exhausting. Inefficient irrigation leads to water wastage, and uncontrolled weed growth reduces crop yield. These issues increase costs and lower efficiency, making it necessary to use automation and smart technologies to improve farming practices.

One of the biggest challenges in agriculture today is low productivity. India is among the world's largest agricultural producers, contributing 25% of global food production. However, it is also the largest consumer, using 27% of global food resources. This means we consume more than we produce, creating a gap that needs to be addressed by improving farming efficiency and productivity through innovative solutions.

Robotics is emerging as a game-changer in modern farming. With advancements in automation and machine learning (ML), robots can now perform tasks like seed planting, irrigation, and weed removal with high accuracy and minimal human effort. These technologies reduce dependence on labor, optimize resources, and improve crop management. To help in solving these problems, we propose AgriBot, a ROS2-based virtual robotic system that is designed to automate the main farming tasks. AgriBot can plant seeds, manage irrigation, and detect weeds using the Random Forest algorithm, to eliminate them with a laser-based removal system. By simulating its functions in Gazebo, we ensure thorough testing and validation before real-world implementation.

This paper explores the development of AgriBot, detailing its design, working principles, and key features. It explains the software and hardware components used, along with the simulation tools that help in testing its performance.

II. Literature Review

Plant Irrigation Water Sprinkler Robot [9] Authors: S. Mathivanan, Vishnudas C, Sidhin Krishna M. S, and Suraj R (2023)

This research introduces an autonomous irrigation system designed to replace traditional irrigation methods that rely on extensive piping infrastructure. The proposed system consists of a mobile robot equipped with a water tank and a sprinkler, both controlled by an Arduino microcontroller and an RF transmitter. To ensure full field coverage, the robot utilizes geo-fencing sensors, eliminating the need for manual intervention. The robot's movement is powered by DC motors, which allows it to navigate smoothly in multiple directions, including forward, reverse, left, and right. A key feature of this robot is its ability to spray water uniformly, simulating natural rainfall. The integrated water pump ensures even distribution, improving irrigation efficiency and optimizing water usage. Unlike traditional irrigation systems, which often suffer from underground pipe leakage or inefficient water distribution, this autonomous system minimizes wastage and provides a more sustainable approach to farming. Given its low-cost design and ease of implementation, this robot presents an ideal solution for regions where conventional irrigation systems are impractical or too expensive to install.

Detection of Weeds Using Machine Learning [5] Authors: P. Kavitha Reddy, R. Anirudh Reddy, Abhishek Reddy, Katkam Sai Teja, K. Rohith, and K. Rahul (2023)

This study explores how machine learning can be used to improve weed detection, reduce the reliance on herbicides, and enhance overall crop yield. The researchers employ a deep convolutional neural network (CNN) to analyze and classify weeds with high accuracy. By processing real-time images captured from agricultural fields, the system effectively distinguishes between crops and unwanted weeds. The entire process is carried out using Python, OpenCV, and deep learning techniques, ensuring fast and precise weed identification with minimal human intervention. Compared to conventional methods such as Support Vector Machines (SVM) and template matching, this machine learning approach provides significantly higher accuracy and robustness. Traditional weed removal methods often involve excessive herbicide application, leading to environmental concerns and increased costs for farmers. However, by detecting weeds more precisely, this system allows for targeted removal, reducing the need for chemical usage and promoting a more sustainable and cost-effective agricultural practice.

Deep Convolutional Neural Network Models for Weed Detection in Polyhouse-Grown Bell Peppers [7] Authors: A. Subeesh, S. Bhole, K. Singh, N. S. Chandel, Y. A. Rajwade, K. V. R. Rao, S. P. Kumar, and D. Jat (2022)

This research investigates the effectiveness of deep learning in identifying weeds among polyhouse-grown bell peppers. The researchers collected a dataset of 1,106 RGB images taken from a controlled farming environment and tested multiple CNN architectures—AlexNet, GoogLeNet, InceptionV3, and Xception—to evaluate their accuracy in weed classification. Among these, the InceptionV3 model outperformed the others, achieving an impressive accuracy rate of 97.7%. The study underscores the significance of AI-driven solutions in precision agriculture, particularly in environments where manual weed detection is inefficient or impractical. By integrating such deep learning models, farmers can reduce their reliance on herbicides while improving productivity through automated weed removal. Future developments in this field may include the real-time deployment of these models on edge devices, as well as the integration of multispectral imaging to enhance the differentiation between crops and weeds.

IoT-Based Automatic Irrigation System Using Robotic Vehicle [8] Authors: Sakshi Gupta, Sharmila, and Hari Mohan Rai (2020)

This paper presents an innovative IoT-based irrigation system that autonomously waters plants based on real-time soil moisture data. The robotic vehicle is specifically designed for areas with limited human accessibility, such as highway medians, remote farms, and urban green spaces. Equipped with moisture sensors, an Arduino Uno microcontroller, and wireless connectivity, the system continuously monitors soil conditions and activates irrigation only when necessary, thereby conserving water and reducing manual labor. To enhance its functionality, the robot features ultrasonic sensors for obstacle detection, ensuring smooth navigation across the field. Additionally, farmers can remotely operate the system through a mobile app, which includes a voice control feature for added convenience. One of the standout advantages of this system is its scalability—multiple moisture sensors can be integrated via an encoder, making it a versatile solution for different types of agricultural settings. This research highlights the potential of IoT-driven automation in optimizing water use and improving overall irrigation management.

Agricultural Robotic Device to Monitor Soil Moisture, Temperature, Humidity, and Illumination [6] Authors: Bharati S. Pochal and Akshata A. Patil (2018)

This research introduces an IoT-enabled agricultural robot designed to provide real-time monitoring of key environmental parameters such as soil moisture, temperature, humidity, and illumination. The system is built around an ATmega328 microcontroller, with sensors connected via an ESP8266 Wi-Fi module, to allow seamless data transmission to a cloud-based platform. Farmers can access this information remotely through a smartphone application, giving them valuable insights into field conditions without needing to be physically present. By automating environmental monitoring, this robotic device helps optimize crucial agricultural processes, including irrigation scheduling, pesticide application, and fertilizer distribution. The research emphasizes how such technology can significantly reduce manual labor while improving precision in farming operations. Furthermore, by leveraging IoT connectivity, this system supports sustainable agricultural practices, minimizing resource wastage and promoting data-driven decision-making in modern farming.

AgriBot - A Multipurpose Agricultural Robot [3] Authors: Akhila Gollakota and M. B. Srinivas (2012)

The AgriBot is a versatile agricultural robot designed to perform core farming tasks such as plowing, seed sowing, and soil covering without requiring human intervention. Built with DC motors, a stepper motor, relays, and a Programmable System-on-Chip (PSoC) controller, the robot automates multiple field operations. One of its key components is the seed-planting mechanism, which consists of a spiked wheel and a flip-flop seed dispenser. This design ensures that seeds are evenly distributed across the field, leading to uniform crop growth. The PSoC-based control system manages all the robot's functionalities, enabling seamless operation in various agricultural environments. This study highlights the potential of autonomous robots in revolutionizing farming practices. By integrating robotics into agriculture, this technology paves the way for more efficient, scalable, and sustainable farming methods, ultimately increasing productivity while minimizing human effort.

III. Existing System Architecture

The existing system [3] of AgriBot is designed to handle basic farming tasks like plowing and sowing. It operates using a combination of hardware components, such as motors, sensors (DC motors and Stepper motors), and mechanical tools, along with software to control its functions. An Arduino microcontroller manages the system to ensure smooth execution of plowing and sowing. Navigation and task execution are guided by algorithms. While this system has helped to automate small-scale farming and reduce manual labor, it still has some drawbacks.

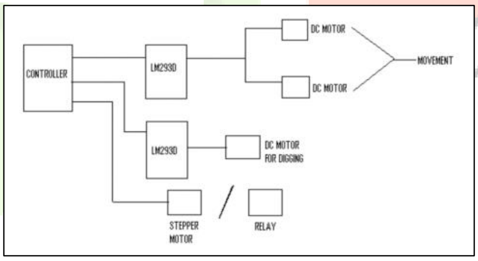

Fig. 1. Existing System Architecture (adapted from [3], p. 4)

One major limitation is that switching between tasks, like moving from plowing to sowing, still requires human intervention, which reduces efficiency. Additionally, the system lacks advanced automation features, hence it is less suitable for larger or more complex agricultural tasks. Without real-time decision-making capabilities, it cannot adapt to changing field conditions on its own. To address these challenges, we propose an improved system that fully automates these processes, reduces the need for human involvement, and enhances overall efficiency.

IV. Proposed System Architecture

The software stack supports end-to-end communication and simulation for AgriBot. The ROS2 framework acts as the system foundation that enables various robotic components to communicate. Machine learning models, especially the Random Forest algorithm, are employed for weed detection and classification, to distinguish crops from weeds based on image data from the RGB camera. Gazebo simulation AgriBot's operation before real-world implementation. RViz is a visualization tool that offers a graphical representation of the AgriBot and its movements.

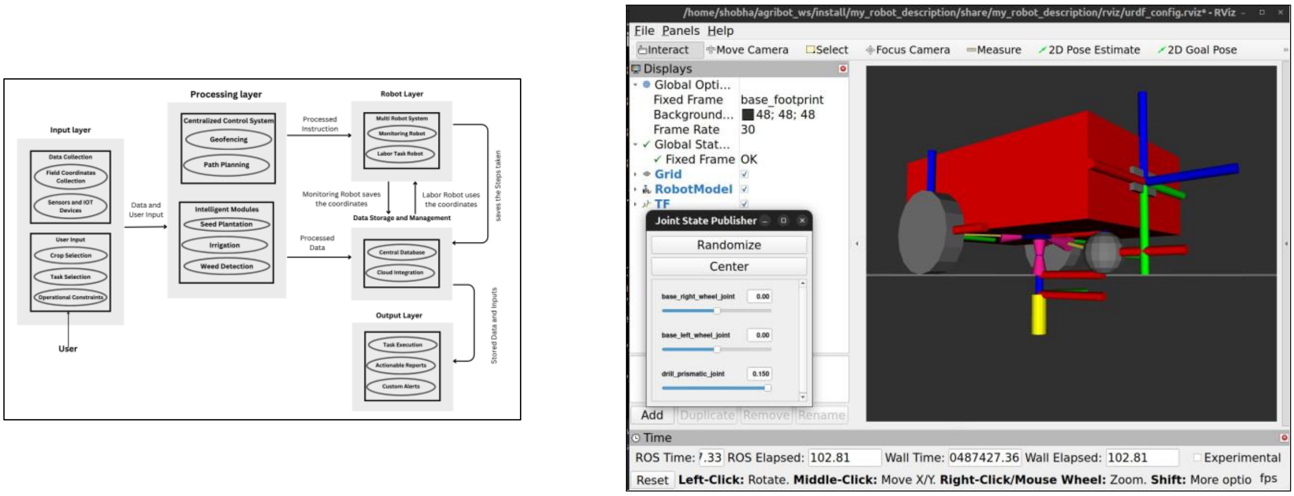

Fig. 2. Proposed System Architecture

AgriBot's system operates in a layered fashion to simplify farming. It begins in the Input Layer, where data is gathered through sensors, IoT devices, and user input (such as selecting crops and operations). This then progresses to the Processing Layer, where the system plots courses and handles tasks such as planting, watering, and surveillance. The Monitoring Robot, in the Robot Layer, collects field data, while the Labor Task Robot performs physical labor. Their outputs are preserved in a central database and cloud that the Output Layer utilizes to make reports, insights, and alerts for users—assisting them in making more informed farming choices.

V. METHODOLOGY

The AgriBot system is meant to automate the most important agricultural activities - seed sowing, watering, and weed management using ROS2, ML, and simulation technologies. The approach emphasizes bringing together virtual hardware and software components. The whole process is simulated in Gazebo, to ensure robust testing prior to any real-world implementation.

5.1 Robot Structure and Design

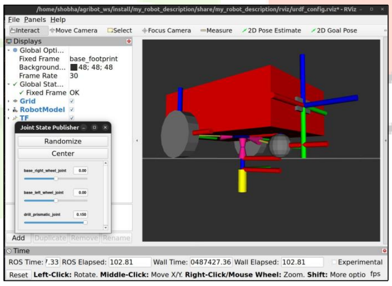

Fig. 3. Structure of the Robot

The AgriBot is modeled using URDF (Unified Robot Description Format) in XML, which specifies its physical properties and mobile capabilities. The robot consists of a rectangular base that is supported by two main wheels at the back and a front caster wheel for balance. The wheels are controlled using continuous joints. A seed drilling mechanism is mounted on the base, which is connected via a prismatic joint, to allow vertical movement and plant seeds at the required depth. The Robot also has a camera plugin at the front of its base. RViz can be used to visualize the robot's motion and joint states, and real-world simulation is done using Gazebo in the respective worlds. The control system is handled using ROS2 nodes, to ensure the functionalities are performed as required.

5.2 Seed Plantation Module

The seed plantation module uses a controlled method to get through the field efficiently and deposit seeds at good locations. First, the BoundaryReceptionNode calculates the limits of the field and the aggregate planting area. After mapping out the area, the DotPlacementNode creates an array of planting locations at regular intervals with uniform seed positioning. Navigation is controlled by GridWaypointController, which instructs the robot to move to every planting point. When the robot arrives at a point, the SowingTaskNode initiates the sowing mechanism. The SeedDrillController coordinates the exact vertical motion of the drill, to deposit the seed precisely into the ground before it withdraws. This is done continuously until all points of coverage have been reached. The whole process of seed sowing is experimented in Gazebo in the world named ”sp world.world”, which is created specifically for the seed plantation functionality.

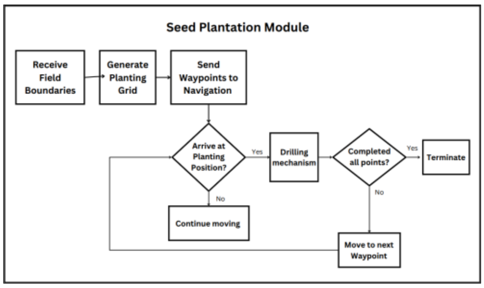

Fig. 4. Flowchart of Seed Plantation Process

5.3 Weed Detection And Removal Module

Weed detection has been explored in research [5], [7]. Weed control is performed through a combination of machine learning and robotic action. A pre-trained Random Forest model is used to classify crops and weeds based on image analysis. Since capturing real-time images is not feasible in the simulation, the system processes pre-saved images of weeds to detect weed locations. The WeedDetectionNode identifies weed-infested coordinates which are then published to the PathPlanningNode. The PathPlanningNode then calculates the most efficient route for the robot to reach the detected weeds. The GridWaypointController directs the robot toward each weed location. Once positioned near the weed, the WeedTaskNode activates a laser-burn-based removal mechanism. This cycle continues until all detected weeds are removed.

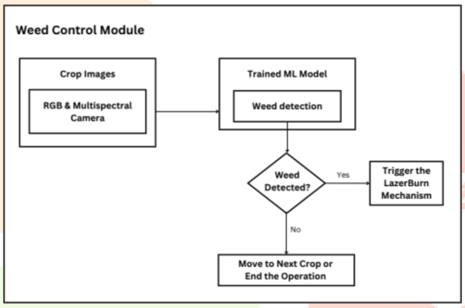

Fig. 5. Flowchart of Weed Detection Process

5.4 Machine Learning Integration For Weed Detection

The weed detection system uses a Random Forest classifier to tell the difference between crops and weeds by learning from labeled images [10]. First, the data set is processed, where images are resized to a standard size, converted to grayscale, and labeled as either crop (0) or weed (1) to make them suitable for training. Once the data is prepared, the system moves on to training the model using 50 decision trees. After training, the model undergoes testing and prediction, where it is evaluated on new, unseen images to measure its performance. Once it proves reliable, the trained model can be deployed for weed detection in the virtual simulation. Once the model is fully trained, it is saved inside the WeedDetectionNode, where it helps in detecting weeds automatically during operation.

5.5 Irrigation Module

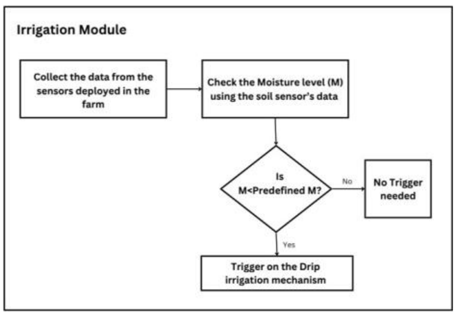

Fig. 6. Flowchart of Irrigation Process

The irrigation system is designed to provide water based on the soil moisture levels. It uses a drip irrigation method, where only a trigger is needed to start watering. The DroneIrrigationNode reads moisture data from a CSV file, to simulate real-world sensor input. When an area falls below the required moisture threshold, the node publishes an irrigation request containing the location that needs water. The IrrigationControlNode listens for these requests after which, the IrrigateWater action is triggered, which supplies water through a drip irrigation system positioned near each plant. This provides accurate distribution of water, conserving less and maximizing plant growth. The module is tested using Gazebo.

5.6 Simulation in Gazebo

Before deploying AgriBot in real-world farming conditions, it undergoes testing within the Gazebo simulation environment to ensure that all components function correctly. This simulation phase allows developers to fine-tune the robot's performance in a controlled, risk-free setting before field implementation. The process begins with creating a virtual field, where a digital replica of the farm—referred to as a Gazebo world—is designed with precise boundaries and structured areas for each module of the robot. This virtual environment simulates real agricultural conditions, including terrain variations and obstacles.

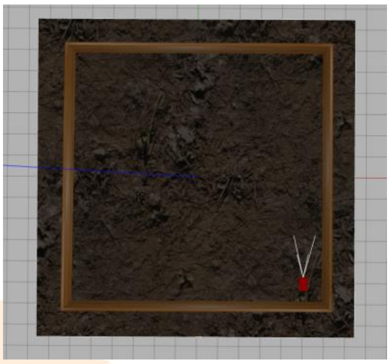

Fig. 7. Gazebo Simulation

Once the simulation environment is established, the AgriBot model is imported into Gazebo. At this stage, the robot's fundamental movements—such as forward and backward motion, turning, and adjusting speed—are thoroughly done. Next, the seed-planting mechanism is evaluated, to make sure that the drill at the bottom of the robot base correctly deposits seeds at the designated intervals. Additionally, the laser-based weed removal system is simulated, which allows the robot to identify unwanted plants and eliminate them without damaging crops. Following the successful validation of individual functions, ROS2 integration is implemented using well-structured launch files. These files connect and synchronize all necessary controller nodes. For instance, the system must coordinate seed planting, irrigation, and weed removal to function harmoniously within the same field.

Through this simulation-first approach, any potential issues such as navigation errors, timing mismatches, or sensor misalignments—can be identified and resolved before the robot is deployed on actual farmland. This testing process not only enhances AgriBot's reliability but also helps in optimizing its performance.

VI. Implementation

The implementation includes developing a user interface, writing ROS2 nodes, integrating sensors and actuators, and making launch files to make sure the system executes smoothly. Below is a breakdown of how each part is implemented.

6.1 User Interface and Control System

A web-based interface is developed to allow the users (farmers) to interact with AgriBot easily. Through this interface, users can sign in/sign up, input field coordinates and choose specific tasks such as seed planting, irrigation, or weed removal. Once a task is selected, the system triggers the corresponding ROS2 nodes, which send commands to AgriBot to carry out the operation.

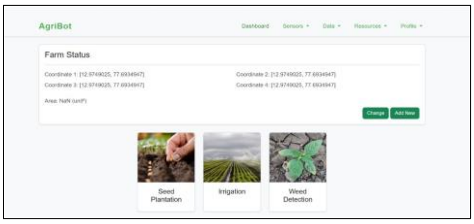

Fig. 8. Website

6.2 Software Implementation

AgriBot's software is built using the ROS2 framework, which facilitates communication between different modules. Separate ROS2 nodes were developed for seed planting, irrigation, and weed removal, each function operating independently. The communication between these nodes or topics can be verified using the command "ros2 run rqt graph rqt graph", which provides a visual representation of the connections between different components. To ensure that AgriBot's functionality is tested before real-world deployment, we utilized Gazebo simulation. In Gazebo, a virtual farm environment/world was created, where AgriBot could navigate, plant seeds, detect weeds, and irrigate according to real-world scenarios. The movement and execution of tasks are controlled by dedicated controller nodes.

6.3 Virtual Hardware Integration

AgriBot's physical structure and movement were designed using URDF (Unified Robot Description Format) in ROS2, where its joints, sensors, and actuators were modeled using XML and Xacro. To carry out different tasks, AgriBot is equipped with specific virtual tools for operations. The seed drill mechanism makes sure to place the seeds accurately, the drip irrigation system delivers water efficiently to crops, and the laser-burn mechanism targets and removes weeds. It also has a camera plugin at the front. Each of these mechanisms is controlled by ROS2 nodes, which coordinate their actions accordingly.

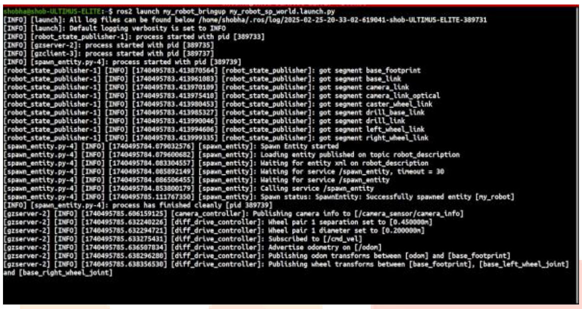

Fig. 9. Terminal while launching robot in the world

6.4 System Execution

The entire system is managed using ROS2 launch files, which start all necessary nodes and modules in a coordinated manner. The system is tested in a Gazebo simulation before being deployed in real-world farming environments.

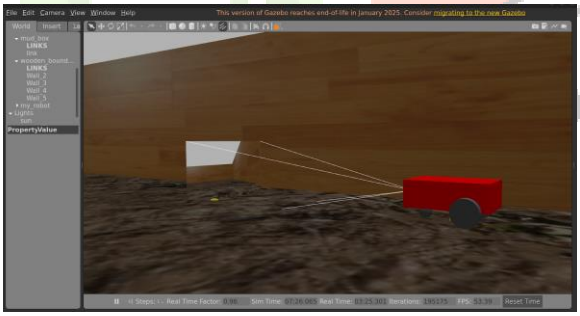

Fig. 10. Robot in the Simulating World

VII. Results And Discussions

The weed detection model had a validation accuracy of 90.38% and a testing accuracy of 100%. In the Gazebo simulation, the seed plantation module was able to track planned paths to deposit seeds precisely at target locations. The irrigation module effectively processed the moisture data and turned on the drip system only where necessary, hence providing accurate water distribution.

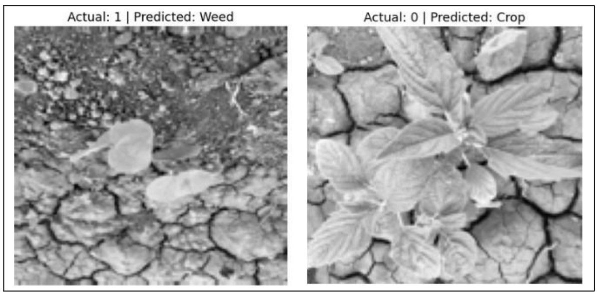

Fig. 11. Predicting Weed using Machine Learning

Some implementation challenges were experienced, mainly in the robot's model and ROS2 nodes integration and launching the robot in the custom world, path planning precision, and machine learning stability. Synchronization methods needed to be refined in order to ensure proper communication between ROS2 nodes, while path planning was improved by modifying the GridWaypointController.

VIII. Applications And limitations

The AgriBot system is designed to bring automation to modern farming so that it can handle essential tasks like seed planting, irrigation, and weed removal with precision. Using ROS2, machine learning, and simulation, it optimizes the use of resources. Its modular design makes it easy to upgrade—once the core system is in place, new ROS2 nodes can be added or modified to introduce more farming operations without major changes to the existing setup. This flexibility allows AgriBot to adapt to different agricultural needs and technological advancements.

However, the system does have some limitations. Weather conditions can affect its performance, which might impact tasks like weed detection and irrigation efficiency. Additionally, since real-time hyper-spectral soil data isn't readily available, the irrigation system relies on pre-recorded moisture levels instead of live readings. Another challenge is that the simulation in Gazebo operates within a fixed environment, which limits the robot's ability to adapt to changing farm conditions.

IX. Future Scope

In the future, AgriBot can be improved by integrating IoT technology for real-time monitoring, to provide live updates on soil health, crop growth, and environmental factors. Expanding its capabilities to support multi-crop farming would increase its usefulness across different agricultural landscapes. Additional features like crop monitoring, automated harvesting, and plant disease detection could further enhance its role in farming.

X. Conclusion

The AgriBot system successfully automates farming tasks, such as seed plantation, irrigation, and weed removal, using ROS2, machine learning, and simulation. The model for weed detection was highly accurate, while the navigation and irrigation modules effectively performed their respective operations in the Gazebo simulation. However, there are areas for improvement, such as real-time soil data integration to be able to adapt to dynamic environments, and adding features like crop health monitoring and automated harvesting. With further development, AgriBot can be a multipurpose, real-life agriculture helper that would be able to contribute to the growth of precision farming and sustainable agriculture.

XI. Acknowledgment

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