Design and Analysis of Automated Pesticide Sprayer with Detection of Grapes using Machine Learning

Darshan Kuwar, Prasad Wakchaure, Rajeshwari Shinde, Tanuja Himparge, Shreekant Patil
School of Mechanical Engineering,
MIT Academy of Engineering Alandi, Pune, India
darshan.kuwar@mitaoe.ac.in, prasad.wakchaure@mitaoe.ac.in, rajeshwari.shinde@mitaoe.ac.in, tanuja.himparge@mitaoe.ac.in, shreekant.patil@mitaoe.ac.in

***Abstract*—In a developing country like India, agriculture is the most important occupation. By using advanced robotic technology to replace labors with intelligent robots, agriculture may increase its productivity and efficiency. The goal of the proposed project is to reduce the length of time that farmers are exposed to unhealthy chemicals by creating a low-cost, high-efficiency pesticide spraying robot. Instead of workers, a robot will apply fertilizers and insecticides. In agriculture, the proposed robot is utilized to spray pesticides and detect healthy and unhealthy grapes to spray at specific plants. The implementations related with this study are divided into four categories: sensing, control, detection and spraying modules. Grape diseases are the main reason behind the reduction in the quantity and quality of agricultural yield. Identifying and managing grape diseases presents significant challenges for farmers. Therefore, it is crucial to identify plant illnesses as soon as possible so that farmers may act appropriately and on time to prevent future losses. The study focuses on a method for identifying grape condition (Healthy or Unhealthy) that involves image processing. In this article, an Android app that enables farmers to control the pesticide sprayer and a Machine Learning model is developed to identify plant illness by sending a picture of a grape to the system. The user's input image is processed in many steps to identify the disease, and the results are delivered to the system to spray pesticide specifically.**

Keywords—Fabrication, Automated Pesticide Sprayer, Grapes detection, Machine Learning, Grape classification.

I. Introduction

Farmers nowadays play an important role by working hard in agricultural fields and cultivating food for people living in various places in order to meet their basic necessities. Pesticide use is higher in India than it is globally, at 70% compared to just 44% globally [1]. Pests in India generate crop losses of more than Rs. 6000 crores per year, of which 33% are caused by weeds, 26% by diseases, 20% are caused by insects, 10% are caused by birds and rodents, and the remaining 11% are attributable to other factors. Pests waste between 30 and 35 percent of India's annual crop yield. Agricultural biosafety is being negatively impacted by widespread crop losses [2]. Detecting plant diseases and pests is a key area of research in the science of machine vision. Disease control procedures may be a waste of time and resources and may result in additional plant losses without accurate identification of the disease and the disease-causing agent [3]. To prevent financial loss of crop yields, the pest population must be managed at a level that minimizes biological activity. It is neither practicable nor necessary to completely exterminate a pest. In addition to controlling the insect population, pesticide treatment should also avoid contamination and harm to non-targets [4,5]. Many agricultural robots that can perform some of these tasks are already on the market, and many more will do so in the near future. Agricultural robots, however, are now far too expensive, slow, and difficult to use for the general public [6]. The pesticide's mechanism of action, relative toxicity, and other physicochemical characteristics aid in determining handling safety measures. To lead a robot platform that is independently developed to drive across the crops in a field in accordance with the designed concept of open architecture, a robotics-based guidance approach is proposed [8,9]. As a result, the robot platform is created in real time to direct the platform based on grape detection using Camera to detect the disease and spray accordingly. In essence, the proposed method was created to implement agricultural production. When need to spray pesticide or fertilizers on various grapes in the agricultural field, this kind of technique is quite helpful [10]. Farming tasks that are sluggish, repetitive, and boring are automated by agricultural robots, enabling farmers to concentrate on improving crop yields, enhancing farm efficiency, and lowering labor costs and operational expenses [11,12]. Large storage reservoirs can be carried by spraying robots for pesticides and fertilizer, and it can be deployed for a fraction of the price of conventional techniques. They can also be handled safely and even autonomously. In fact, it is predicted that agricultural robots can spray pesticides and fertilizers with up to five times less effort than human labors using knapsack sprayers [13]. The purpose of this study is to create an affordable agricultural robot that can spray pesticides and fertilizers on farmland. To keep costs to a minimum, the prototype fertilizer and pesticide spraying robot was constructed from simple, affordable, and easily accessible components. The two main uses for the agricultural robot created for this research project are the spraying of pesticides and fertilizers in addition to regular crop monitoring. The system consists of a four-wheeled robot, a mobile base, a wireless controller for controlling the robot, and a camera that delivers a live video feed for tracking the general health and growth of crops.

II. Literature Survey

Chuandong Zhang proposed in their paper that with strong robustness, generalization, and real-time adaptability, In addition to being a high precision, high speed, and lightweight solution for grape cluster detection, the detection network can respond to variations between commodities and complex environmental interference [3]. In their study, Goutami G. Manvi made a proposal depends on deep convolutional neural networks which improve accuracy and also the training effectiveness. The plant illness may be precisely identified by using CNN Algorithm. According to accuracy data, this model outperforms all conventional framing [4]. In their work, Chiagoziem C. Ukwuoma recommended doing a thorough investigation into and use of deep learning models for fruit detection and categorization. A deep learning model for fruit categorization was created from scratch using the well-known dataset "Fruit 360" to make it easier for new agricultural researchers to understanding the role of deep learning with the agriculture domain [5]. Ibaphyrnaishisha Kharir proposed in their paper that reviewed multiple image processing methods to use machine learning to identify multiple plants using its leave feature in the form of an image and focuses on the identification and classification of different parts of leaves to identify the plant species [6]. Thenmozhi Kasinathan proposed in their paper that the machine learning and insect pest detection algorithms were used in this study is to classified and detection various insect datasets, and the outcomes were compared. To extend the dataset and boost accuracy, every bug image was rescaled, pre-processed, and enhanced [7]. The classification of nine different tomato crop diseases has been proposed by Mohit Agarwal using convolution neural network technology. Data from the plant village dataset has been used for the experimental purpose. In order to balance the samples in each class, data augmentation techniques are applied afterward. Traditional Machine Learning methods and well-known pre-trained neural network models have been used for performance evaluation [8].

III. METHODOLOGY

It has caused a significant after-effect situation by possibly causing plant diseases. A severe decline occurs in agricultural product quality and output. Early insect detection is a significant issue for planting. Initially project goes from design and fabricating of pesticide vehicle which explain in detail in this chapter. Actual work on machine learning concept also introduced briefly. The first phase entails carefully and frequently monitoring the crop. The impacted crop component is then photographed using scanners or cameras after the affected plants have been identified. These things are after that preprocessed, altered, and grouped. Following that, the ML model receives these photos as input and compares them. An automatic pesticide sprayer is used to spray if the image is tainted.

A. Design and Fabrication of Sprayer

The four-wheeled agricultural robot has an aluminium frame and is operated by an operator in the concept design for spraying pesticides and fertilizer. To make it easier to manoeuvre among grape crops in an agricultural field and to avoid damaging the crops and soil structure, the agricultural robot prototype was made to be compact and lightweight. Each plant in the crop can be treated with fertilizer and insecticides using the agricultural robot. To carry out the spraying process, sprayer uses a liquid sprayer as liquid insecticides are much more effective at quickly locating and eliminating pests.. The spray system was created to only apply the perfect amount of pesticides and fertilizers to each individual plant, minimizing waste and attaining precision agriculture objectives. The prototype agricultural robot has four external wheels for mobility on uneven terrain in an agricultural field. The wheels of the agricultural robot may be readily turned by either turning the adjacent wheel counter clockwise, pushing the opposing wheels ahead, or breaking the two adjacent wheels and turning the opposite wheels. For instance, the left wheel will be hit the brakes and the right wheel advanced if the robot is being moved left. The wheels can be turned in opposing directions for even tighter turns. For instance, while turning sharply to the right, when the right wheel travels backward, the left wheel advances. The prototype system has four wheels and a caster, is mechanically simpler and less expensive for the agricultural robot than installing a differential gear and pinion and rack steering. The agricultural robot model has a connected action camera allows for live video monitoring of the movement of sprayer in the field as it sprays fertilizer and pesticides. This will make it easier for the operator to position and control the robot manually. In addition, the camera will help farmers monitor the general health and development of their crops as well as identify pests in the agricultural area.

The specifications of pesticide sprayer are presented in Table I. Firstly the CAD model of prototype pesticide sprayer is designed in CATIA V5 software as shown in Fig.1.(a). The prototype pesticide sprayer is fabricated by standard techniques and final model is assembled as shown in Fig.1.(b).

TABLE I. Specifications of Pesticide sprayer components

Sr. No.	Name of component	Specifications
1	Frame	450x450x300 mm
2	Storage Tank Capacity	3 liters
3	Adjustable Bar	600x600 mm
4	Wheels	100 mm
5	Motor	Gear DC Motor 100rpm
6	Battery	12V, 7Amp
7	Arduino	ATmega38P-8 bit AVR
8	Motor driver	L298N – 2A
9	Voltage Regulator	LM-7805, 5V

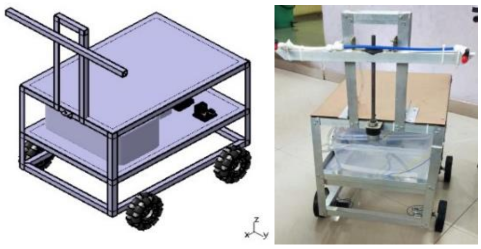


Fig. 1. (a) CAD Model of Sprayer (b) Fabricated Model of Sprayer

Flowchart for the connections of electrical parts of the pesticide sprayer is shown in Fig.2. The sprayer has main four types of output i.e. driving motor for movement of sprayer, for steering of sprayer and pump for spraying of fertilizers and these are controlled by a micro controller. Charging controller is provided for controlling the overcharging of battery. Battery supplies power to operate motor driver and relay board. Motor driver and relay board are controlled by microcontroller. Motor for movement and steering are operated and controlled by motor driver. Pump for spraying of pesticides is operated and controlled by motor driver. Camera is provided to capture images for machine learning concept.

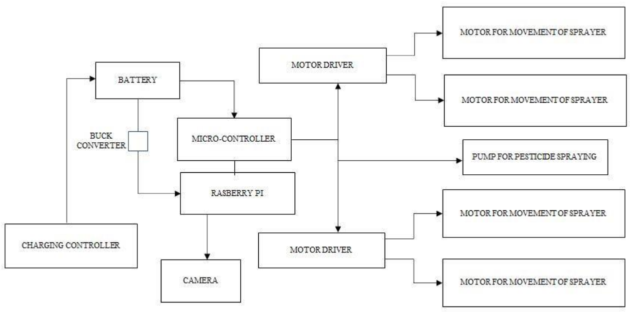


Fig. 2. Electrical Connection Flowchart

B. Proposed Machine Learning Concept

An elevated, processed general-purpose programming language is identified as Python. The grape identification algorithm using the Python Web Framework is used to identify grape. Using the camera, pictures of the grape cluster are taken.. An image is pre-processed to remove noise and other undesired elements. The machine learning process used in the current work is depicted in Fig.3. Data acquisition is the process of sampling signals that reflect actual physical conditions and converting those resulting data into digital numeric values that a computer can process. Integrating data from various sources, including relational and non-relational databases, data cubes, files, etc., is necessary for data interpretation.

Data Preparation and pre-analysis is the most important step in building ML algorithms. First, pre-processing of the data will be done based on the previous knowledge gained from Data Acquisition. Then, images will be divided into Training set, Testing set and Validation set. Data preprocessing is the process of transforming raw data into an understandable format. The quality of the data should be checked before applying machine learning or data mining algorithms. Further, the Image Augmentation will be carried out as per the requirement of ML Model. Data pre-processing consisted of resizing and rescaling of dataset, followed by Data Augmentation like the images a random flip or random rotation is provided to avoid bias behavior of our model.

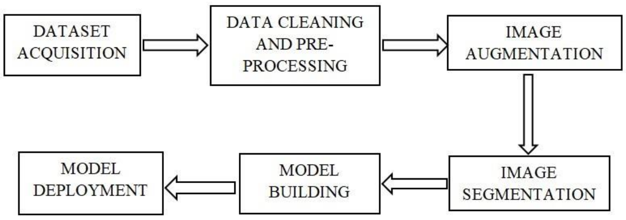


Fig. 3. Flow Chart of conceptual Machine Learning / Image Processing

Smart farming based on the Machine Learning (ML) has been found to improve the quality of fruit and vegetable yields. To classify photos of grapes captured by the camera, an image classifier was developed and assessed. The work will look into convolutional neural networks (CNN) architectures for classification, considering their huge success in recent years in a variety of object recognition and classification problems. The dataset have been acquired from Kaggle named as "Grape Database". This Dataset consists of total 850 images of different classes. This dataset contains 2 different classes (Healthy Grapes and Unhealthy Grapes) as shown in Fig. 4. (a) and (b). After data cleaning, there were 787 grape photos in the Grape dataset utilized in this study. They were then manually labeled with Labeling and randomly cropped to various dimensions (ranging from 514 460 pixels to 4160 3120 pixels).

The 787 images were enhanced into 2361 images using transformations like rotation, horizontal mirroring, scaling, translation, and changing brightness, and 80% (1888 images) of the enhanced dataset was randomly chosen as training data to train the python-based target detection algorithm. This improved the model's capacity for generalization. The remaining dataset was divided into a validation dataset made up of 10.00% (236 photos), and a testing dataset made up of the remaining 237 images. The images in the dataset also differ in terms of shooting angle, distance, equipment, imaging size, resolution, shooting light, as well as various levels of occlusion and overlap. All of the aforementioned variations are a result of the dataset's complexity and diversity, which significantly raises the bar for detection and presents more difficulties for the detection network, allowing it to more thoroughly test the robustness, generalizability, and adaptability of the detection algorithm.

(a) (b)

Fig. 4. Dataset collected to train and validate ML model (a) Healthy grape cluster (b) Unhealthy grape cluster

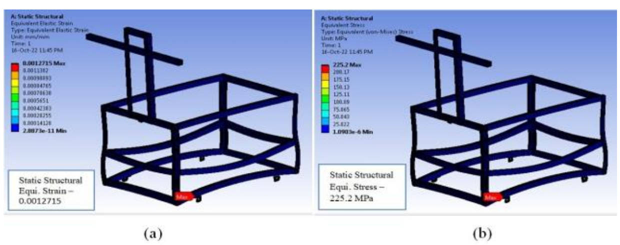
IV. Results and Discussion

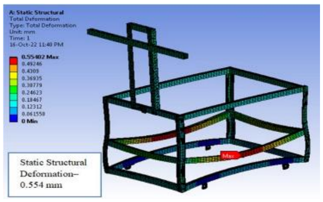
Simulator analysis is used to verify that the product meets all operational requirements. Simulation modelling allows for the secure and efficient resolution of real-world problems. It provides a crucial analytical method that is easy to verify, interpret, and explain. Simulation modeling offers useful solutions across sectors and disciplines by giving precise insights into complicated systems.

Artificial intelligence, especially machine learning (ML) and deep learning (DL) algorithms, is emerging as a key tool in the fields of materials and mechanical engineering due to its capacity to forecast material characteristics, design materials, and uncover novel mechanisms that go beyond intuitions. When machine learning (ML) strategies are combined with appropriate image processing principles, there is a lot of promise for the creation of an automated system that can differentiate grapes based on their variety, maturity, and intactness. Using the Fruit Detection Process, this image processing method can distinguish between good and unhealthy grapes.

A. Mechanical Design Frame Analysis

Design frame analysis done on ANSYS Software with static structural and modal analysis. Static structural analysis measures Total Deformation, Equivalent Stress, and Equivalent Static Strain of material. Maximum and minimum deformations measured by considering with Front-End and Back-End.





(c)

Fig. 4. Static Structural Analysis Results (a) Equivalent Elastic Strain (b) Equivalent Von-Mises Stress (c) Total Deformation

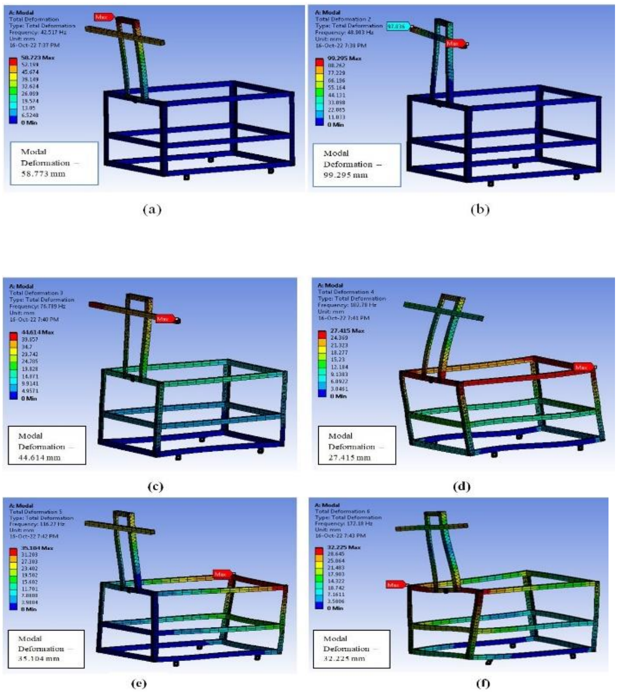


Fig. 5. Modal Analysis Results (a) Total Deformation Mode 1 (b) Total Deformation Mode 2 (c) Total Deformation Mode 3 (d) Total Deformation Mode 4 (e) Total Deformation Mode 5 (f) Total Deformation Mode 6

B. Spray test

The agricultural robot prototype's capacity to decrease labor requirements and associated costs for the fertilizer and pesticide spraying process was demonstrated by the number of plants it covered in 5 minutes compared to a human worker using a knapsack sprayer. To lower the total testing costs, water was used in place of the liquid fertilizer and insecticide for this test.

The agricultural robot prototype could spray liquid fertilizers and pesticides on 22 plants per minute while operating in remote control mode, as shown in Table II, as contrasted to the human worker's knapsack sprayer's 30 plants per minute[16]. As a result, the robot was able to cover 110 plants in 5 minutes as opposed to the human worker's 150 plants. The crop coverage productivity of the agricultural robot prototype is somewhat below that of a human worker, but the labor expenses it saves are significantly higher.

There is no reason why you should require a second worker to apply pesticides and fertilizer. This is especially true in large farms where a significant number of workers are required for the task. Using numerous agricultural robots for this process results in long-term cost savings because the robots only need to be purchased once and maintained seldom, as opposed to paying employees by the hour.

TABLE II. Comparison of Human Worker and Prototype Robot Plant Coverage [16]

Time (Minutes)	Plants sprayed by the prototype robot	Plants sprayed by human worker
1	22	30
2	22	30
3	22	30
4	22	30
5	22	30
Total	110	150

C. Battery life test

The agricultural robot prototype underwent a battery life test to make sure it could carry out all the necessary tasks for a lengthy amount of time, including spraying insecticides, liquid fertilizer, and general crop monitoring. In order to avoid having to recharge the robot frequently, which lengthens operation times and reduces efficiency, a strong battery life is essential. The prototype system was developed to take the place of human workers in an effort to reduce labor expenses and requirements. The robot base and action camera are powered by different battery packs, thus the time it took for both batteries to totally discharge from a full level was monitored. The agricultural robot prototype was operated continuously throughout the first crop path while in autonomous mode in order to test the robot base's battery life. The spraying mechanism was sporadically turned on throughout this time to mimic actual usage. When the robot arrived at the first crop path's end point, the operator took over control of it in manual mode and moved it to the second crop path's beginning point. Once the autonomous mode was restarted and the robot had moved toward the end of the second crop path, the operator sent it back to the beginning of the first crop path to repeat the procedure. The battery life test results show that it takes the robot base 5.5 hours to completely drain from a full battery level. The battery life for the action camera, meanwhile, was found to be 7 hours. These findings are quite respectable considering that a typical human worker shift for applying fertilizer and pesticides lasts three hours, with a two-hour break in between each shift throughout an eight-hour workday. Therefore, before needing to refuel, the agricultural robot prototype can work for up to two shifts. As a result, when the prototype system replaces human workers, there won't be an increase in operating times or a decline in the efficiency of the process of applying fertilizer and pesticides owing to recharging times. Recharging times for the robot base is 2 hours.

D. Training and Validation of Machine Learning Model

Object detection is a method for training computers to recognize objects in pictures or movies; over the years, numerous firms and researchers have developed various object detection structures and algorithms. The Google Brain team recently unveiled the EfficientDet model, which develop the most accurate and efficient model by achieving the highest accuracy with the fewest training iterations.

With the least number of computational resources, this architecture defeats YOLO and AmoebeaNet. This EfficientDet model is used to train the machine learning model to train the grape dataset and detect the condition of grape cluster. There are five sub-models of EfficientDet available for training the dataset as listed in Table III. These sub-models are differing by its latency and average precision to train the dataset which are compared Fig. 7. Also, the speed of training the model is differ and depend upon precision and latency required. The sub-model selected and used to train dataset of grapes is EfficientDet-Lite4 as its latency and accuracy is better than other four available sub-models of EfficientDet.

TABLE III. EfficientDET-LITE model details

Sr. No.	Model Architecture	Size	Latency (ms)	Precision
1	EfficientDet-Lite 0	4.4	146	25.69
2	EfficientDet-Lite 1	5.8	259	30.55
3	EfficientDet-Lite 2	7.2	396	33.97
4	EfficientDet-Lite 3	11.4	716	37.70
5	EfficientDet-Lite 4	19.9	1886	41.96

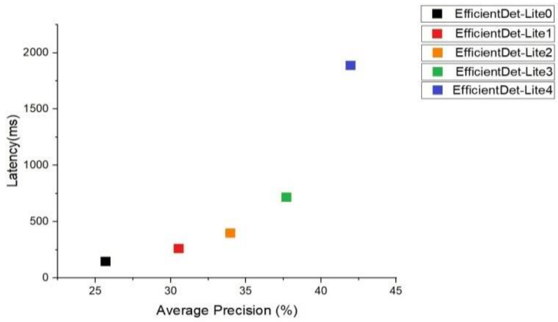


Fig. 6. Comparative Graph of Efficientdet Sub-Models

Model validation in machine learning is the procedure where a trained model is assessed using a testing data set. A different portion of the same data set from which the training set is created makes up the testing data set. To evaluate a trained model's capacity for generalization, the testing data set is primarily used. The entire process of developing a machine learning model is centered on acquiring data and calibrating the model. It is less important than it should be to test the model and validate the results. The proper validation techniques aid in determining the performance of objective generalized models and shed light on the training approach.

Building the model includes implementing and building of model will be done using the Dataset. This model will be trained using the training and validation datasets respectively. Then the model will be assessed on the basis of accuracy and prediction of different images from testing dataset. After image preprocessing, the dataset was divided into training, validation, and test datasets in the ratio of 8:1:1 (80% training, 10% validation and 10% testing data.)

After splitting the dataset, we build the model using the CNN architecture layers and our pre-defined image processing and augmentation functions. Fitting or training of model is done after successful building and compiling of model, so we fitted the model with training dataset (train_ds), 30 epochs, validation dataset (val_ds), etc. After running the script, the model starts learning or training on the basis of loss and accuracy and using back propagation algorithm. Evaluation will be a very important step in this process, as the Model will be evaluated on the basis of its accuracy and successful execution. The live feed given by camera built on spryer is inspected in two categories i.e., healthy and unhealthy as shown in Fig.8. The model will be reviewed carefully to make sure it is able to achieve the research objectives.

Fig. 7. Grape Condition Detection in Developed ML Model

V. CONCLUSION

A low-cost agricultural robot that could monitor crops and apply pesticides and fertilizer to farm fields was the aim of this research which is completed during the work. A four-wheeled robot with a movable base, a spraying mechanism, a wireless controller to direct the robot's movements, and a camera for observing crop health and growth as well as spotting pests in an agricultural setting are all included in the prototype system.As the vehicle goes forward, the pump operates, creating pressure in the tank and causing the nozzle to spray insecticide. There will be no negative effects on human health because this vehicle will be driven forward by a geared motor. Additionally, it covers a wider area in less time, saving a significant amount of time, money, and labor.

Machine learning and image processing were used to successfully diagnose the plant condition. It is now possible to lessen plant, leaf, and grape diseases by spraying pesticides effectively. The farmer will benefit because this may be managed from any location without requiring them to work in the field and expose themselves to pesticides. User will stay unaffected with health condition. The proper application of technology to support agricultural expansion is recommended in this research. A farmer can maximize their wealth by increasing productivity by eliminating the sickness from their crop. This can be viewed as a development in the agricultural sector that prevents a food crisis, appeals to youth, and demonstrates the aroma of agriculture.

The agricultural robot prototype has somewhat lower crop coverage productivity than a human worker because it is not completely autonomous and just requires the operator's control to place it at the start of the crop path, but the labor costs it saves are much higher. In addition, the agricultural robot prototype does not spray fertilizers and insecticide in the spaces between individual plants, as human employees do when utilizing backpack sprayers to cover the entire crop route. As a result, the prototype system can save more resources, reduce resource consumption, and lessen the leeching-related contamination of subsurface water sources. As a result of the prototype system's success in lowering labor costs and requirements for the fertilizer and pesticide spraying process. one suggestion has been made for further development, Making the robot completely autonomous will save labor expenses even more because no operator is required to manually direct the robot to each crop path.

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