



Design and Control of an Intelligent Mobile Gardening Robot Supported by Deep Learning-Based Image Processing

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ABSTRACT

In this study, the design and control of a mobile gardening robot based on image processing and artificial intelligence were implemented. The system, running on Raspberry Pi 4B, can distinguish different plant species and weeds using a YOLOv5-based object detection and classification model; it performs tasks such as cutting weeds, watering useful plants, and moving autonomously while avoiding obstacles. Experiments conducted in a pot environment demonstrated that the robot can successfully perform plant detection, classification, and maintenance

functions. With these features, the developed robot offers a low-cost and sustainable solution for small and medium-scale agricultural businesses. The mobile gardening robot designed within the scope of the study was experimentally tested for image processing-based plant recognition, autonomous plant orientation, plant cutting, and watering operations for different scenarios. When the results obtained were examined, it was seen that the developed deep learning-based plant detection model achieved an 82% mAP@50 success rate, while the plant classification model achieved a 92.9% mAP@50 success rate.

Keywords: Smart Agriculture, Deep Learning, Image Processing, Autonomous Gardening Robot, Cutting Weeds, Irrigation

1. Introduction

Today, the growing world population, climate change, and dwindling natural resources are forcing the agricultural sector into a process of radical transformation. Sustainable and efficient agricultural practices have become a fundamental requirement in terms of both ensuring food security and optimizing the use of natural resources. Advances in Artificial Intelligence (AI), robotic systems, image processing, and sensor technologies enable the development of smarter, more efficient, and autonomous solutions to replace traditional methods in agriculture (Khosla 2015; Sharma & Shivandu 2024).

According to the Food and Agriculture Organization of the United Nations (FAO), the world population is expected to reach approximately 9.7 billion by 2050, and it is estimated that agricultural production must be increased by at least 60% to meet this increase (FAO 2017). However, the decline in the rural workforce, the aging profile of farmers, and the limitations of traditional methods pose serious obstacles to achieving this goal. Furthermore, the fact that approximately 70% of the world's freshwater resources are used in agriculture (UN Water 2025) shows that inefficient irrigation techniques pose a major threat to environmental sustainability. Furthermore, the failure to detect and intervene against weeds in a timely manner also negatively affects crop productivity. Therefore, the need for autonomous and AI-supported agricultural systems is increasing day by day (Shamshiri et al. 2018; Catala-Roman et al. 2024).

The literature contains many plant robots developed in this direction (Bac et al. 2014; Del Dottore et al. 2018; Liang et al. 2025). The See & Spray system, developed by US-based Blue River Technology, stands out in weed control. This robot, which detects weeds using AI-powered camera systems, reduces chemical use by applying pesticides only to detected areas, offering an environmentally friendly approach (John Deere 2025). In addition, there are studies in the literature on autonomous mobile robots for harvesting purposes. An image processing-based autonomous robotic harvester was designed for protected agricultural environments, and sweet peppers were successfully harvested using this harvesting robot (Lehnert et al. 2017). A harvesting machine consisting of a mobile robot and manipulation system was designed for squash, a heavy agricultural product, and squash harvesting was successfully performed using this system (Roshanianfard et al. 2022).

Recent studies have further expanded the scope of autonomous agricultural robots in areas directly related to this study. Bajraktari & Toylan (2025) proposed a vision-based autonomous agricultural robot integrating the YOLOv8 model with the ByteTrack object tracking algorithm for real-time weed detection and destruction, achieving a precision of 93.8% and an mAP@0.5 of

92.1% (Bajraktari & Toylan 2025). Visentin et al. (2023) developed a mixed-autonomous robotic platform capable of performing both intra-row and inter-row mechanical weed removal using a vision system mounted on a mobile rover, demonstrating that a dual-camera setup significantly improves plant detection and classification performance (Visentin et al. 2023). Mwitta & Rains (2024) presented a small-scale autonomous robot employing a diode laser for chemical-free weed elimination in cotton fields, combining deep learning-based weed detection with PID-controlled autonomous navigation on uneven terrain (Mwitta & Rains 2024). Mookkandi et al. (2026) introduced Agrova, an AI-powered autonomous rover built for small-scale farms that integrates YOLOv5-based real-time weed detection and plant disease classification on a custom six-wheel chassis modeled in SolidWorks, achieving approximately 89% weed detection accuracy and 95% disease classification accuracy in field experiments (Mookkandi et al. 2026). Hernández-Terrazas et al. (2026) presented a simulation-based vision framework integrating convolutional neural networks with a 2-DOF robotic manipulator for selective weed detection and mechanical intervention in precision agriculture (Hernández-Terrazas et al. 2026). Furthermore, Apu et al. (2026) developed SmartWeed, an autonomous rover for real-time weed detection and classification using advanced YOLO models combined with a Convolutional Block Attention Module (CBAM), with YOLOv9-E achieving the highest detection accuracy on a dataset of 5,997 weed images (Apu et al. 2026).

As seen in studies in the literature, plant robots are not only harvest-focused; they also make significant contributions to weed control, irrigation, and general maintenance processes. The AI-based "Smart Gardening Robot" developed in this study brings together weed removal, irrigation, and plant classification functions on a single platform, making a unique contribution to the literature.

2. Gardening Robots

Gardening robots developed in recent years stand out in tasks such as irrigation, weed removal, and plant care. Various systems are used in this field at different scales.

Figure 1 shows the Growver, an irrigation robot developed for lawns. It detects dry areas with its sensors and waters only the necessary spots, thus providing significant water savings (Robotic Gizmos 2020).



Figure 1- Growver robot (Robotic Gizmos 2020)

Figure 2 shows GardenSpace, a system that operates in a fixed position, monitoring plants with cameras and sensors. It can determine the plant's watering needs and also provide protection against animals or pests (TechCrunch 2018). Thanks to its solar panel-supported operation, it has low energy consumption.



Figure 2- GardenSpace robot (TechCrunch 2018)

FarmBot, shown in Figure 3, is an open-source CNC-based agricultural robot that can perform numerous tasks such as sowing seeds, watering, and weeding on a rail mechanism. Its modular design allows it to be customized for different agricultural tasks (Kar et al. 2023).



Figure 3- FarmBot robot (Kar et al. 2023)

Tertill, shown in Figure 4, is a solar-powered compact gardening robot focused on weed removal. Using height sensors to protect plants, this robot can operate autonomously in small-scale gardens (Sanchez & Gallandt 2021).



Figure 4- Tertill robot (Sanchez & Gallandt 2021)

The smart mobile gardening robot developed in this study differs from these systems in that it combines multiple functions on a single platform. The robot detects plants using a YOLOv5-based detection model, classifies them into five categories using a classification model, and can perform watering or weed removal based on this classification. It also offers a more comprehensive and integrated solution by bringing together the functions that gardening robots perform separately into a single system. Thanks to its pallet wheel structure, the robot can move on uneven terrain and, unlike stationary systems, can perform its task by targeting different plants. The image processing on plants, autonomous plant targeting, plant cutting, and watering performance of the mobile gardening robot designed within the scope of the study were experimentally tested, and as a result, it was observed that the robot successfully performed the desired movements.

3. Design of the Mobile Gardening Robot

The deep learning and image processing-based mobile gardening robot developed in this study was designed to reduce the need for human labor in agricultural production and to make plant care processes autonomous. The system runs on a low-cost embedded platform, the Raspberry Pi 4B, and is supported by computer vision-based AI algorithms.

The robot can detect plants in real time using a YOLOv5-based object detection model on images obtained through the Raspberry Pi camera module V3 (Raspberry Pi 2025). It can classify plants as tomatoes, potatoes, cucumbers, peppers, and weeds using a classification model. Movement planning for detected plants is performed by combining image-based distance estimation with data obtained from the VL53L1X Time-of-Flight sensor. This allows the robot to navigate towards the target plant while avoiding obstacles.

After plant classification, the soil moisture sensor evaluates the watering needs of useful plants, and if the threshold value is below, the water pump on the robot activates for automatic watering. If the classification identifies the plant as a weed, the cutting mechanism positioned on the robot activates and cuts the plant. After these processes are completed, the robot moves to the next plant in its vicinity and continues its task in the same manner. Experimental tests have shown that the robot can accurately detect plants in pots, distinguish and remove weeds, and successfully perform watering tasks. With all these features, the system offers a low-cost, scalable, and sustainable solution, especially for small and medium-sized agricultural businesses.

3.1. Hardware design

The robot's mechanical design was carried out in the SolidWorks environment (Dassault Systèmes 2023), taking into account the integration of all physical components and the placement of task-oriented mechanisms. The robot's body structure, sensor locations, motion units, and task-oriented mechanisms were modeled in detail using SolidWorks. This facilitated the assembly process and prevented potential design errors by simulating the system's overall working principle in advance. Figure 5 shows the robot's design created in the SolidWorks environment.

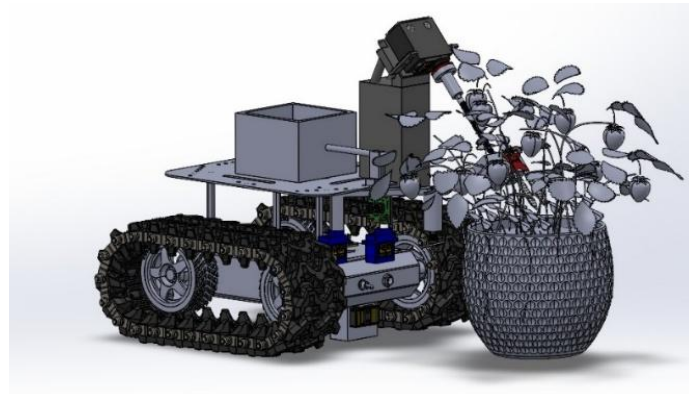


Figure 5- The robot's SolidWorks design

Multiple sensors, modules, and hardware components are integrated into the design of the gardening robot. The Raspberry Pi 4B (4 GB RAM) shown in Figure 6 serves as the central control unit of the system with its 1.5 GHz quad-core ARM Cortex-A72 processor. Image processing, sensor data analysis, and decision-making processes are performed on this board. The mini water pump performs the watering operation. The MG995 servo motor moves the crank-connecting rod mechanism used to insert and remove the moisture sensor into the soil. The moisture sensor measures the moisture level in the soil, and this data is used to make watering decisions. The SG90 micro servo motor shown in Figure 6 allows the camera to rotate between 40° and 140° on the horizontal axis, enabling wide-angle scanning. The Raspberry Pi camera module V3, with its 12 MP resolution Sony IMX708 sensor and HDR support, ensures high-quality images. The VL53L1X Time-of-Flight (ToF) sensor provides millimeter-level accuracy up to 4 meters by measuring distance using laser technology. DC gear motors (6 V, 200 rpm) enable the robot's movement via pallets. The speed and direction control of these motors is performed by the L298N motor driver module shown in Figure 6. As a result of the coordinated operation of all these components, the robot can correctly perform the processes of sensing, decision-making, movement, and action.

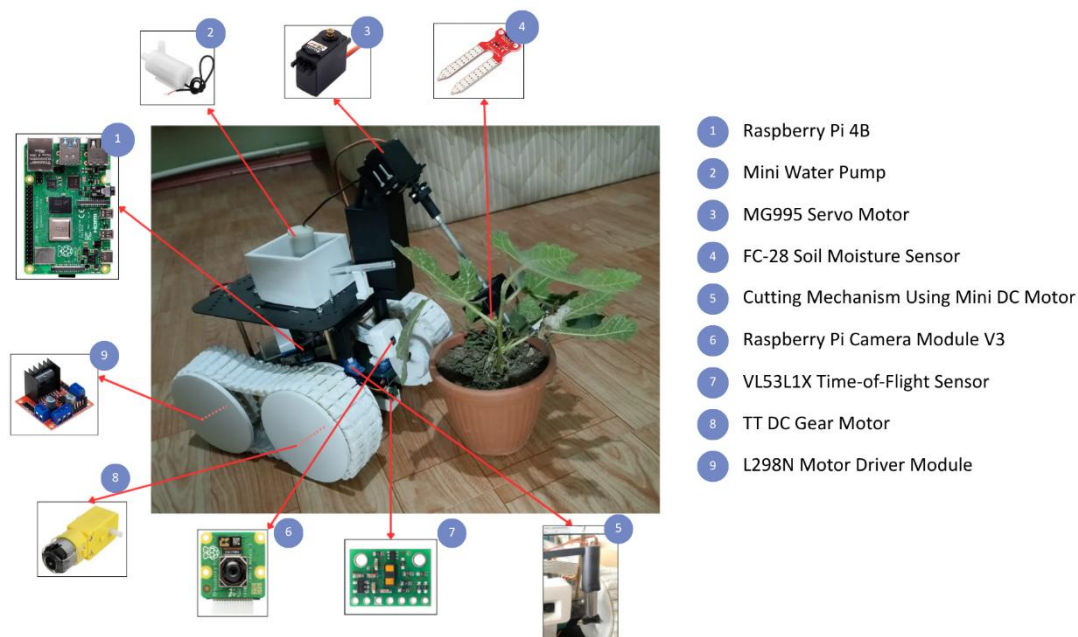


Figure 6- Hardware components of the gardening robot

As seen in Figure 6, the robot's hardware structure consists of an embedded processor, sensors, motion units, and task-oriented mechanisms. The Raspberry Pi 4B is used as the central processing unit of the system, and all image processing, AI model execution, sensor data processing, and motor control are performed on this platform. The Raspberry Pi camera module V3, shown in Figure 7, was chosen for scanning the environment and detecting plants. The camera was mounted on a servo motor to enable rotation on the horizontal axis, thus providing wide-angle scanning capability.



Figure 7- Camera mechanism

For distance measurement, a high-precision laser-based VL53L1X Time-of-Flight sensor was integrated into the robot, as shown in Figure 8, enabling high-precision measurements. In addition, distance measurement is also performed using an image processing algorithm based on images obtained from the camera used for plant detection. As the robot moves toward the pot, both the image processing-based distance measurement system and the information from the distance sensor are evaluated together to enable the robot to detect and overcome obstacles in its path. In the distance measurement process, a computer vision-based plant detection model is first run to detect the plant, and the robot's distance to the plant is approximately calculated using the bounding box scaling method. The distance is then measured using the ToF distance sensor and compared with the distance measurement value obtained through computer vision. If the distance measured by the image processing model is approximately the same as the distance measured by the ToF sensor, the robot moves toward the plant. When the distance between the robot and the plant is 15 cm, the robot slows down, and when it is 5 cm, it stops. If the distance measured by the image processing model differs from the distance measured by the ToF sensor, it is determined that there is an obstacle in front of the robot, and the robot maneuvers to avoid this obstacle. After this maneuver, distance measurements are taken again using the image processing-based plant detection model and the ToF sensor.



Figure 8- Distance detection mechanism

When the robot reaches the target plant, the FC-28 soil moisture sensor shown in Figure 9 is used to determine the irrigation requirement. Thanks to the designed slider crank mechanism, the sensor is easily inserted into the soil. The values obtained from the sensor are compared with predefined thresholds to determine the irrigation requirement. The mini water pump (6 V, 0.2-0.5 A, 100 L/hour) and hose system integrated into the robot's body are activated for the irrigation process. The cutting mechanism shown in Figure 9 includes a servo motor that positions the cutting tip toward the plant and a DC motor (6 V, 0.3 A, 10,000 rpm) that drives the cutting tip.

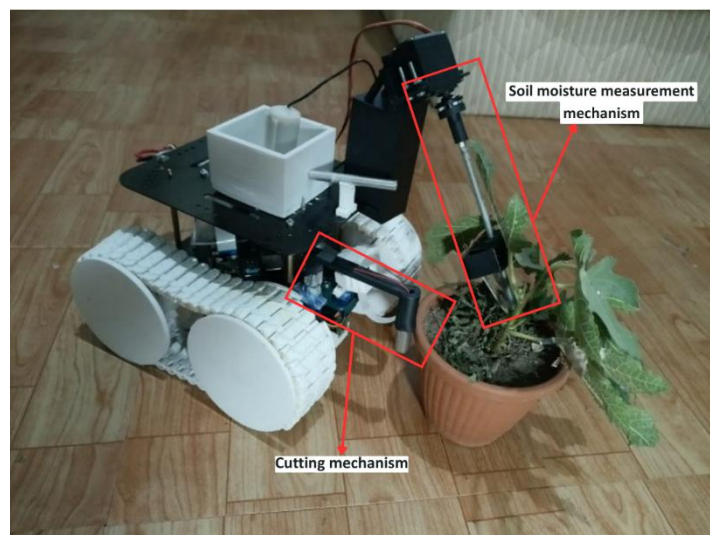


Figure 9- Soil moisture measurement and cutting mechanism

Plants identified as weeds through plant classification are cut using a servo motor-supported rotating blade mechanism.

As shown in Figure 5, a wheeled pallet system is used for the movement of the mobile robot. The wheels used to move the pallet system are driven by DC motors controlled by dual-sided L298N motor drivers, which allow for forward and backward movement as well as direction changes with differential drive.

With this hardware configuration, the robot consumes approximately 30 W of power. During experimental testing, the robot was powered by an external power source. However, it is estimated that when using a 2S 5000 mAh LiPo battery, the robot will be able to operate independently and wirelessly for approximately 1 hour.

3.2. Dataset creation and preprocessing

A specialized dataset was created for training the detection and classification models. The datasets were prepared by combining open-access plant datasets available on the Roboflow (Roboflow 2023) platform with images manually collected from the internet. The images, selected to cover different camera angles, distances, and lighting conditions, aim to make the model more resilient to real-world conditions.

A total of 1,870 labeled images were initially obtained for the plant detection model. All images were resized to 480×480 resolution to be suitable for model input. The images were subjected to various data augmentation processes in the Roboflow environment. The applied operations included horizontal flipping, 90° clockwise and counter clockwise rotations, cropping

between 0% and 30%, random rotation between -15° and $+15^\circ$, horizontal $\pm 11^\circ$ and vertical $\pm 15^\circ$ shear, converting 18% of the images to grayscale, hue adjustment (-24° to $+24^\circ$), saturation (%-25 to %+25), brightness (from -25% to +25%), exposure (from -11% to +11%), blurring up to 2.5 px, and adding noise up to a ratio of 1.33%. As a result of these operations, the plant detection dataset was expanded to 15,451 images.

For the plant classification model, a dataset consisting of 1,438 images was initially prepared. The classification model contains five classes: "chilli_pepper", "cucumber", "potato", "tomato", and "weed". All images were scaled to a resolution of 640×640 . Horizontal flipping, 90° rotation, 0–30% cropping, random rotation between -15° and $+15^\circ$, $\pm 9^\circ$ horizontal and $\pm 15^\circ$ vertical shear, grayscale conversion of 10% of the images, hue (-24° to $+24^\circ$), saturation (from -29% to +29%), brightness (from -25% to +25%), exposure (from -14% to +14%), up to 3.5 px blur, and up to 1.96% noise. As a result of these operations, the classification dataset was increased to 14,380 images.

The image labeling process was performed semi-automatically using the Box Prompting Tool available on the Roboflow platform. This tool provides preliminary bounding box suggestions for each image; these suggestions are checked by the user, the correct ones are accepted, and the incorrect ones are deleted and manually relabeled. This approach speeds up the labeling process while ensuring data quality is maintained.

Data augmentation techniques were applied to reduce class imbalance, prevent overfitting, and enhance the model's generalization ability across different environmental conditions. The created datasets were divided into training, validation, and test subsets, and the models were trained.

3.3. Deep learning-based software design

The software infrastructure of the developed gardening robot is based on a structure where sensor data processing, deep learning-based image processing for plant detection, plant classification, and decision-making mechanisms work in an integrated manner. This architecture is designed as a two-stage AI system: In the first stage, the locations of plants are determined using a YOLOv5-based object detection model; in the second stage, the classification model comes into play to distinguish the type of detected plants.

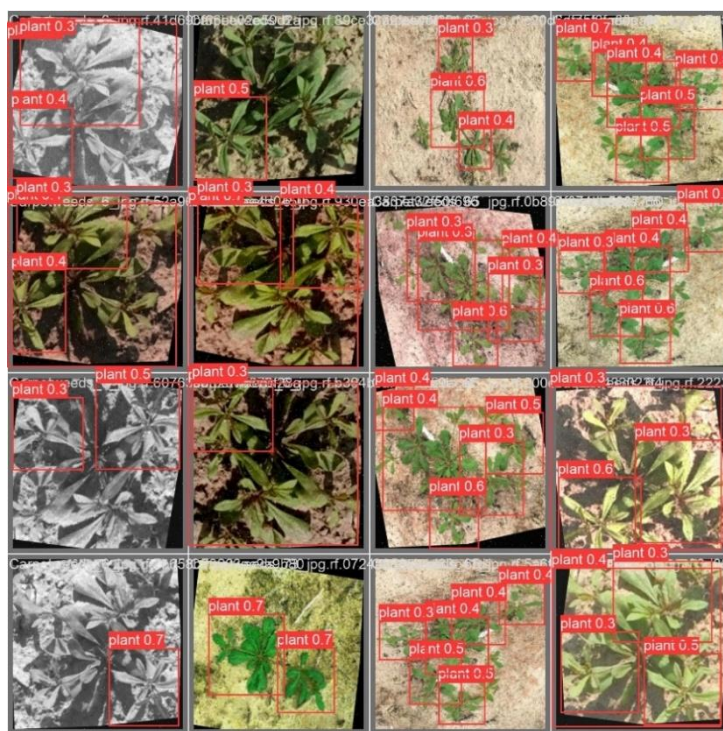


Figure 10- Plant detection model training output

The object detection model detects plants using images obtained through the Raspberry Pi camera module V3 (Ultralytics 2024). Figure 10 shows the training output of the plant detection model. After the plant detection process, the robot autonomously moves towards the plant. When the robot approaches the plant, it moves into the appropriate position and proceeds to the plant classification stage. The plant classification model is labeled with one of five different classes: tomato, potato, cucumber, pepper, and weeds. The training output of the plant classification model is shown in Figure 11. This two-stage structure ensures that plants are correctly detected and reliably classified by type.



Figure 11- Classification model output

Both models were prepared using Roboflow, and augmentation techniques were applied. The models were trained using Google Colab and made suitable for running on an embedded system. After training, the models were converted to ONNX format and run in an optimized manner on a Raspberry Pi 4B (Jocher et al. 2022; ONNX Runtime 2025).

During the software phase, OpenCV was used for image processing, ONNX Runtime for model integration, and Python-based GPIO libraries for sensor and motor control (Howse & Minichino 2020; OpenCV 2024). This structure enables simultaneous data flow between the camera, distance sensor, humidity sensor, and motors, allowing the entire system to work in a coordinated manner.

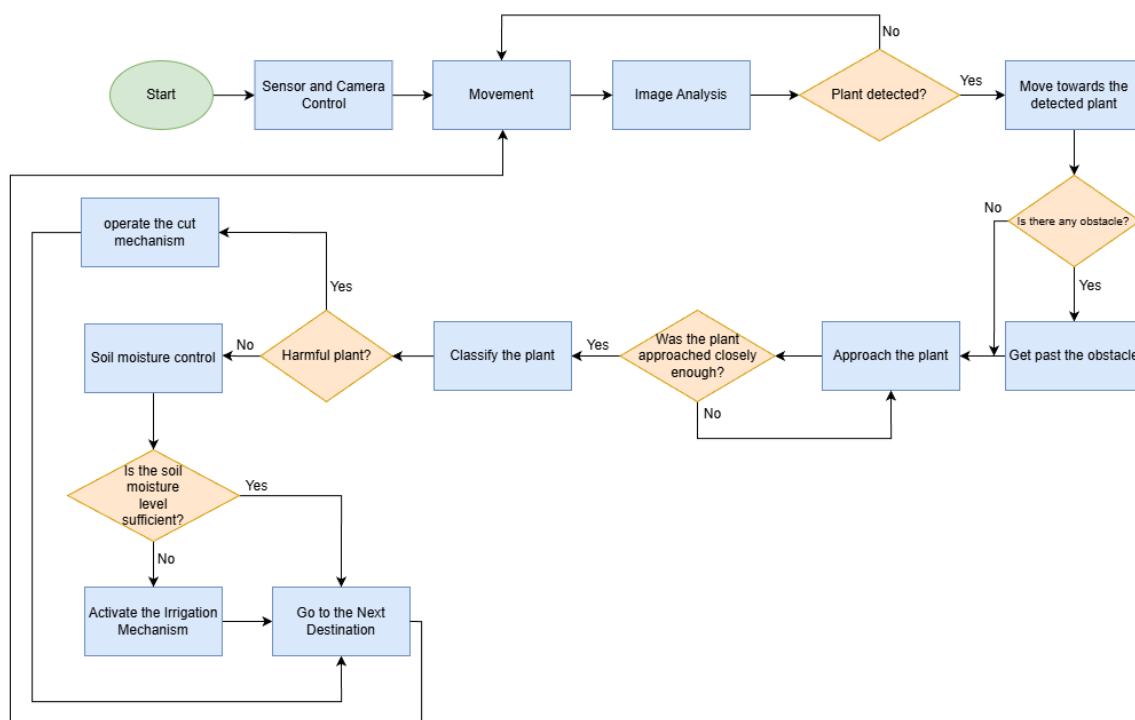


Figure 12- Flowchart of the robot's working algorithm

The flowchart of the robot's operating algorithm is shown in Figure 12. As seen in the flowchart, the robot scans its surroundings using the camera; the object detection model detects plants, and the classification model determines their type. If a harmful weed is detected, the cutting mechanism is activated; if a beneficial plant is detected, the humidity sensor values are examined and, if necessary, the watering process is initiated. After these operations, the robot moves on to the next plant and continues the task cycle. Thus, the system not only detects and classifies but also functions as an AI-based autonomous control system that interprets data and performs appropriate actions. Consequently, the software and AI architecture developed in this study not only provide agricultural robots with environmental awareness but also enable them to analyze situations and perform physical interventions.

4. Working Principle of the Robot and Experimental Results

The robot's working process begins with sensing its surroundings. At this stage, the Raspberry Pi 4B, which is the central unit of the system, performs all image processing, sensor data evaluation, and motor control operations. The Raspberry Pi camera module V3, used to collect data from the environment, is mounted on a servo motor that can rotate on the horizontal axis. As shown in Figure 13, the robot first scans its surroundings, capturing images from different angles to determine the locations of plants.

The collected images are transferred to the robot's AI-based analysis system. This system has a two-stage architecture. In the first stage, the YOLOv5-based object detection model identifies the plant in the image. In the second stage, these detected plants are sent to a specially trained classification model. The model predicts which class the plant belongs to: tomato, potato, cucumber, pepper, or weed. Both models were trained via Google Colab and converted to ONNX format for efficient operation on Raspberry Pi.



Figure 13- The robot detecting the plant

After determining the plant type, the robot proceeds to the movement phase toward the plant, as shown in Figure 14. Thanks to its palletized wheel structure, the robot can move steadily even on uneven terrain. DC motors controlled by L298N motor drivers enable the robot to move forward and backward and rotate around its own axis using the differential drive method. The robot performs both image-based and laser-based distance measurements as it approaches the target. The VL53L1X ToF sensor used for this purpose provides high-precision measurements, helping to detect potential obstacles. If a certain difference is detected between the image prediction and the sensor data, the robot perceives this as an obstacle and avoids collision by performing an appropriate maneuver.



Figure 14- Robot moving towards the plant

As shown in Figure 15, when the robot reaches the target plant, it performs the appropriate action based on the result of the AI classification. If the plant is a beneficial species, the FC-28 soil moisture sensor is first inserted into the soil via a crankshaft-connecting rod mechanism. If the sensor data is below the predetermined threshold value, in this scenario, when the moisture level is measured at 25%, the mini water pump mounted on the body and the hose system activate to perform controlled irrigation with a water volume determined by the robot's operating algorithm based on the plant species and moisture value. As shown step-by-step in Figure 15, the irrigation mechanism pumps approximately 190 ml of water over a 7 second operation period. If the soil is sufficiently moist, irrigation is not performed, and the robot moves on to the next plant.

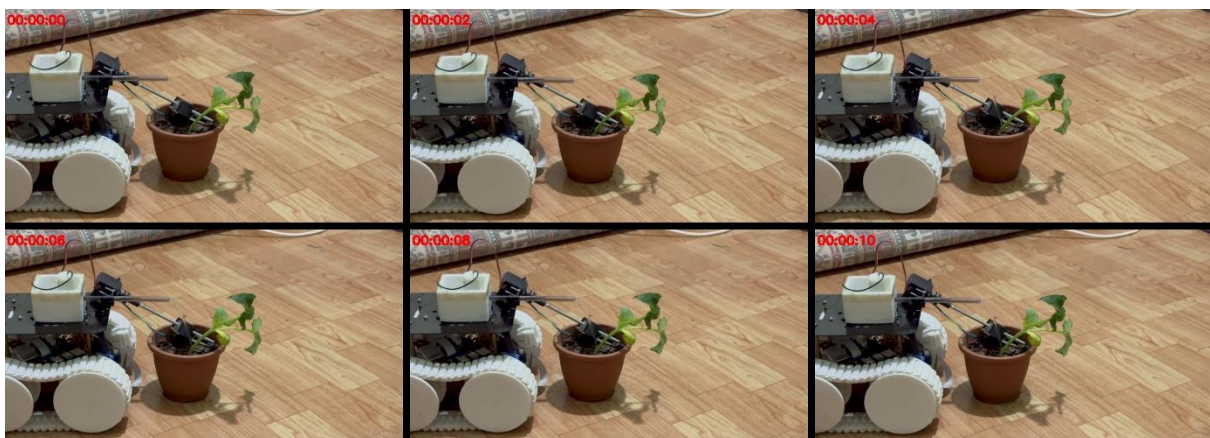


Figure 15- The robot watering the plant

If a plant is detected as a weed by the image-processing-based plant detection system, the cutting mechanism is moved toward the plant by a servo motor, and the cutting operation is performed by moving the blade attached to the DC motor shaft. The frames shown in Figure 16 illustrate the cutting mechanism cutting the weed.

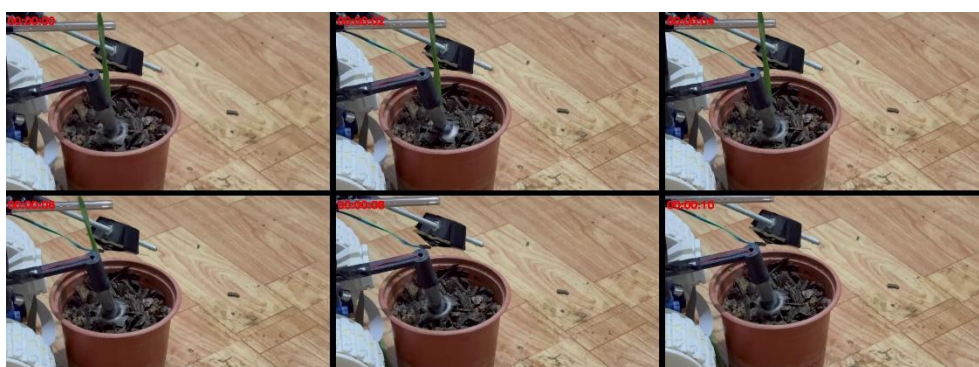


Figure 16- The robot cutting the weeds

After completing the task for each plant, the robot continues the cycle by scanning its surroundings again, as shown in Figure 17, or by moving to other targets in its memory. Thanks to this continuous working structure, the robot performs all plant-related operations autonomously. This results in an efficient and sustainable agricultural maintenance system that minimizes human intervention.



Figure 17- Shifting focus to another plant

The performance of the gardening robot developed in this study was tested in the initial phase through experiments conducted in a controlled environment. The experiments were conducted on three potted plants, specifically tomatoes, chili peppers, and potatoes. The tests were performed during daytime and night-time hours in a sunlit but enclosed area. These conditions were chosen to evaluate the effect of natural light and to observe the system's basic performance by limiting environmental variables.

The YOLOv5-based model used in the detection task was trained on a total of 15,451 images and achieved high accuracy rates after 150 epochs. According to the results obtained, the model's overall accuracy (precision) value was recorded as 83.6%, sensitivity (recall) value as 76.4%, mAP@50 value as 82.0%, and mAP@50–95 value as 49.9%. These results show that the robot can detect plants in the field with high accuracy. Furthermore, Precision-Recall (PR) and F1 score curves were examined to evaluate the overall performance of the model. As shown in Figures 18 and 19, the model achieves high precision and sensitivity values in a balanced manner. The change in the training process metrics of the plant detection model according to the epoch value is shown in Figure 20. The "results" curves shown in Figure 20 display the training and validation performance metrics aggregated at the end of each epoch. The "smooth" curves, on the other hand, illustrate the model's convergence and overall learning trends, obtained by applying a moving average filter to these metrics.

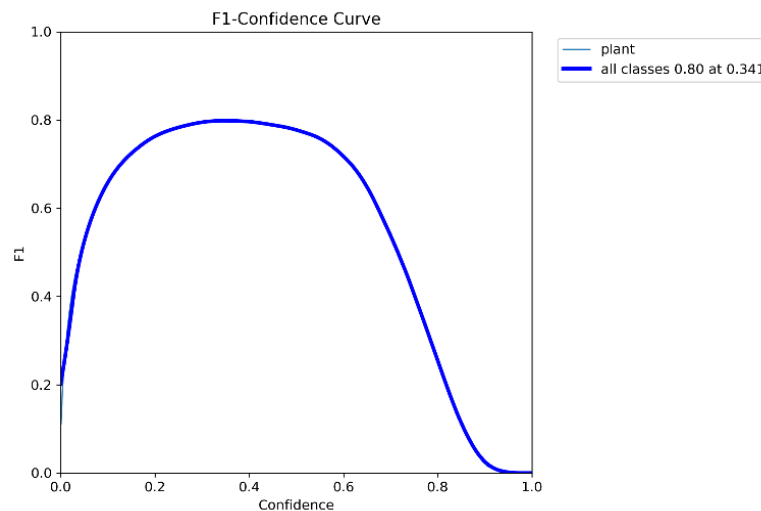


Figure 18- F1-Confidence curve for the plant detection model

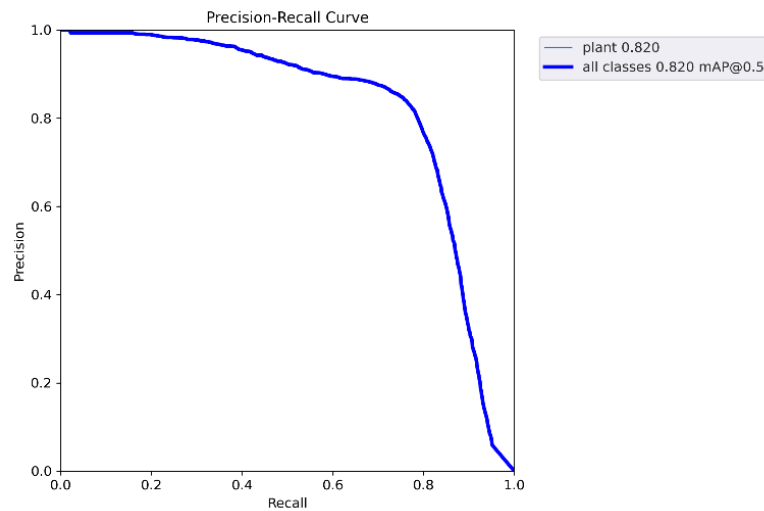


Figure 19- Precision-Recall (PR) curve for the plant detection model

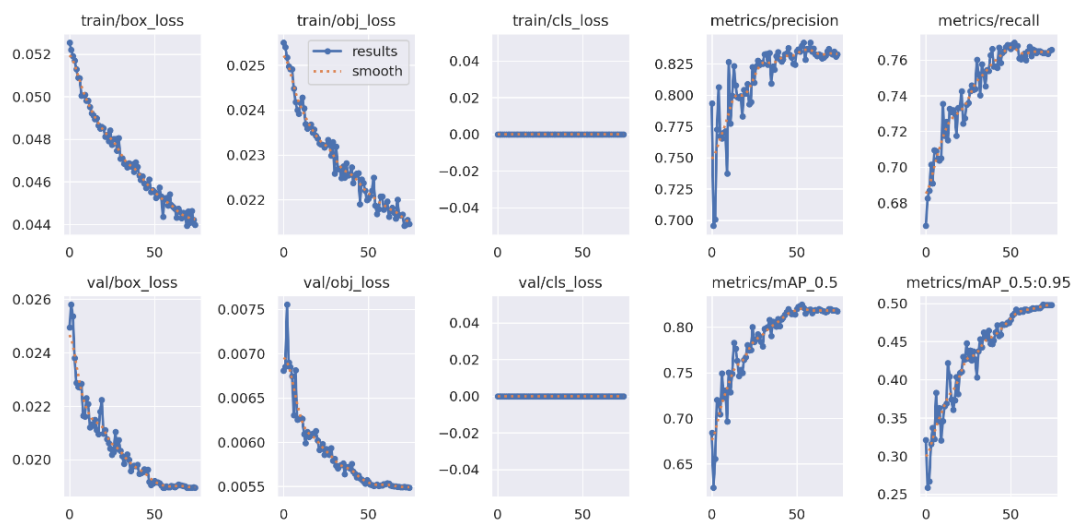


Figure 20- Change in training process metrics of the plant detection model according to epoch value

The model used in the classification task was trained on 14,380 images and achieved satisfactory performance after 225 epochs. Overall accuracy (precision) was 88.5%, sensitivity (recall) was 88.8%, mAP@50 was 92.9%, and mAP@50-95 was 55.5%. When examined by class, mAP values of 93.0% for chili peppers, 94.0% for cucumbers, 90.5% for potatoes, 92.5% for tomatoes, and 94.3% for weeds were achieved. These results demonstrate that the system is quite successful in distinguishing between different plant types. As seen in Figures 21 and 22, the model achieves high accuracy and sensitivity values in a balanced manner. The change in the training process metrics of the plant classification model according to the epoch value is given in Figure 23, and the confusion matrix is given in Figure 24.

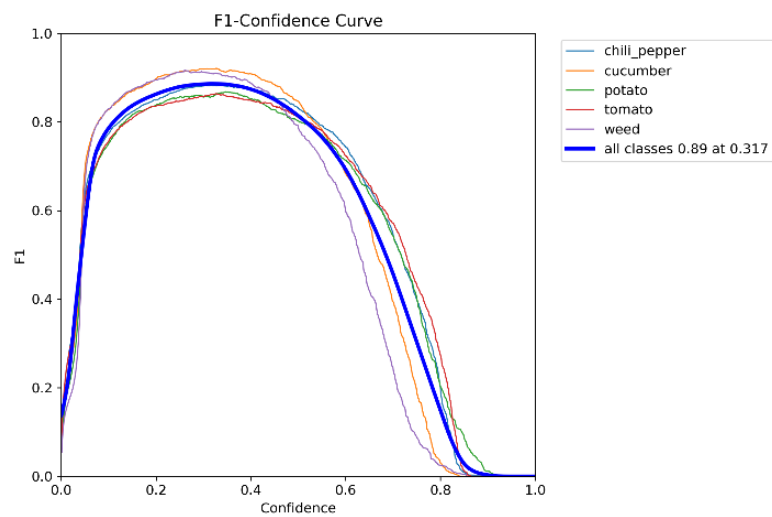


Figure 21- F1-Confidence curve for the plant classification model

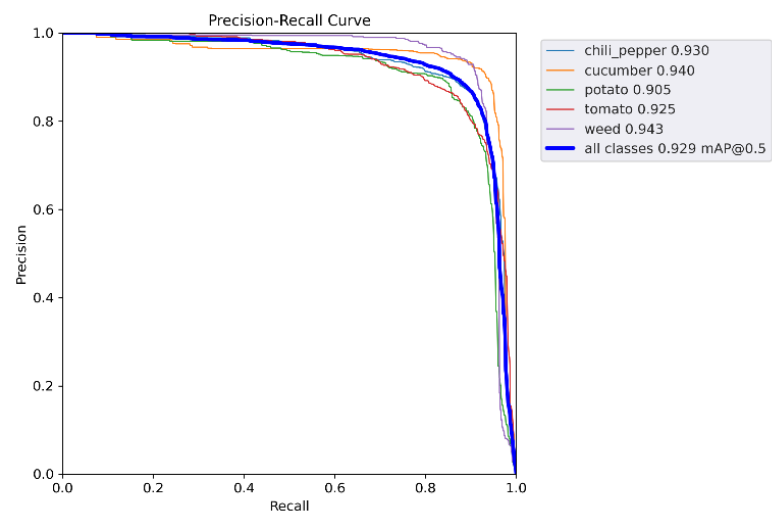


Figure 22- Precision-Recall (PR) curve for the plant classification model

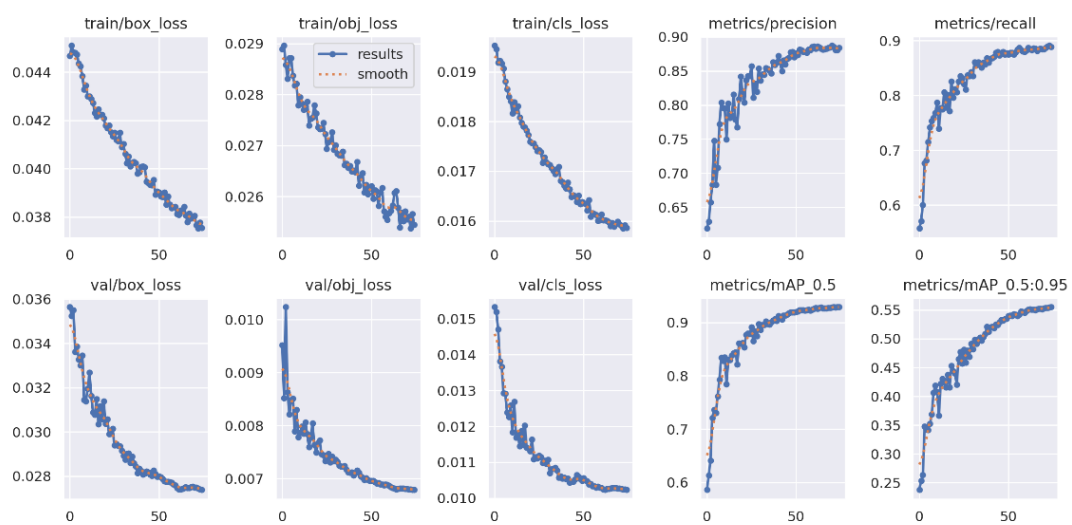


Figure 23- Change in training process metrics of the plant classification model according to epoch value

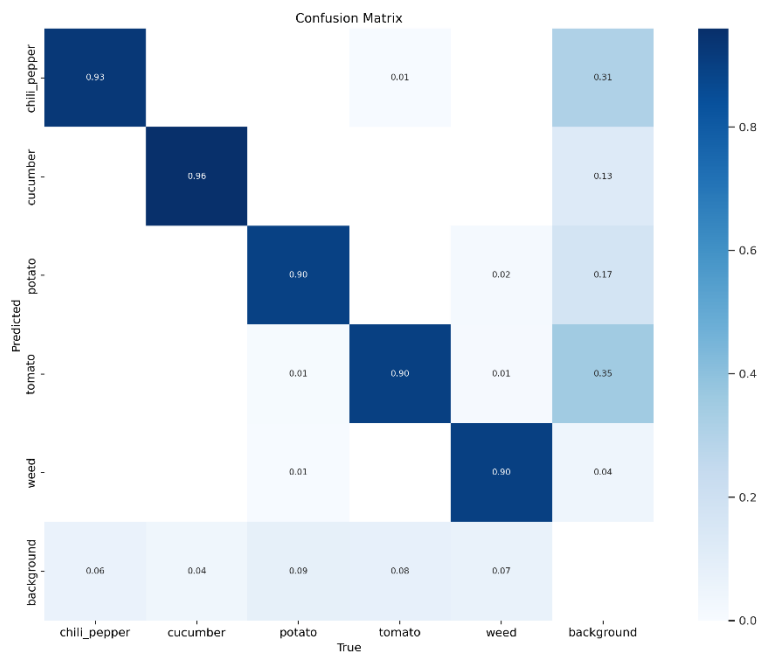


Figure 24- Confusion matrix for plant classification

In field tests, the robot moved towards the detected plant according to the created scenario and performed the necessary operations based on the classification result. The cutting mechanism worked correctly for samples classified as weeds; for useful plants, watering operations were successfully performed based on moisture sensor data. This task chain was applied smoothly in all tested samples.

Figure 25 shows sequential frames taken from video footage of the robot's operation. These sequential frames show the robot scanning its surroundings with its camera, detecting the plant, and moving towards the target.



Figure 25- Robot's working process

Overall, the experiments demonstrate that the robot performs the tasks of plant detection, classification, irrigation, and weed removal in an integrated and reliable manner.

When the performance of the YOLOv5s-based models developed in this study is compared with similar YOLOv5-based studies in the literature, the results are competitive for an embedded, real-time robotic deployment. Regarding the plant detection model, Sonawane & Patil (2025) evaluated multiple YOLOv5 variants for crop-weed detection using the Weed1000 dataset and reported that the proposed YOLOv5x model achieved a precision of 95.3%, recall of 92%, and mAP@50 of 94.5% (Sonawane & Patil 2025). Similarly, Wang et al. (2022) proposed TIA-YOLOv5, an improved YOLOv5 architecture for real-time crop and weed detection in sugarbeet fields, where the baseline YOLOv5 yielded an mAP@50 of 84.1%. The plant detection model developed

in the present study achieved a precision of 57.3%, recall of 90%, and mAP@50 of 90% (Wang et al. 2022). Regarding the five-class plant classification model, Ali et al. (2025) evaluated YOLOv5 variants on the PlantVillage dataset, with their best YOLOv5x model achieving a precision of 98.5%, recall of 96.4%, and mAP@50-95 of 88.1% (Ali et al. 2025). Kaur et al. (2025) reported that the standard YOLOv5 baseline achieved a precision of 86.1%, recall of 86.8%, mAP@50 of 94.4%, and mAP@50-95 of 81.5% on a multi-class plant disease dataset (Kaur et al. 2025). The literature indicates that enhanced performance is typically attained by larger or modified forms of YOLOv5. In this study, however, the YOLOv5s architecture—a smaller version of YOLOv5—was used to perform real-time image processing on a Raspberry Pi embedded system, yielding a precision of 83.6% and 82% mAP@50 for plant detection and 88.5% precision and 92.9% mAP@50 for plant classification. It can be seen that these performance metrics are close to the values reported in the literature for YOLOv5-based plant detection and classification studies.

The results obtained demonstrate the system's effectiveness in small-scale controlled environments and also hold promise for its applicability in large agricultural areas.

5. Conclusions

This study presents the design, prototype production, and experimental testing of an image processing and AI-based "Smart Gardening Robot". The study was conducted on the Raspberry Pi 4B, a low-cost embedded platform. The proposed AI-based system detected plants using the deep learning-based YOLOv5 model and classified them into five different classes using the YOLOv5 model. The results obtained show that the developed plant detection model achieved 82.0% mAP@50, 49.9% mAP@50-95, 83.6% precision and 76.4% recall for the developed plant detection model; for the plant classification model, high-accuracy classification was achieved with 92.9% mAP@50, 55.5% mAP@50-95, 88.5% precision and 88.8% recall across all classes. Experimental studies were conducted on four different plants (tomatoes, chili peppers, potatoes, weed) in a closed environment, and it was observed that the robot could reliably execute its autonomous task chain.

Furthermore, it was observed that the robot could perform weed removal and watering functions with high accuracy. In this regard, the robot can work effectively in small-scale agricultural environments and contribute to sustainable agricultural production by minimizing human intervention.

The original garden robot proposed in this study possesses superior features such as a low-cost hardware infrastructure, low energy consumption, a multifunctional design, and the ability to operate autonomously. Additionally, thanks to its track-wheel design, it can operate on uneven terrain. Due to this low-cost hardware structure, the robot's performance has only been tested in controlled indoor environments. To test the robot in real-world field and greenhouse environments, it will be necessary to increase motor power and utilize more advanced sensors.

In future studies, it is planned to test the robot in open fields and under larger-scale field conditions to fully demonstrate its performance. Additionally, the use of faster embedded hardware systems and the optimization of artificial intelligence models are also planned. The study also aims to improve the plant irrigation system used to control water usage more precisely and to expand its classification capabilities to include different plant species. In this context, it is anticipated that the garden robot being developed will make a significant contribution to agricultural production in terms of efficiency and sustainability in future smart farming applications.

Author Declarations

Authors' contributions: Concept: M.R., A.E.A., H.Ç., M.K., Design: M.R., A.E.A., H.Ç., Data collection: M.R., A.E.A., M.K., Analysis: M.R., A.E.A., H.Ç., Writing: M.R., A.E.A., H.Ç.

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