ENG40001 Final Year Research Project 2

Progress Report

Visual Feedback Control of Mobile Robot Arm

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Declaration

I hereby declare that this report entitled **"Visual Feedback Control of Mobile Robot Arm"** is the result of my project work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Swinburne University of Technology Sarawak Campus.

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Abstract

This research addresses pressing challenges in traditional agricultural weed management, including inefficient manual labor, widespread herbicide use, and associated environmental impacts. The study focuses on developing an autonomous robotic system capable of precise weed detection and targeted herbicide application within a controlled laboratory environment. Utilizing advancements in computer vision and robotics, the system uses the YOLOv5 object detection model to achieve accurate real-time weed identification and discrimination from crops. A Raspberry Pi 5 serves as the processing unit for the model, offering an accessible and cost-effective solution.

The robotic system features a 3-degree-of-freedom (DOF) arm with a precision sprayer. Its operation is guided by a grid-based mapping mechanism, with predefined servo angles calibrated to specific grid cells within the robot's field of view. This design ensures reliable weed targeting while optimizing resource efficiency. The system underwent extensive testing across five diverse scenarios to evaluate its detection accuracy, crop avoidance reliability, and herbicide application efficiency. The results demonstrated an overall accuracy of 89.73% in weed detection, a reliability score of 98.73% in avoiding crops, and a perfect spray efficiency of 100% for larger weeds. These metrics highlight the system's capability to dynamically adjust herbicide usage based on weed size, reducing wastage and promoting sustainability.

Key limitations were identified, such as difficulty detecting smaller or edge-positioned weeds and the system's reliance on controlled environmental conditions. To address these challenges, future work will include hardware upgrades to support more advanced detection models, the development of adaptive navigation systems, and the application of inverse kinematics for enhanced precision in unstructured environments.

This project validates the feasibility of AI-powered robotic systems for precision agriculture, offering a sustainable alternative to traditional practices by reducing labor dependence, minimizing herbicide use, and supporting environmentally friendly farming practices.

Chapter 1: **Introduction**

1.1 Research Background

Rapid technological advancements in robotics and artificial intelligence (AI) are transforming agriculture, offering solutions to the escalating challenges of feeding a growing global population [1], managing finite resources, and ensuring environmentally sustainable practices [2]. Among these advancements, weed management is a critical area where these technologies demonstrate significant potential in combating a persistent agricultural challenge that negatively affects crop yields and productivity [3]. Traditional weed control methods, including manual removal and widespread herbicide application, often suffer from inefficiencies, pose high environmental risks, and require a large labor force [4].

Powered by robotics and AI, precision agriculture provides transformative strategies to overcome these challenges. For instance, advanced computer vision and AI systems can accurately identify and target weeds and then apply precise weeding methods such as herbicide targeting, weed uprooting, and laser targeting, which significantly improve operational efficiency and reduce resource waste [2], [3].

With global initiatives such as the Food and Agriculture Organization's (FAO) call for sustainable intensification of crop production, technologies like robotics and AI are increasingly recognized as key enablers for achieving sustainable food security goals [5]. Companies such as Blue River Technology, with its "See & Spray" technology, and Naïo Technologies, known for its autonomous weeders, have demonstrated the real-world potential of precision agriculture in addressing challenges like weed management and resource optimization [6].

This project explores these innovations by developing a visual feedback-controlled robotic system. By utilizing the YOLOv5 machine learning model for weed detection and applying a grid-based targeting mechanism, the project aims to emulate precision agriculture practices, ensuring effective weed management that minimizes herbicide usage and protects crops.

1.2 Research Problem

Weeds remain a persistent and costly issue in modern agriculture, significantly reducing crop yields by competing for essential resources such as nutrients, light, and water. Traditional weed management methods, including manual removal and indiscriminate herbicide spraying, have become increasingly inefficient, unsustainable, and resource-intensive. These conventional practices contribute to soil degradation and water pollution through chemical runoff and accelerate the emergence of herbicide-resistant weed species, further complicating weed control efforts.

Additionally, the agricultural sector faces rising labor costs and an aging workforce, with fewer young workers entering farming professions. This labor shortage worsens the challenges of manual weed management, making it clear that traditional methods are neither economically viable nor sustainable. In the face of these challenges, there is a pressing need for innovative, sustainable solutions that address these limitations while maintaining productivity.

To address these issues, this project proposes developing an autonomous robotic system that integrates computer vision and artificial intelligence (AI) for weed detection and targeted herbicide application. By using advanced object detection algorithms such as YOLOv5 and grid-based robotic control systems, this approach seeks to overcome traditional methods' inefficiencies and environmental impacts. Unlike conventional practices, the proposed system will offer a sustainable, precise, and automated alternative, reducing reliance on manual labor and minimizing herbicide usage while maintaining high accuracy and reliability in weed management.

1.3 Research Questions

a) What level of accuracy can be achieved in weed detection using computer vision and AI-based algorithms, such as the YOLOv5 model, in controlled agricultural settings?
b) How do robotic arm configurations and end-effector designs ensure precise and reliable weed targeting in controlled agricultural settings?
c) What factors affect the accuracy and reliability of the weed detection and spraying system in controlled environments?

1.4 Scope

This research focuses on the development and experimental evaluation of an autonomous robotic system designed for precision weed detection and targeted herbicide application in a controlled laboratory environment. The system employs an image-based weed detection algorithm to enable accurate differentiation between crops and weeds. A control algorithm dynamically regulates herbicide application based on detected weed density and size.

The robotic arm, equipped with a calibrated 3-DOF configuration and a precision spraying end-effector, autonomously navigates to the vicinity of detected weeds and applies the appropriate amount of herbicide. Comprehensive testing is conducted under controlled conditions to validate the system's performance in terms of detection accuracy, spraying efficiency, and crop avoidance reliability. Insights gained from these tests will inform iterative improvements needed to improve system functionality and robustness.

1.5 Hypothesis

An AI-powered robotic system integrating computer vision and precision control mechanisms is hypothesized to accurately differentiate weeds from crops and effectively execute targeted herbicide application. By using advanced object detection algorithms like YOLOv5 and a grid-based control system, this approach is expected to enhance weed detection reliability, minimize herbicide usage, and improve operational efficiency in a controlled environment.

1.6 Research Aim and Objectives

1.6.1 Aim

To design and develop an AI-powered robotic system capable of reliable weed detection and precise, targeted herbicide application. This system will combine advanced computer vision algorithms with a grid-based control mechanism to optimize herbicide usage and improve weed management efficiency.

1.6.2 Objectives

1. **Conduct a comprehensive literature review.**
    - Perform an in-depth review of existing weed management practices and precision agriculture technologies. This will include identifying the limitations of conventional methods, exploring the capabilities of robotic systems, and assessing the potential of AI-based solutions for addressing key challenges in weed detection and control. The literature review will establish a foundation for the project's design and development phases by highlighting research gaps and informing design decisions.

2. **Develop and fine-tune a weed detection algorithm.**
    - Build and optimize a weed detection model utilizing the YOLOv5 object detection algorithm. This process will involve training the model on a diverse dataset of weeds and crops to improve its ability to differentiate between the two with high precision.

3. **Design and implement a robotic control system**
    - Develop a control system integrating grid-based mapping and servo mechanisms to enable precise robotic arm movement and herbicide application. This system will use calibrated grid coordinates to target weeds. A dynamic control algorithm will also be incorporated to adjust herbicide dosage based on the density and size of the detected weeds, significantly improving application efficiency compared to conventional methods.

4. **Perform extensive testing and validation.**
    - Conduct systematic testing of the fully integrated robotic system in a controlled laboratory environment. Evaluation metrics include weed detection accuracy, crop avoidance reliability, and herbicide application efficiency. The testing phase will identify performance trends and limitations, offering actionable insights for future iterations and refinements of the system.

1.7 Expected Outcomes

The outcomes of this project are anticipated to align closely with the defined scope and research aims, addressing key challenges in integrating robotics into weed management. The expected outcomes include:

1. **High Accuracy in Weed Identification:** Successfully develop a computer vision system using the YOLOv5 algorithm to distinguish weeds from crops with high precision.
2. **Optimized Herbicide Usage:** Successfully implement a control algorithm that adjusts herbicide dispensing based on the density of the detected weeds once it reaches a certain threshold.
3. **Automation of Weeding Process:** Achieve full automation of the robotic system, including weed detection, navigation to the target area, and precise herbicide application, guided by grid-based mapping and calibrated servo movements.
4. **Insights into Challenges and Limitations:** Comprehensive analysis of challenges encountered during the project, including:
    - The adaptability of the computer vision system to variable lighting and environmental conditions.
    - Mechanical limitations of the robotic arm and end effector in maintaining precision and reliability.
    - Broader reliability concerns include system alignment, prolonged use efficiency, and scalability.

These insights could support the development of scalable solutions for real-world applications, such as small-scale farms, greenhouses, or high-value crop environments. By addressing these challenges, the system aligns with global trends in sustainable agriculture, precision farming, and resource-efficient automation.

1.8 Timeline

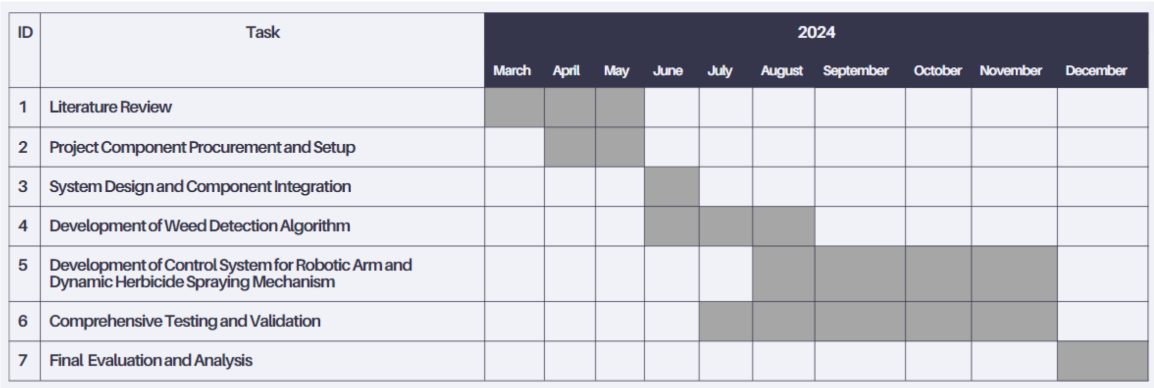


Figure 1. Gantt Chart for Proposed Timeline.

1.8.1 Task Summary

Table 1: Task Summary

Task	Description
Literature Review	Conduct comprehensive research into existing literature to establish a foundation for the project. Identify current weed management practices gaps, explore precision agriculture solutions, and assess computer vision and robotics advancements.
Project Component Procurement and Setup	Acquire and assemble necessary materials and equipment for the robotic system, including the Raspberry Pi, camera module, robotic arm, and spray nozzle. Ensure proper calibration and setup for testing.
System Design and Component Integration	To ensure seamless functionality and compatibility, design and integrate the robotic system's components, including the Raspberry Pi-based processing unit, 3-DOF robotic arm, and the dynamic herbicide spraying mechanism.
Development of Weed Detection Algorithm	Train and fine-tune the YOLOv5 object detection model to distinguish weeds from crops accurately. This involves using a diverse weed dataset and evaluating the model for precision, recall, and detection accuracy in a controlled environment.

Development of Control System for Robotic Arm and Dynamic Herbicide Spraying Mechanism	Implement a grid-based mapping system and pre-calibrated servo angles to control the robotic arm's movements and align it with target weeds for precision spraying. Develop the control algorithm to dynamically adjust herbicide dosage based on weed size and density.
Comprehensive Testing and Validation	Conduct systematic, integrated system testing to evaluate weed detection accuracy, spraying efficiency, crop avoidance reliability, and overall performance. Address issues identified during testing to optimize system functionality.
Final Evaluation and Analysis	Perform a detailed evaluation and analysis of the system's performance. Identify areas for improvement, assess the system's reliability, and document findings and recommendations in the final report.

Chapter 2: **Literature Review**

2.1 Issues in Agriculture

Robotics and artificial intelligence (AI) are revolutionizing agriculture, promising increased productivity and sustainability. With increasing global food demands [1], this shift is essential for addressing the limitations of traditional, labor-intensive, and environmentally detrimental practices, including weed management. This section explores the challenges faced by modern agriculture and the role of technology in overcoming these obstacles to promote sustainable farming practices.

2.1.1 Labor Shortage

Figure 2: Labourers planting crops

Labor shortages pose a significant challenge to global food security and agricultural sustainability. According to the International Labor Organization (ILO), the percentage of people working in agriculture has decreased globally, from 44% in 1991 to 27% in 2020 [7]. Urban migration, an aging farming population, and declining interest in agricultural careers among younger generations are key drivers of this decline [4], [8]. This lack of appeal is mainly due to poor wages, physically demanding work and limited career prospects.

Mechanization and productivity growth have also played a paradoxical role. While these advancements improve efficiency, they reduce the number of manual jobs available, leading to a diminished workforce. In regions like Europe, reliance on migrant labor temporarily fills gaps but fails to offer a sustainable solution [9]. The consequences of labor shortages include escalated costs, reduced productivity, and increased reliance on chemical-intensive farming methods, which have environmental implications.

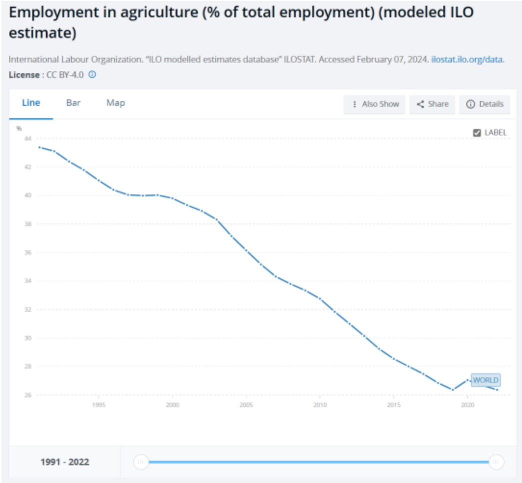


Figure 3: Employment in Agriculture Line Graph.

Technological innovations in robotics and AI present promising solutions by automating labor-intensive tasks such as planting, weeding, and harvesting. These technologies increase scalability and precision, reducing reliance on manual labor [2], [10].

2.1.2 Weed Management

Figure 4: Weeds growing between rows of crops.

Weeds are a persistent and significant challenge in agriculture, competing with crops for essential resources such as light, water, and nutrients. This competition reduces crop yields [11] and increases production costs, making weed management a critical component of agricultural productivity [3]. Traditional weed control methods, primarily reliant on chemical herbicides and manual labor, are environmentally and economically unsustainable.

Figure 5: .Workers spraying herbicide across a crop field.

Chemical herbicides, while initially effective, have significant downsides. Studies show that the majority of herbicide sprayed fail to reach their intended weed targets, leading to environmental contamination through drift and runoff [12]. This contamination affects non-target plants and animals, disrupts ecosystems, and poses health risks to humans and wildlife. Additionally, prolonged herbicide use has led to the emergence of herbicide-resistant weed species [13].

Figure 6: Workers manually pull out weeds.

Although effective for small-scale operations, manual weeding is labor-intensive, time-consuming, and unscalable for large-scale farming due to growing labor shortages. The physical demands and high costs associated with manual weeding further limit its viability [14], [15].

In response, the agricultural sector is moving towards smart farming practices that introduce advanced technologies for more efficient and sustainable weed management. For example, robotic systems equipped with computer vision and AI are continuously being developed to enable precise weed identification and targeted control through advanced imaging and machine learning algorithms [2].

This evolution towards high-tech, sustainable strategies highlights a broader agricultural transformation to improve productivity, environmental sustainability, and labor efficiency. The integration of these smart farming technologies not only addresses the immediate challenges posed by weed management but also supports the long-term health and viability of the agricultural industry.

2.2 Farming Methods

The agricultural industry employs two primary farming approaches: conventional farming and precision agriculture. These methods differ in addressing challenges such as weed management, labor shortages, and sustainability. This section compares their unique practices, limitations, and future potential.

2.2.1 Conventional Farming

Conventional farming is a longstanding agricultural model focused on maximizing crop yields through intensive use of synthetic inputs such as fertilizers, pesticides, and herbicides. Over the decades, these methods have been refined to address global food demands. Farmers employ chemical agents to control pests and weeds, synthetic fertilizers to boost soil fertility, and genetically modified organisms (GMOs) to enhance crop resilience against environmental stressors. Cultural practices like crop rotation and tillage also play essential roles in maintaining productivity [16].

Weed management in conventional farming relies heavily on chemical herbicides applied across large areas to suppress weed growth. However, as stated previously, this method presents significant challenges, such as chemical wastage, environmental contamination, and the emergence of herbicide-resistant weed strains. This makes weed management increasingly challenging and necessitates the application of even higher herbicide doses or development of new chemical formulations [17]. This heavy reliance on chemical herbicides leads to a vicious cycle of increasingly using chemicals to make up for the negative effects of using those chemicals in the first place.

Manual Mechanical methods like pulling, tilling, and hoeing provide an alternative to chemical herbicides but are labor-intensive and can harm soil health over time. These practices disturb soil structure, leading to potential erosion and soil fertility loss [16].

Figure 7: Farmer tilling soil.

Future improvements in conventional farming may involve gradually integrating mechanized tools and targeted herbicide applications to reduce environmental impact. However, the limitations of labor-intensive and chemical-dependent practices highlight the need for broader adoption of innovative approaches such as precision agriculture.

2.2.2 Precision Agriculture

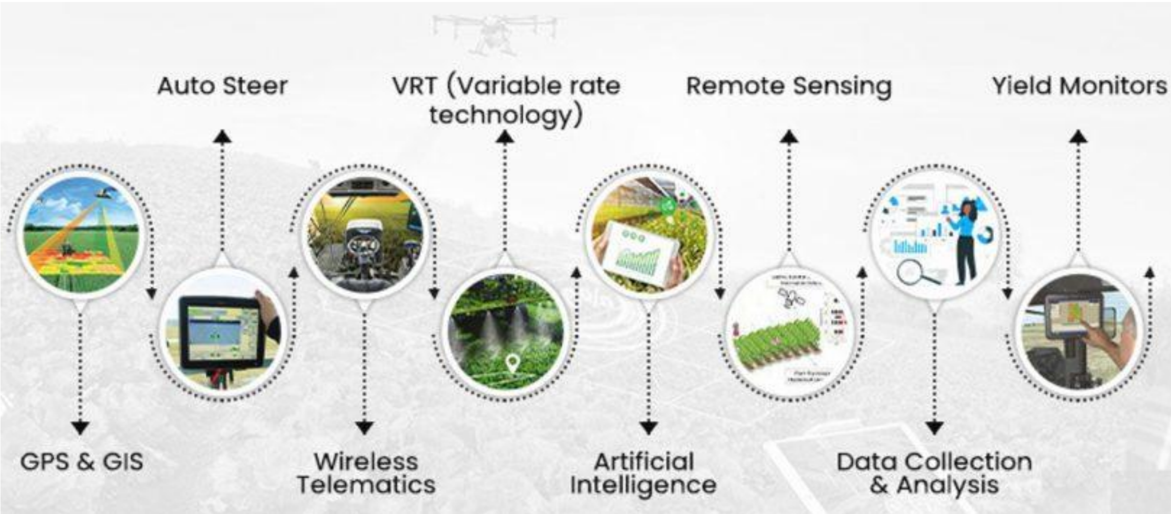


Figure 8: Components of Precision Agriculture

Precision agriculture, also known as smart farming, signifies a transformative shift in farming, utilizing cutting-edge technologies like the Internet of Things (IoT), artificial intelligence AI, robotics, and machine learning to optimize resource use and increase productivity [18]. This approach enables precise field management and informed decisions through real-time data from sensors and satellites. For example, real-time data from IoT nodes can be used to inform specific irrigation and fertilization actions, directly responding to the needs of each plant. In another example, real-time data can provide information on soil and crop health, facilitating targeted adjustments that minimize resource wastage and environmental impact. Furthermore, AI analytics can augment this by forecasting crop yields and proactively identifying problems, improving efficiency and output [4].

Robotics also play a crucial role in reducing the need for physical labor, automating various tasks such as planting, harvesting, and weeding. Automating these tasks ensures sustained high-level productivity even with a smaller workforce [19], [20].

Another significant advantage of precision agriculture's approach is its adaptability. For example, these technologies use vast datasets to predict weed emergence patterns and proactively adjust their management methods to combat it [21]. This helps farmers stay ahead of weed growth cycles and reduces the likelihood of herbicide resistance development.

This transition to smart farming requires overcoming obstacles such as significant technological investments and training for farmers to adeptly handle these new tools. Contrary to popular belief, the transition to smart farming does not eliminate the need for human workers. It significantly reduces the demand for conventional manual labor but creates a new demand for workers with digital literacy and advanced technical skills. However, this is where farmers must evolve and become proficient in operating and maintaining these advanced technologies, highlighting the importance of technical training programs and ongoing education within the agricultural workforce [22].

While high initial costs and a steep learning curve are unavoidable in this transition, the long-term benefits are compelling. Reduced chemical dependency, improved crop yields, and environmental sustainability make a strong case for investing in precision agriculture.

2.3 Proposed Solution

The literature review shows that developing an autonomous weed detection and removal robot is an optimal approach to address the pressing challenges in agriculture. This solution uses advanced technologies such as computer vision, robotics, and machine learning to create a system capable of precise, efficient, and sustainable weed management. This section explores the key components, methodologies, and technologies supporting the proposed solution.

2.3.1 Similar Projects

Several prior projects have paved the way for advancements in automated weed management. Some examples include:

Table 2: Similar Projects

Project	Description
Automated Computer Vision-based Weed Removal Bot [2]	This project employed computer vision to distinguish crops from weeds based on their unique visual features. It used a mechanical arm with a small hoe or cutter to selectively remove weeds. The precision of this system depends on the weed's size and root depth. While promising, its efficiency decreases in deep-rooted weeds or densely populated weed patches.
Automatic Weed Detection and Killing Robot [10]	This robot utilized machine learning algorithms for weed identification and a targeted herbicide spraying mechanism for weed removal. This precision-based approach minimized herbicide usage. The system demonstrated significant environmental benefits by reducing chemical usage, but its effectiveness depends on accurate weed classification.

Pulling Out Weeding Device for Intra-row Weeding Robots [14]	This project utilized a gripper to physically pull weeds, including their roots, from the soil. This approach was tailored for intra-row weeding to avoid damaging crops. Physical pulling showed limited success due to challenges in grasping soft weeds and ensuring complete root removal, often leading to regrowth.

2.3.2 Computer Vision in Agriculture

Computer vision, a branch of artificial intelligence, enables computers to interpret visual data. This technology plays a transformative role in agriculture, automating crop and weed monitoring, detecting plant health issues, and optimizing resource use for increased yields. In weed management, computer vision's ability to precisely differentiate crops and weeds allows for targeted applications.

- **Image-Based Weed Detection Process**

1. **Image Acquisition:** High-quality field images are captured using ground-based robots, drones, or static cameras [23].

2. **Preprocessing:** Raw images are often preprocessed for better analysis. Techniques include conversion into different color spaces like Hue Saturation and Value (HSV) for clearer plant-soil distinction and noise-reduction filters [22].

3. **Segmentation:** Plants, including crops and weeds, are isolated from the background. Techniques include color or intensity thresholding, clustering algorithms that group similar pixels [22], and edge detection to mark plant boundaries even with overlap.

4. **Feature Extraction:** Distinguishing features of crops and weeds are extracted, including shape, leaf shape, size, color variations, and texture patterns [22].

5. **Classification:** Classification algorithms label features as "crop" or "weed." Machine learning models like Support Vector Machines (SVMs) and Decision Trees use labeled data. Deep learning with Convolutional Neural Networks (CNNs) is increasingly preferred for their automated feature learning and high accuracy in complex settings [24], [25].

- **Challenges**

1. **Environmental Variability:** Inconsistent lighting, shadows, and overlapping plants can complicate weed detection. Solutions include robust algorithms, training models on diverse datasets, and applying image preprocessing techniques [23].

2. **Similarity Between Weeds and Crops:** Distinguishing between visually similar species, especially in early growth stages, presents a challenge. Utilizing spectral information or analyzing images over time can improve accuracy [22].

3. **Deep Learning's Data Needs:** CNNs often require large, labeled datasets for optimal performance [26]. Data augmentation and collaborative data-sharing initiatives can help address this need [24].

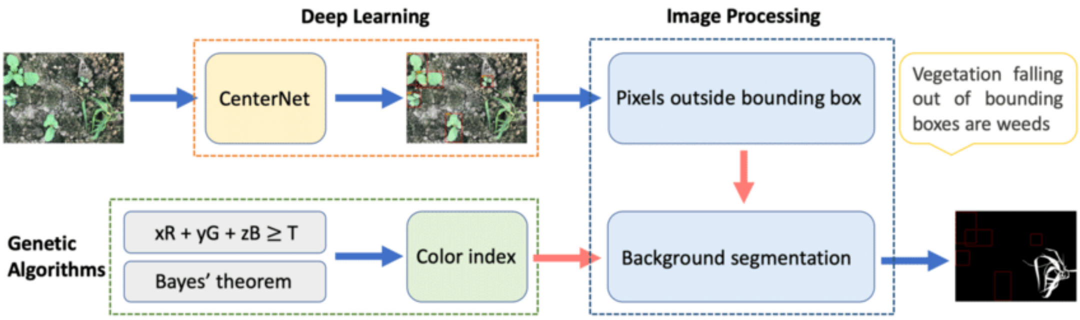


Figure 9: Example of Image-Based Weed Detection.

- **Convolutional Neural Networks (CNNs)**

CNNs are a powerful deep-learning architecture designed for image analysis. They excel in weed detection due to their strengths in:

1. **Automated Feature Learning:** CNN networks discover intricate patterns directly from the image data during training. It learns the specific features that best differentiate crops from weeds[22], [27].

2. **Hierarchical Representation:** CNNs analyze images through layers, progressively extracting more complex features. This allows them to identify subtle plant differences, crucial for weed detection [27].

3. **Robustness to Variability:** By training CNNs on diverse datasets, they become adaptable to real-world challenges like varying lighting, different growth stages, and a wide variety of weed species[25].

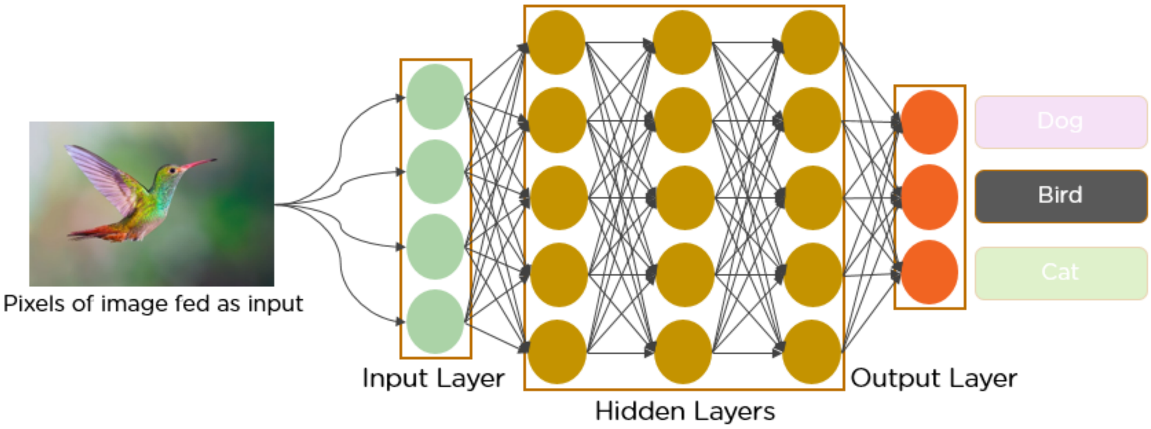


Figure 10: Representation of CNN Layers.

- **Comparison of Different CNN Models for Weed Detection –** This section compares three prominent CNN models:

  1. **YOLO (You Only Look Once) -** YOLO is a real-time object detection system that divides an image into a grid and simultaneously predicts bounding boxes and probabilities for each grid cell[28]. This approach significantly speeds up the detection process, allowing YOLO to achieve high accuracy and efficiency in detecting objects in images and videos.

  2. **Faster R-CNN (Region-based Convolutional Neural Network) -** Faster R-CNN improves upon earlier R-CNN models by integrating a Region Proposal Network (RPN) with the convolutional neural network. This integration allows the model to propose regions and detect objects within those regions more efficiently, leading to faster and more accurate object detection [29].

  3. **SSD (Single Shot Multibox Detector) -** SSD is an object detection model that eliminates the need for a separate region proposal stage by predicting both the bounding boxes and class scores for multiple objects directly from feature maps [30]. This single-shot approach enables SSD to perform real-time object detection with high accuracy and speed.

- **Key Comparison Metrics:**

  1. **Speed -** Measured in Frames per second (FPS); this metric indicates how many images a model can process per second.

  2. **Mean Average Precision (mAP) -** This metric measures the accuracy of object detection models by considering both precision and recall across different thresholds. It represents the average precision for each class, averaged over all classes.

  3. **Precision –** This metric is the ratio of true positive detections to the total number of positive detections.

  4. **Recall –** This metric is the ratio of true positive detections to the total number of actual objects.

- **Comparison Table**

Table 3: Comparison of CNN algorithms.

Model	Speed (FPS)	mAP (%)	Precision (%)	Recall (%)
YOLO	67	76.8	78.6	59.0
Faster R-CNN	7	73.2	84.9	53.9
SSD	46	74.3	87.4	59.0

According to [31], the values in the comparison table were obtained using the PASCAL VOC 2007 and 2012 test sets. These datasets are widely used benchmarks in object detection and provide a comprehensive set of images and annotations for evaluating the performance of various models. They offer a variety of scenarios and object instances, which test the robustness and accuracy of the detection algorithms in real-word conditions.

Analysis

1. **Speed** – The model's processing speed is one of the most critical factors for real-time weed detection. YOLO processes images at an impressive 67 frames per second (FPS), significantly faster than Faster R-CNN's 7 FPS and SSD's 46 FPS. This high speed is crucial for the weed

detection robot, as it allows the system to analyze images and make decisions quickly, reducing the operation time on each weed detection and herbicide application cycle.

2. **Mean Average Precision (mAP)** – YOLO has the highest mAP (76.8%), outperforming both Faster R-CNN (73.2%) and SSD (74.3%). A higher mAP indicates better overall performance in detecting objects accurately and consistently. This means YOLO is more effective at correctly identifying and localizing weeds, which is critical for the precision required in weed management.

3. **Precision** – While YOLO has a slightly lower precision (78.6%) compared to Faster R-CNN (84.9%) and SSD (87.4%), it is still relatively high. Precision for weed detection is important for ensuring that the detected objects are actual weeds, minimizing false positives, and ensuring precise herbicide application. Despite slightly lower precision, YOLOv5's performance remains acceptable, given its significant speed advantage.

4. **Recall** – YOLO has a recall of 59.0%, similar to SSD and slightly higher than Faster R-CNN (53.9%). High recall suggests that the model detects most of the objects present, possibly reducing the chances of missed weeds for weed detection.

Overall, YOLO offers a superior balance of speed and accuracy. Its high speed makes it ideal for real-time applications, ensuring the robot can process images quickly and operate efficiently. While its precision is slightly lower than Faster R-CNN and SSD, the differences are minimal and acceptable given the significant speed and mAP advantage. Therefore, YOLO is the best choice for this weed detection robot, providing a balanced approach to efficient and accurate weed management.

- **YOLO Version Selection**

The YOLO series of models has seen several versions, each bringing speed, accuracy, and efficiency improvements. The two most prominent widely discussed and adopted versions are the YOLOv5 and YOLOv8. This section aims to determine the most suitable YOLO version for a weed detection project of similar scope, usually equipped with a Raspberry Pi.

Table 4: Description of YOLOv5 and YOLOv8

Version	Description
YOLOv5	Released in 2020, YOLOv5 has become popular due to its balance of speed, accuracy, and ease of use. It introduced several improvements in architecture and training techniques [32], making it suitable for real-time applications with relatively modest hardware requirements.
YOLOv8	This version is one of the latest iterations, offering significant advancements over its predecessors. It provides higher speed and accuracy, better handling of diverse and complex datasets, and more customization options, making it a powerful tool for various object detection tasks [33].

- **Comparison**

Table 5: Comparison of YOLO versions.

Factor	Comparison
Resource Efficiency	Resource efficiency is crucial for projects running on the Raspberry Pi, and YOLOv5 is highly optimized for performance on devices with moderate computational power [34]. YOLOv8, while offering superior performance, has higher computational demands that may strain the Raspberry Pi, leading to low performance and overheating issues.
Speed and Real-time Processing	Although YOLOv8 can achieve higher FPS on high-end GPUs, its performance on more modest hardware like the Raspberry Pi 5 may not fully take advantage of its high speeds without significant optimizations [33].
Ease of Use and Community Support	YOLOv5 is widely adopted and has extensive community support, making it easier to implement and troubleshoot [32]. It offers a streamlined training, testing, and deployment pipeline, simplifying the development process. YOLOv8, being newer, has fewer resources available in comparison, but it does offer more advanced features [33].

Conclusion

For a project using a Raspberry Pi, YOLOv5 is the most suitable choice. It balances speed and resource efficiency, ensuring reliable real-time weed detection without overwhelming the hardware. Additionally, YOLOv5 is better adopted and documented than YOLOv8, making it easier for setting up and debugging. While YOLOv8 offers superior performance, its higher computational demands make YOLOv5 a more practical and feasible option for this project.

- **Current application of YOLOv5 in Weed Management**

Table 6: YOLOv5 Processes in Weed Management

Process	**Description**
Dataset Preparation	A large, meticulously labeled field image dataset containing various weed species is important [24]. Images should capture diverse conditions such as lighting, growth stages, and viewpoints for robustness.
Training	The chosen model undergoes training on the prepared dataset, learning to distinguish weeds from crops. Additionally, data augmentation, which involves generating modified versions of images, enhances the model's generalization ability [26].
Deployment	Once trained, these models theoretically can perform precision weed management such as: • **Real-time Weed Mapping:** Integrated onto robots, the system surveys fields, creating detailed weed infestation maps that guide targeted weed management. • **Targeted Control:** The model directly guides precision herbicide applicators or mechanical weeding tools for efficient, crop-safe weed elimination [25].

2.3.3 Robot Joint Movement

- **Robotic Arm Movement:** The movement of the robotic arm for this project is guided by pre-calculated servo angles corresponding to its joints. Each joint is actuated to align the end effector precisely with the targeted location. The arm operates with three degrees of freedom (3DOF), enabling basic movement across a defined workspace. Servo motors control these joints, and their angular positions are determined by referencing pre-mapped grid coordinates. This straightforward approach ensures efficient targeting without the need for complex kinematic computations.

- **Grid Mapping:** Grid mapping is a foundational approach in robotic targeting systems, offering a structured method to translate the camera's detection of weeds into actionable physical locations within the robotic arm's workspace. It is particularly effective in scenarios where depth sensing or advanced spatial perception is not implemented.

Table 7: Grid Mapping Method.

Concept	The workspace of the robotic arm is divided into a grid of discrete cells, each representing a specific area within the operational field. These cells provide a systematic layout, allowing the robot to navigate its end effector accurately to any point within the grid. **Structure:** • A grid comprises rows and columns that define the robotic arm’s reach. • Each cell corresponds to a specific combination of servo angles for the base, middle, and end effector joints. • The camera view is mapped onto the grid to ensure detected weeds are matched to their respective cells. **Benefits:** • Simplifies the targeting process by limiting the workspace to manageable, predefined areas. • Enables systematic weed coverage without overlapping or missed spots. • Reduces computational requirements compared to continuous localization methods.

Grid Calibration	Calibration is critical to ensure that the grid aligns accurately with the physical workspace of the robotic arm. **Calibration Process:** • A flat surface matching the camera's field of view overlaps the grid layout. • Each cell is tested to determine the servo angles required to center the end effector in the cell. • The angles are stored in a lookup table for quick retrieval during operation.
Detection and Targeting Workflow	Once a weed is detected within the camera frame, its pixel location is mapped to the corresponding grid cell using transformation algorithms. **Mapping Process:** • The camera captures the weed's position in pixels. • The pixel coordinates are converted into grid indices (row and column) using a scaling factor derived from the camera's resolution and the grid's physical dimensions. **Servo Activation:** • The grid indices retrieve the pre-calibrated servo angles for the corresponding cell. • The robotic arm moves to the position, aligning its end effector with the weed. **Execution:** After positioning, the robot activates the herbicide sprayer or the weeding tool for targeted application.

Advantages of Grid Mapping	Grid mapping offers several advantages for agricultural robots: • **Precision:** Ensures accurate and consistent alignment with weeds for efficient removal. • **Simplicity:** Reduces the need for real-time depth computation or advanced localization systems. • **Scalability:** With larger robotic arms, the grid size can be increased to adapt to larger workspaces. • **Efficiency:** Systematically covers the field, minimizing missed targets.

2.4 Hardware Implementation

This section outlines the hardware components necessary for developing the autonomous robotic arm for weed detection and removal.

2.4.1 Camera

For weed detection and removal, the requirements for the camera are that it must have high-resolution imaging, be capable of integrating with the robot's processing unit, specifically a Raspberry Pi, and be affordable. After surveying the camera market, I found that the Raspberry Pi Camera 8MP Module V2 fits all the requirements.

Raspberry Pi Camera 8MP Module V2 [45]: The Raspberry Pi Camera 8MP Module V2 is an official camera module from the Raspberry Pi Foundation, featuring an 8-megapixel Sony IMX219 image sensor. It offers a significant upgrade in image quality and resolution compared to earlier versions, making it highly suitable for this project's image processing tasks like weed detection.

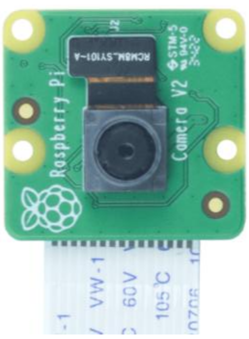


Figure 11:. Raspberry Pi Camera 8MP Module V2.

Key Specifications

Table 8: Key Specifications of the Raspberry Pi Camera.

Specifications	Description
Price	RM82.50
Resolution	• Capable of capturing still images at 3280 x 2464 pixels • Supports 1080p 30fps, 720p 60fps, and 640x480p 90fps video modes
Sensor	Sony IMX219
Interface	• Camera Serial Interface (CSI) • Allow high-speed data transmission directly to the Raspberry Pi • Enable real-time video processing without significant latency
Compatibility	• Raspberry Pi 5 (FPC cable required) • Raspberry Pi 4 Model B 8GB, 4GB, 2GB, 1GB • Raspberry Pi 3 Model B • Raspberry Pi 3 Model B+
Size	25 mm x 23 mm x 9mm

2.4.2 Edge Device

As the robotic system's central processing unit, the edge device must handle real-time data processing and support complex algorithms for image analysis and machine learning. Essential capabilities include powerful processing power, substantial memory, and excellent connectivity options to effectively manage sensor inputs and control outputs. After personally working with a raspberry pi previously on another project, along with compatibility with other components in this project, the Raspberry Pi 5 is decidedly the best option as the edge device for this project.

Raspberry Pi 5 (8GB Model) [35]**:** The Raspberry Pi 5 is an advanced edge computing device that would suit this project well as it fits all the requirements. The Raspberry Pi 5 features a powerful Broadcom BCM2712 quad-core Arm Cortex A76 processor clocked at 2.4GHz, making it up to three times faster than the previous generation, offering substantial processing power for handling complex computational tasks. It supports up to 8GB of LPDDR4X RAM, which provides ample memory for running sophisticated image processing and machine learning algorithms required for accurate weed detection.

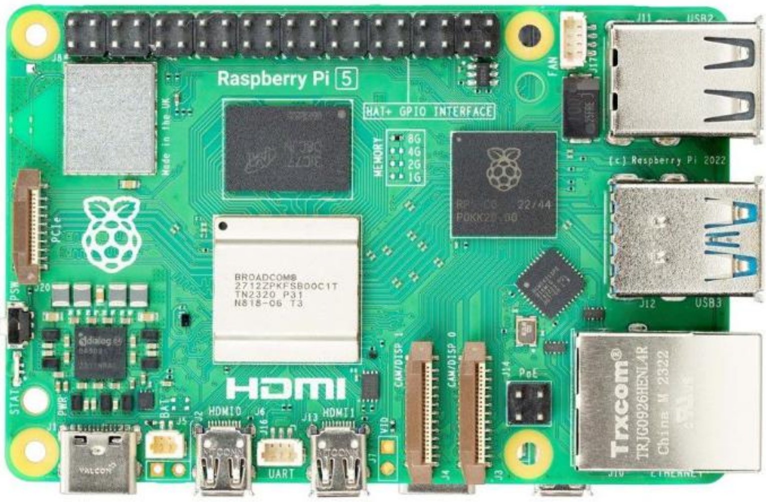


Figure 12: Raspberry Pi 5 (8GB model)

Key Specifications

Table 9: Key Specifications of Raspberry Pi 5.

Specifications	**Description**
Price	RM409.00
Processor	• Broadcom BCM2712 • 64-bit ARM Cortex-A76 (ARMv8-A ISA) • Quad-core • 16nm Processor SoC • Clocked @ 2.4GHz • 64KB I and D caches • 512KB pre-core L2 caches and a 2MB shared L3 cache • With a metal body for better heat dissipation
SDRAM	8GB LPDDR4X-4267

Camera	• 2 x USB3.0 Port, capable of simultaneous 5Gbps • 2 x USB2.0 Port • VideoCore: VII GPU, clocked at 800MHz • Dual micro-HDMI port, support true 2x 4Kp60 with HDR • 4Kp60 HEVC decoder • Image/Camera input: 2 x 4-lane MIPI 22-way CSI/DSI port
Storage	• MicroSD slot, with support for high-speed SDR104 mode • Optional interface via PCIe socket (NVMe SSD)

Connectivity	• Gigabit Ethernet, with PoE+ HAT support (require a new PoE+ HAT for Raspberry Pi 5)
	• Wireless: 2.4GHz and 5GHz IEEE 802.11.b/g/n/ac wireless LAN, Bluetooth 5.0, and BLE (Bluetooth Low Energy)
	• PCIe 2.0 x 1 interface for fast peripherals, for example, NVMe SSD (requires compatible HAT)
	• Dedicated UART debug port, independent from 40-pin GPIO. Always Enabled
	• Dedicated Fan port for cooling fan, PWM, and Tachometer feedback ready, independent from 40-pin GPIO
	• Expanded 40-pin GPIO Header
	• Low-Level Peripherals:
	    ○ 27 x GPIO
	    ○ UART
	    ○ I2C bus
	    ○ SPI bus with two chip selects
	    ○ +3.3V
	    ○ +5V
	    ○ Ground

Power	5V/5.0A via USB type C connector, with PD (Power Delivery) support.
OS	Raspberry Pi OS Bookworm

Suitability: The Raspberry Pi5's advanced features make it well-suited for this project, requiring intensive computation and real-time data processing, specifically the weed detection function. Compared to edge devices like older Raspberry Pi models or less powerful microcontrollers, the Raspberry Pi stands out for its superior processing capabilities, cost-effective price point, and small build footprint.

2.4.3 Robotic Arm

For this project, a 3 DOF robotic arm has been modified from the initial 6 DOF robotic arm to reduce the complexity and enhance the efficiency of the weed removal process. Additionally, a 6DOF is unnecessary since the robotic arm will only spray the herbicide slightly above the weed, which a 3DOF robotic arm is sufficiently capable of doing. The 3DOF robotic arm can also move in a wide rotational envelope along the horizontal axis.

2.4.4 DC Pump

A micro submersible DC pump [36] was used to pump the herbicide from its storage container. Controlled by the Raspberry Pi through its GPIO pins, the pump operates at a maximum within the voltage range of 3V to 5V, allowing for adjustable flow rates. The water pump uses the water suction method, draining the water in the storage container through its inlet and pumping it through the outlet. It is connected to the end-effector through a provided flexible tube. Through testing, it successfully pumped water from its storage container to the end-effector at an approximate height of 15cm with a voltage of 5V.

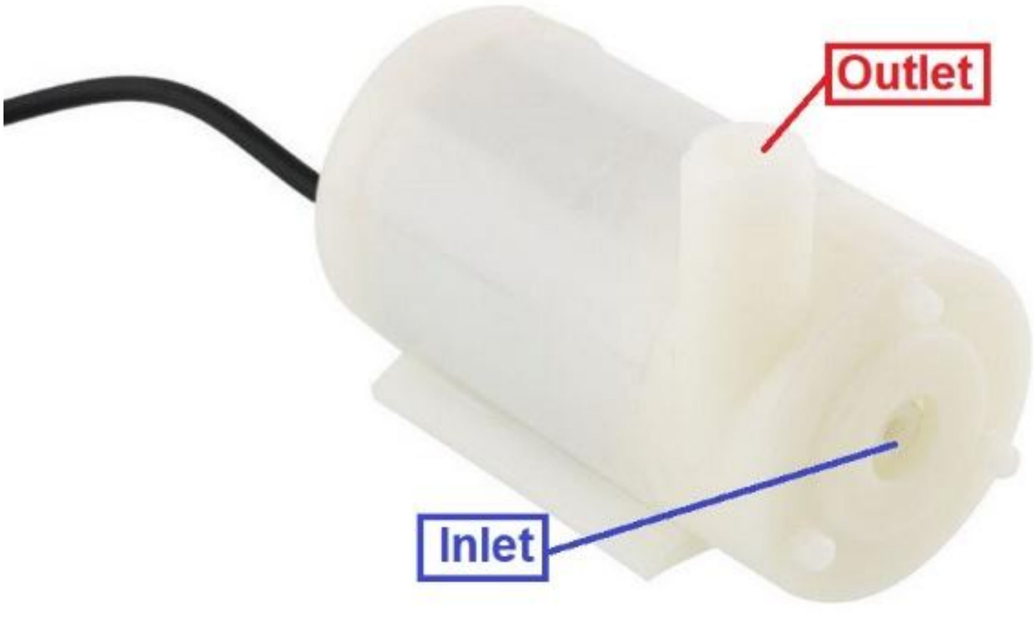


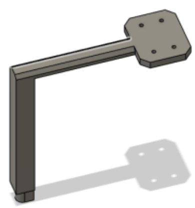
Figure 13: Micro Submersible DC Pump

Specifications	Description
Price	RM3.90
Input Voltage	DC 3V-5V
Flow Rate	1.2-1.6 L/min
Operation Temperature	80 ℃
Operating Current	0.1-0.2A
Suction Distance	0.8 meters (Max)

Table 10: Key Specifications of DC Pump

2.4.5 Mounts

There are two mounts for this part of the robot system. One is for holding the camera, and the other is for holding the herbicide sprayer, which also acts as the end-effector.

<table>
<tr><td rowspan="2">Camera Mount</td><td>
Figure 14: Camera Mount Design</td></tr>
<tr><td>The camera mount is approximately 30 centimeters above the robot's base, directly aligning with the robotic arm. This elevated placement ensures a comprehensive and unobstructed 30cm x 31cm field of view, enabling the camera to capture a 700 x 700 resolution video stream of the robotic arm’s surrounding environment. By maintaining a consistent vantage point, the camera ensures that the captured area consistently aligns with the predefined grid layout, ensuring the precision of the grid mapping solution and allowing the robotic arm to accurately move it is end-effector over the grid cell with the detected weeds.</td></tr>
</table>

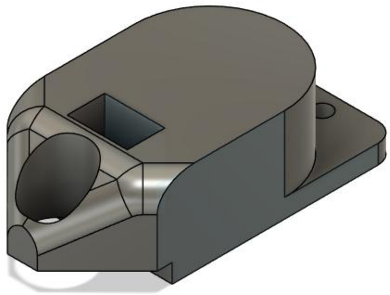
End-Effector Mount	 *Figure 15: End-Effector Mount*
	The end effector mount is designed to securely hold the herbicide dispensing tube and spray mechanism, affixed slightly above the robotic arm's end effector. This configuration ensures the dispenser remains stable during arm movements, maintaining consistent positioning relative to the target weeds.

Table 11: Mounts and Description.

2.5 Software Implementation

Implementing an effective software stack is crucial for ensuring the successful operation of the autonomous weed detection and removal robotic arm. The chosen software components interface seamlessly with the hardware to perform tasks such as image processing, device control, and data management. The following table provides detailed descriptions of the functionalities and roles of each software component within the project.

Table 12: Software Implemented in the Project.

Software	Purpose	Role
Raspberry Pi OS	Linux-based OS for Raspberry Pi [37]	Serves as the foundational platform, managing system resources and hardware interfaces and executing software applications essential for robotic arm operations.
YOLOv5	Real-time object detection [38]	Analyzes camera images in real-time, identifying and locating weeds for targeted removal.

OpenCV	Image processing and analysis [39]	Preprocesses images for YOLOv5, such as color space conversions and noise filtering.
GPIOZero	Python library for GPIO device control [40]	Manages interactions with GPIO devices, enabling the control of motors, pumps, and other hardware components necessary for the robotic arm's movement and herbicide dispensing
Adafruit Servokit	Servo motor control library [41]	Provides an interface for controlling servo motors, allowing precise movements of the robotic arm.

Chapter 3: **Research Methodology**

This section focuses on the methodology for developing an autonomous robot for efficient weed removal in a controlled environment. The focus is on minimizing herbicide use through visual feedback and precision spraying. The robot will use computer vision and machine learning to identify and selectively target weeds. It will then dynamically adjust herbicide dosage based on the density and size of weeds detected.

3.1 System Architecture

This section details the components and their integration to form a comprehensive system capable of autonomously identifying, targeting, and treating weeds.

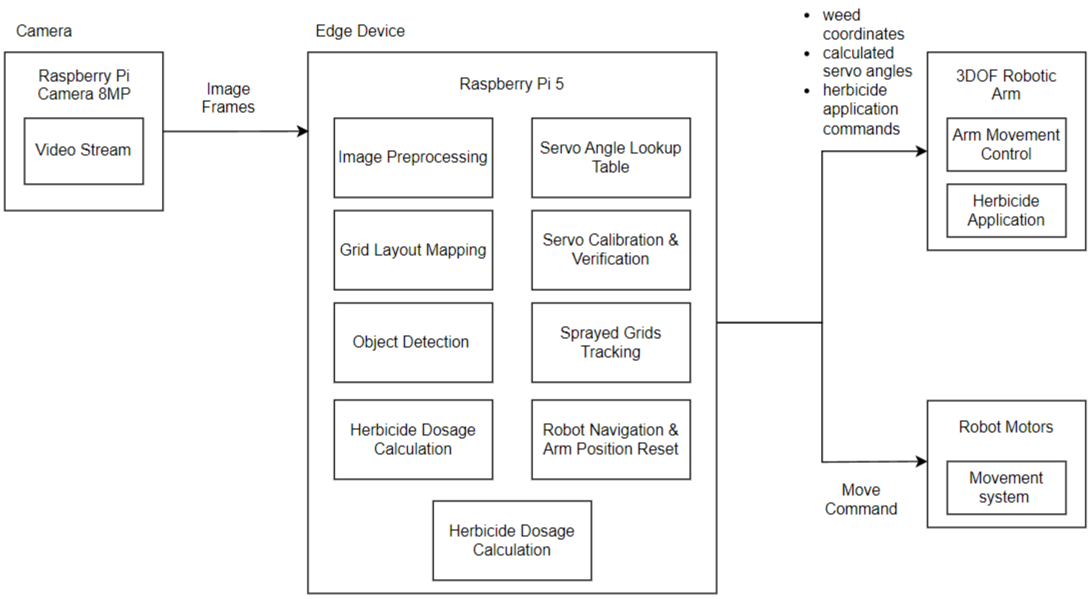


Figure 16: System Architecture Block Diagram.

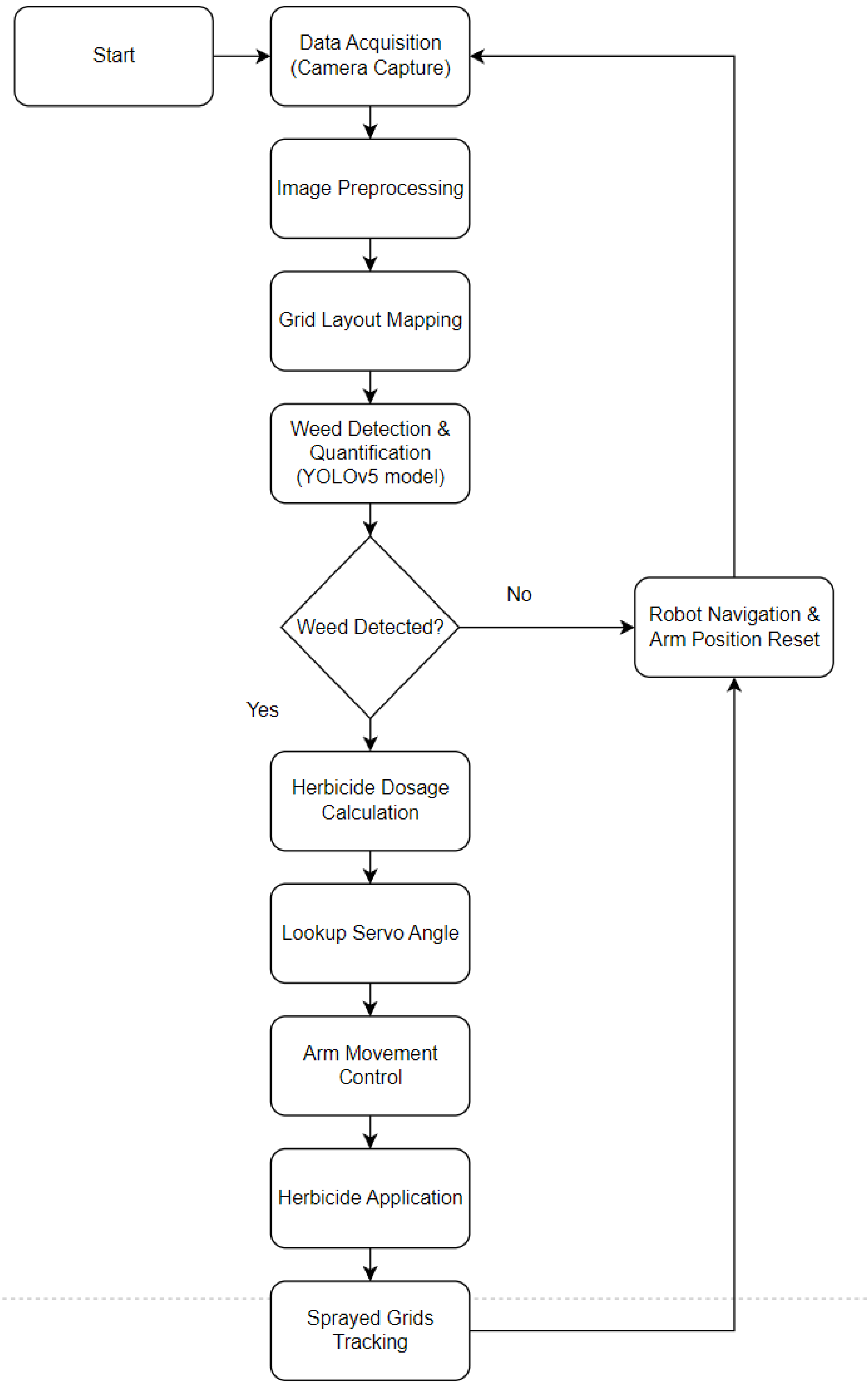


Figure 17: System Flowchart.

Table 13: Flowchart Phase and Description.

Component	Phase	Description
Camera	Data Acquisition	The robotic arm's camera captures a continuous video stream containing data on crops and weeds within its field of view. These frames serve as the primary input for the YOLOv5 model.
Edge Device	Image Preprocessing	Captured frames are pre-processed to enhance image quality and optimize them for analysis by the YOLOv5 object detection model. This includes resizing, normalization, and noise reduction.
Edge Device	Grid Layout Mapping	The preprocessed image is divided into an 11x11 grid layout. Each grid cell corresponds to a specific physical area in the real world.
Edge Device	Weed Detection & Quantification (YOLOv5 model)	The preprocessed and grid-mapped images are fed into the YOLOv5 object detection model, which identifies and locates weeds within each grid cell. Bounding boxes are drawn around detected weeds, and their coordinates are estimated.
Edge Device	Herbicide Dosage Calculation	Based on the bounding box area of detected weeds from the YOLOv5 model, the system calculates the precise amount of herbicide to apply. If the bounding box exceeds a certain threshold, the detected weed will either be determined as small or large and sprayed for an appropriate duration.
Edge Device	Servo Calibration & Verification	The system calibrates and verifies servo mappings to ensure that joint angles are accurately translated into servo motor positions.
Edge Device	Sprayed Grids Tracking	The system records grid cells sprayed during the current cycle to avoid redundant herbicide application. This ensures resource efficiency and prevents over-spraying onto the same weed.

Edge Device	Robot Navigation & Position Reset	After completing the spraying cycle, the system resets the arm to its default position and commands the robot to move forward, repositioning it for the next set of detections and spraying actions.
Robotic Arm	Arm Movement Control	Based on the grid cell chosen and the predefined servo angles used to reach it, the robotic arm smoothly transitions to the target position within the designated grid cell.
Robotic Arm	Herbicide Application	Once positioned over a weed within a grid cell, the herbicide dispenser releases the calculated herbicide dosage onto the targeted weed. This action is executed for each detected weed in the frame.
User Interface	Calibration & Maintenance	Provides an interactive mode for users to perform calibration, verification, and manual testing of the robotic arm. Users can input coordinates, initiate calibration routines, and monitor system status.

3.2 Test Environment

3.2.1 Test Focus

Table 14: Test Focuses

Test Focus	**Description**
Accuracy in robotic arm movement.	The system's ability to accurately move the robotic arm to the detected weed coordinates through the grid mapping solution was tested.
Reliability in detecting and differentiating between weeds and crops	Weed detection is performed using the YOLOv5 model, which processes images and calculates weed density within specific grid cells of the test bed. The system's reliability to distinguish between baby bok choy (crop) and fake weeds was tested.
Adjustable herbicide dispensation based on weed density.	The herbicide spraying mechanism adjusts its output based on the detected weed bounding box size.

3.2.2 Test Setup and Operation

Figure 18: Test Setup

Figure 19: Baby Bok Choy (Crop) and two fake Weeds (Middle and Right)

Operation:

1. The robot will move slowly, starting from the left side of the test bed. It will stop after a set time. This set time was hardcoded and determined by checking if the new detection area is a new area in the camera view so that no detection overlaps and prevents the robot from continuously spraying onto the same weed.

2. The system will have a short detection window at each stop to take an image from the video feed and perform weed detection using the train YOLOv5 model. The system then will put bounding boxes on all detected weeds and record their X and Y coordinates with the best grid cell to dispense herbicide for each weed.

3. The system will then move the robotic arm and dispense herbicide on all the detected weeds in one sweep.

4. After spraying, the robot will continue moving for a set time and repeat the process.

Table 15: Test Setup

3.2.3 Test Sets

Five test sets were designed, each presenting unique challenges such as dense crop arrangements, scattered planting patterns, and varying weed densities to systematically evaluate the system's performance under realistic conditions. These test sets are:

Table 16: Test Set Setup

<table>
<tr><th>Test Set</th><th colspan="2">Setup</th></tr>
<tr><td rowspan="2">1</td><td colspan="2">
Figure 20: Test Set 1 Setup
Description: Both trays simulate a dense crop environment with crops planted in a single row and smaller weeds interspersed closely. This setup mimics real-world weed infestations in structured fields, challenging the system to detect weeds near overlapping crop leaves and ensure precise spraying.</td></tr>
<tr><td>**Total Crops: 6**</td><td>**Total Weeds: 8 (small)**</td></tr>
<tr><td>2</td><td colspan="2">
Figure 21: Test Set 2 Setup</td></tr>
</table>

<table>
<tr><td rowspan="2"></td><td colspan="2">Description: The crops are arranged in a scattered, irregular pattern with smaller weeds dispersed unevenly throughout. This setup simulates a less structured planting scenario, testing the system's ability to identify and differentiate weeds in a disordered, cluttered environment while maintaining precision in spraying.</td></tr>
<tr><td>Total Crops: 6</td><td>Total Weeds: 8 (small)</td></tr>
<tr><td rowspan="2">3</td><td colspan="2">
Figure 22: Test Set 3 Setup
Description: Crops are spaced in a consistent row pattern, while weeds of varying sizes are scattered across the trays. This setup evaluates the system’s capability to adapt herbicide applications based on weed density.</td></tr>
<tr><td>Total Crops: 5</td><td>Total Weeds: 7 (5 small + 2 big)</td></tr>
<tr><td>4</td><td colspan="2">
Figure 23: Test Set 4 Setup
Description: The crops are arranged in a cluttered, randomized pattern, with weeds of varying sizes dispersed throughout the trays. This scenario also tests the system to accurately detect weeds among irregular crop placements and its ability to differentiate between weeds of different densities.</td></tr>
</table>

	Total Crops: 7	**Total Weeds: 7 (5 small + 2 big)**
5	 *Figure 24: Test Set 5 Setup* **Description:** In Test Run 5, the crops are arranged in a row pattern with ample spacing, while weeds of varying sizes are closely positioned across the trays. This setup is intended to test the system's precision in detecting weeds in possible overlapping scenarios and its ability to adjust herbicide application based on the density of weeds in a cramped environment.	
	Total Crops: 5	**Total Weeds: 6 (4 small + 2 big)**

3.2.4 Performance Metrics

The performance of the robotic weed detection and spraying system was evaluated using three key metrics: accuracy, reliability, and spray efficiency.

Accuracy measures the percentage of weeds successfully sprayed out of the total weed instances, reflecting the system's ability to correctly detect and target weeds. A high accuracy score indicates the effectiveness of the YOLOv5 detection model and the robotic arm's precision in spraying weeds. The formula for accuracy is:

$$Accuracy = \frac{Weeds\ Sprayed}{Total\ Weed\ Instances} \times 100\%$$

Equation 1: Accuracy Equation

Reliability evaluates the system's ability to avoid spraying crops by calculating the percentage of crops correctly identified and skipped. This metric ensures that the system can reliably distinguish between crops and weeds. High reliability minimizes crop damage and highlights the system's ability to maintain precise classification. The formula for reliability is:

$$Reliability = \frac{Crops\ Missed}{Total\ Crops\ Instances} \times 100\%$$

Equation 2: Reliability Equation

- **Spray Efficiency** assesses the system's ability to apply different amounts of herbicide on weed size. For larger weeds, the system dynamically increases spraying duration and vice versa. This metric verifies the system's responsiveness to varying weed sizes and its capacity to optimize herbicide usage while maintaining accuracy.

$$Spray\ Efficiency\ (SE) = \frac{Big\ Weeds\ Sprayed}{Total\ Big\ Weeds} \times 100\%$$

Equation 3: Spray Efficiency Equation

3.3 Model Training

3.3.1 Datasets Obtained

A comprehensive dataset was compiled to develop an effective weed detection model by combining several publicly available datasets with custom images captured specifically for this project. The datasets used are detailed below:

Table 17: Model Training Parameters

Dataset	Reference	Images
Weed detection Computer Vision Project • This dataset contains many images featuring various weed species in different environments and lighting conditions.	[42]	9658
Crops, Weeds Computer Vision Project	[43]	4898
Crop and Weed Identifier Dataset	[44]	3220
WeedCrop Image Dataset • Dataset of annotated food crops and weed images for robotic computer vision control	[45]	2822
Weed 1 and 2 Computer Vision Project	[46]	2476
Artificial Crop and Weed Dataset • Dataset obtained from taking pictures of artificial succulents representing crops and weeds that will be used during testing	-	83
A Crop/Weed Field Image Dataset and Weed detection dataset with RGB images taken under variable light conditions • This dataset was combined and augmented to a total of 237 images. It contains field images, vegetation segmentation masks, and	[47], [48]	237

crop/weed plant type annotations. It also contains RGB images from carrot seedlings with weeds (Carrot-Weed dataset).			
		Total Images	22,394

These datasets were obtained separately and combined into a single combined Dataset to train the model. In this way, the model benefits from a large and diverse array of images featuring various weed species, crop types, lighting conditions, and backgrounds.

3.3.2 Model training

```
python train.py --img 640 --batch 4 --epochs 40 --data "H:/FYRP2/WEED DATASET/combined_dataset_3/combined_v3/data.yaml" --cfg models/yolov5s.yaml --weights yolov5s.pt --name yolov5s_custom_5 --patience 10 --device 0
```

Table 18: Parameters for Model Training

Parameters	**Description**
--img 640	Sets all input image resolution to 640x640 pixels.
--batch 4	Uses a batch size of 4 images, depending on the GPU memory.
--epochs 40	Trains the model for 40 epochs.
--cfg models/yolov5s.yaml	Specifies the model configuration file for YOLOv5s.
--weights yolov5s.pt	Loads a pre-trained yolov5s weight to initialize the model.
--patience 10	Implements early stopping if no improvement is seen in validation loss for ten epochs. This prevents overfitting
--device 0	Ensures training uses the first GPU device.

- **Training Environment:** The training was conducted on a pc machine equipped with the following specifications:
    - CPU: i5-11400f
    - RAM: 32GB
    - GPU: RTX 3060ti 8GB

  Specific software libraries and dependencies were required to utilize the NVIDIA GPU for training the YOLOv5 model. These libraries ensure that the training process uses the GPU for accelerated computation, significantly reducing training time.
    - CUDA Toolkit 11.7
    - cuDNN 8.5
    - PyTorch 1.13.0

- **Performance Evaluation**
    - At the end of the model training, yolo automatically outputs the resulting graphs, visualizing the model's performance. These will be discussed in the Results section.
    - **Metrics Used:** Mean Average Precision (mAP), precision, recall, and F1-score were calculated to assess the model’s detection capabilities.
    - **Results Analysis:** Confusion matrices and loss curves were analyzed to identify areas for improvement, such as class imbalance or misclassified samples.

3.4 Robot Joint Movement

This section details the methods to determine the necessary joint angles to position the 3DOF robotic arm's end effector to the detected weed. Due to the limitations of the robot in its inability to obtain depth data as reliable pixel accuracy, a calibrated servo grid map was used to allow the robotic arm to cover a 30cm x 31cm target area in the camera view, allowing the robotic arm to reach the detected weed within the area and allow precise targeted herbicide spraying.

3.4.1 Grid Map

The robot's operational area is divided into a grid to systematically cover the target area, and the detected weeds are mapped to real-world coordinates.

- **Justification:** The grid mapping method was selected for its simplicity, cost-effectiveness, and compatibility with the robot's hardware limitations. Unlike real-time depth localization, which requires advanced depth sensors or extensive computational resources, grid mapping translates image coordinates into predefined servo positions using a calibrated 2D grid. This approach significantly reduces computational overhead and hardware complexity while ensuring reliable targeting in controlled environments.

- **Examples of Real-life Use:** Grid-based methods have been widely utilized in precision agriculture for their simplicity and effectiveness in structured mapping and task execution. These approaches enable systematic spatial localization by dividing the operational area into a structured grid, which is particularly useful for applications requiring precise navigation and targeting. For example, Potena et al. [49] developed a multimodal environment representation in their AgriColMap system, structuring agricultural maps into grids to efficiently align aerial and ground robotic data. This grid representation allowed unmanned aerial vehicles (UAVs) and ground vehicles (UGVs) to collaborate seamlessly in agricultural fields, enhancing data integration and resource management precision. The study highlights the utility of grid-based systems in enabling precise and detailed spatial alignment, which is critical for tasks like spraying, seeding, and mapping in controlled agricultural settings.

  Additionally, Ding et al. [50] discuss the application of structured mapping techniques in agricultural robotics, emphasizing their utility in navigation and operational precision, particularly when environmental challenges limit the effectiveness of other sensory data. The study underscores the relevance of grid-mapping in scenarios where complex SLAM

(Simultaneous Localization and Mapping) technologies may be unnecessary or resource-intensive, making grid-based systems an efficient alternative. These examples affirm the viability of grid-based approaches in agricultural robotics, demonstrating their effectiveness in ensuring accuracy and simplicity in data management and operational execution.

- **Grid Map Configuration:** The grid map covers an area of approximately 29.5cm (width) x 25.5 (height) divided into a series of grid cells of seven columns and six rows. This will be the robot's operational area, as the robotic arm's maximum reach can only reliably target the weeds in this area. The primary function of the grid map is to guide the robotic arm to specific cells where the weeds are detected. Within each grid cell, there is a set of predefined servo angles for the base (B), middle (M), and spray (S) servos. By transposing the grid layout from the camera view onto a flat surface, these angles to target the center of the grid cell were obtained.

(0,1) B:130.81 M:157.75 S:180	(0,2) B:122.61 M:161.85 S:180	(0,3) B:110.90 M:165.95 S:180	(0,4) B:98.60 M:163.60 S:180	(0,5) B:86.89 M:163.60 S:180	(0,6) B:74,59 M:163.60 S:180	(0,7) B:60.54 M:165.95 S:180
(1,1) B:134.90 M:165.95 S:180	(1, 2) B:124.95 M:159.50 S:170.63	(1, 3) B:110.90 M:159.50 S:164.77	(1, 4) B:96.84 M:153.65 S:148.96	(1, 5) B:82.79 M:153.65 S:148.96	(1, 6) B:70.49 M:161.85 S:156.58	(1, 7) B:56.43 M:161.85 S:168.87
(2,1) B:140.76 M:167.70 S:180	(2, 2) B:132.57 M:173.56 S:174.73	(2, 3) B:122.61 M:159.50 S:147.79	(2, 4) B:104.46 M:151.89 S:135.49	(2, 5) B:86.89 M:147.79 S:123.78	(2, 6) B:70.49 M:153.65 S:137.84	(2, 7) B:54.68 M:159.50 S:151.89
(3,1) B:146.62 M:145.45 S:125.54	(3, 2) B:138.42 M:145.44 S:121.44	(3, 3) B:120.85 M:139.59 S:101.53	(3, 4) B:104.46 M:143.69 S:95.67	(3, 5) B:84.55 M:143.69 S:95.67	(3, 6) B:64.64 M:143.69 S:95.67	(3, 7) B:46.48 M:151.89 S:115.58
(4,1) B:160.68 M:147.79 S:121.44	(4, 2) B:148.96 M:135.49 S:89.82	(4, 3) B:130 M:131.98 S:73.42	(4, 4) B:110.90 M:131.98 S:61.71	(4, 5) B:82.79 M:131.98 S:61.71	(4, 6) B:56.44 M:131.98 S:59.95	(4, 7) B:36.52 M:131.98 S:71.66
(5,1) B: 170.63 M:135.49 S:95.67	(5, 2) B:164.77 M:141.94 S: 75.76	(5, 3) B:148.96 M:127.88 S:53.51	(5, 4) B:118.51 M:127.88 S:43.55	(5, 5) B:84.55 M:127.88 S:33.60	(5, 6) B:46.48 M:127.88 S:43.55	(5, 7) B:22.47 M:127.88 S:53.51

Figure 25: Grid Map Coordinates and Servo Angles.

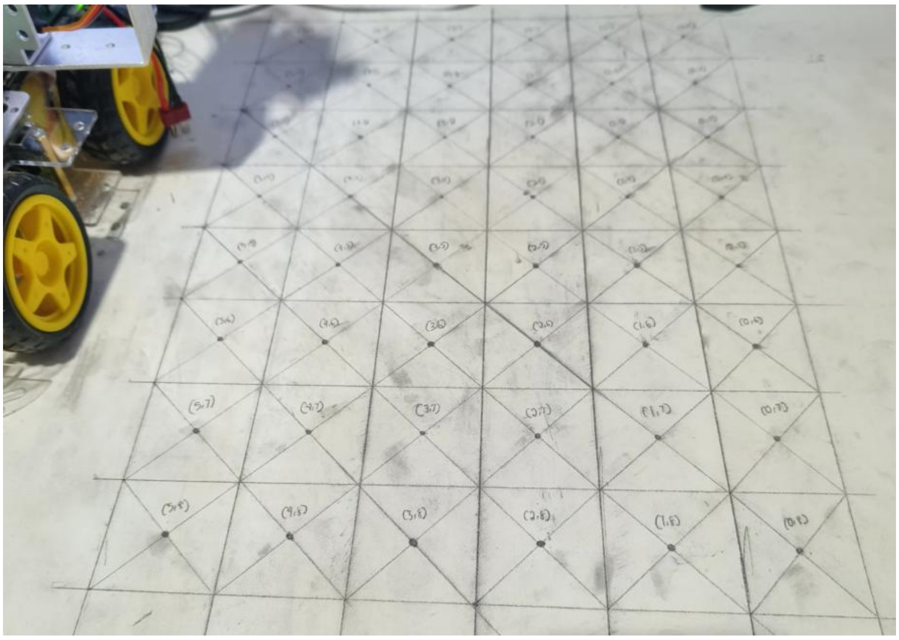


Figure 26: Grid Map on a Flat Surface

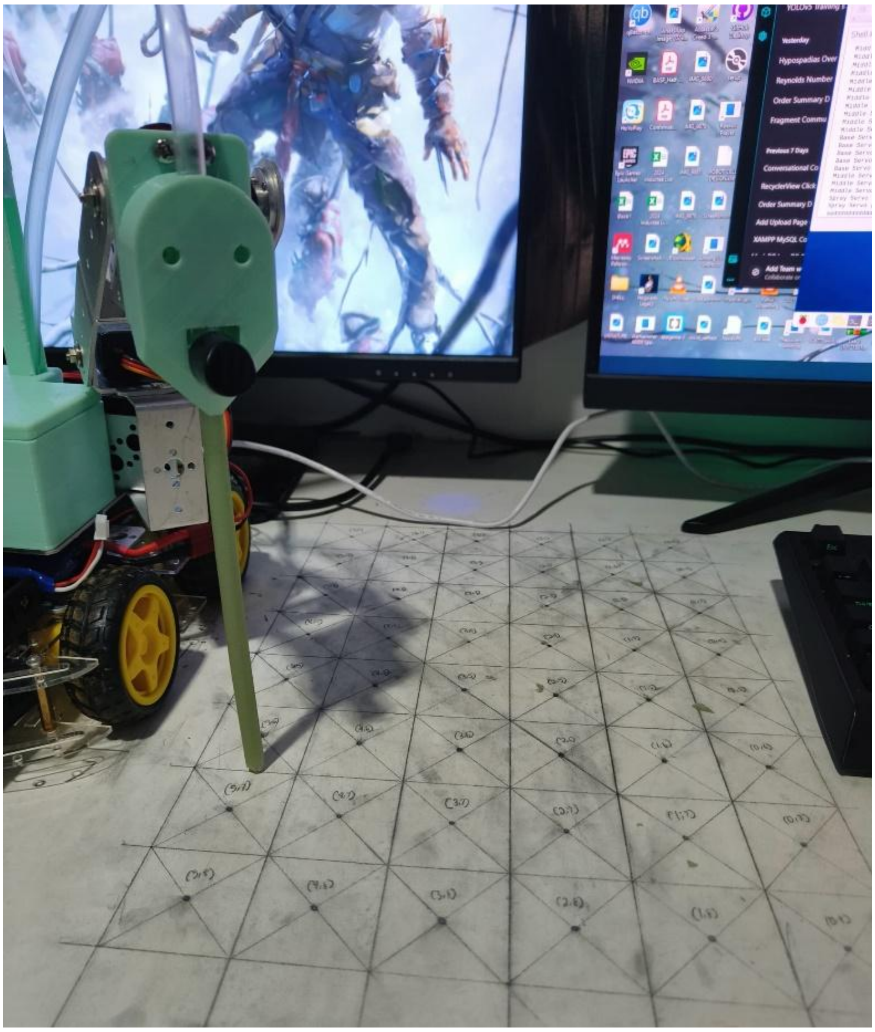


Figure 27: Calibration Process

3.4.2 Robotic Arm Movement

When a weed is detected within a frame, the system identifies the specific grid cell containing the weed by calculating the detection coordinates in row and column positions. This coordinate-based approach ensures that each detected weed is associated with a unique cell, allowing the robotic arm to focus on one cell at a time. When a cell is selected, the system retrieves the appropriate servo angles from the grid map and moves the robotic arm to target the grid cell. The arm moves smoothly between its current position and target angles using a linear easing function to avoid abrupt movements that could lead to mechanical strain or misalignment. This function divides the movement into incremental steps, gradually allowing each servo to reach its target angle. Once the servos reach the required angles for a specific grid cell, the arm is in the correct position to target the detected weed. The system then activates the pump for a specified duration, spraying the weed with herbicide. This process is repeated for each detected weed across the grid map, moving from cell to cell as weeds are detected. The grid map and robotic arm control system operate in a real-time loop, with the arm continuously adjusting its position based on new detections within the detection window. This ensures the robotic arm can respond to dynamically detected weeds, recalibrating its movement for each detection cycle.

3.5 Project Budget

3.5.1 Components

Table 19: Procured Components

Item	**Quantity**	**Price (RM)**	**Total (RM)**
Raspberry Pi 5 Computer with 8GB RAM	1	409.00	409.00
Raspberry Pi 8MP Camera Module V2	1	82.50	82.50
ESUN Matte PLA Filament 1.75MM, Low Density Matte 3D (Mint Green)	1	64.90 18.00 (shipping)	75.50
Raspberry Pi USB-C PD 27W PSU	1	60.00	60.00

Battery 7.4V (LiPo)	1	60.00	60.00
SANDISK 64GB Ultra Micro SD 140MB/S	1	34.00	34.00
Battery 1200MAH 18650 2PCs	3	9.99	29.97
FPC 22-Way to 15-Way for Camera – 50cm	1	16.50	16.50
Charger 18650	1	15.99	15.99
Acrylic Case Holder for Camera Module	1	14.50	14.50
Mini Succulents Artificial - Succulents Plants Artificial Mini Plants	6	2.06	12.36
USB Charger	1	10.00	10.00
FPC 22-Way to 15-Wat for Camera – 20cm	1	5.50	5.50
Micro Submersible Water Pump DC 3V-5V	1	3.90	3.90
1CH Active H/L 5V OptoCoupler Relay Module	1	3.50	3.50
3x18650 Battery Holder	1	3.50	3.50
1CH Active H/L 5V OptoCoupler Relay Module	1	3.50	3.50
Male to Female Jumper Wire	1	2.00	2.00
2x18650 Battery Holder	1	1.80	1.80
		Total	844.50

In the initial budget plan, an allocation of RM600 was provided to cover the costs associated with developing the robotic system. However, due to unforeseen requirements and components, the final expenditure amounted to RM844.50, surpassing the initial budget by RM223.12. The increase in costs was attributed to the following factors:

- **Energy Requirements:** As the project progressed, it became apparent that additional power sources were necessary to support the robotic system's operations. This led to the including a 7.4V LiPo battery, 1200MAH batteries, and a corresponding charger. These components ensured sustained power supply and stability during testing and implementation.

- **3D Printing Materials**: To optimize the design and functionality of the robotic system, custom parts were fabricated using a 3D printer. As I can access a 3D printer, I must only purchase the PLA filament.

- **Miscellaneous Components**: Various other items, such as additional jumper wires and connectors, were necessary to ensure all components' proper integration and functionality.

Chapter 4: **Results**

4.1 Development of Weed Detection Algorithm

The following section describes the training results obtained from training a YOLOv5 Small model for weed detection. The model was trained on a dataset containing 22,394 images, divided into two classes: "weed" and "crop."

4.1.1 F1-Confidence Curve

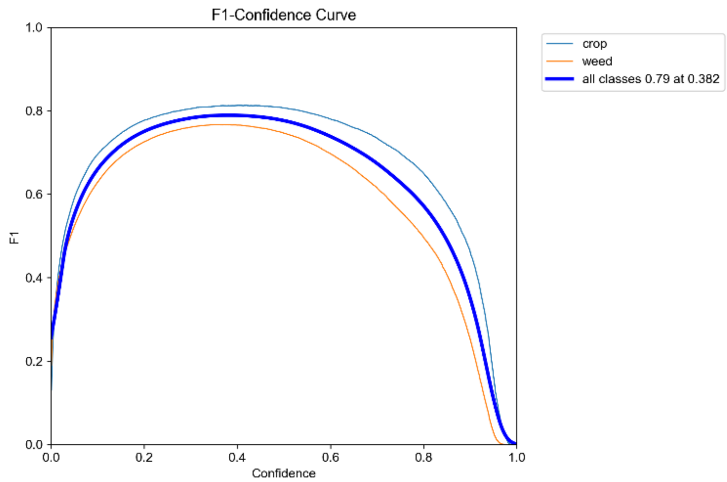


Figure 28: F1-Confidence Curve

The F1-Confidence Curve shows the relationship between the F1 Score and the confidence threshold for detecting "weed" and "crop." The F1 score here is the evaluation metric that measures a model's accuracy by combining the precision and recall scores of a model [51]. In this model, the peak F1 score for all classes is 0.79 at a confidence threshold of 0.382, which means that the precision and recall at this threshold are optimally balanced. Additionally, the model performs slightly better detecting "crop" than "weed," as its F1 score is marginally higher across all confidence levels. This suggests that the model is more effective in identifying crops than weeds.

4.1.2 Precision-Confidence Curve

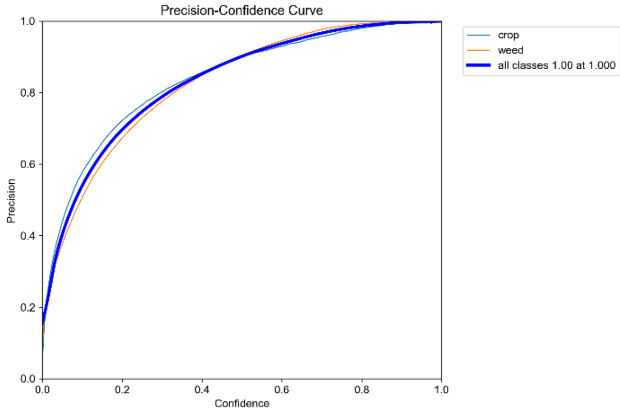


Figure 29: Precision-Confidence Curve

The Precision-Confidence Curve shows how precision changes at different confidence thresholds. As shown in the curve, the model achieves a precision of 1.0 for all classes at a high confidence threshold of 1.0, indicating that all detections are correct at this level, though fewer instances are detected overall as this threshold is very conservative. However, this behavior is not that beneficial in the case of detecting weeds because if the threshold is too conservative, weeds with all kinds of variations and features will most likely not be detected.

4.1.3 Precision-Recall Curve

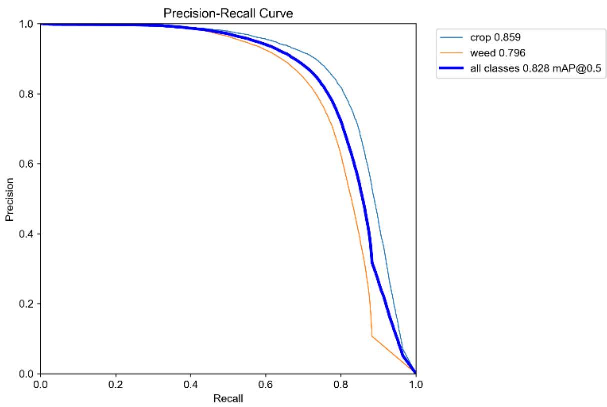


Figure 30: Precision-Recall Curve

The Precision-Recall Curve shows the trade-off between precision and recall across different thresholds. The mean average precision (mAP@0.5) for all classes is 0.828, indicating a high precision level even as recall increases. The curve suggests that “crop” is easier for the model to detect with high precision across different recall levels, while “weed” shows a minor drop in precision, especially at higher recall levels, showing a need for further fine-tuning to specifically improve weed detection in future model training.

4.1.4 Recall-Confidence Curve

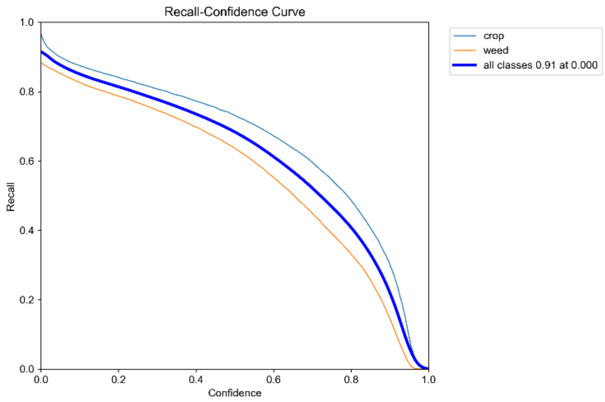


Figure 31: Recall-Confidence Curve

The Recall-Confidence Curve shows how recall decreases as the confidence threshold increases. At a confidence threshold of 0.0, the maximum recall for all classes is 0.91, suggesting that most instances are detected without a confidence threshold. However, recall gradually decreases as confidence increases, especially for “weed” detections. The difference in recall between “weed” and “crop” suggests that the model could benefit from a confidence threshold tuned to optimize recall specifically for weed detection, depending on the application’s tolerance for false negatives.

4.1.5 Training and Validation Losses and Metrics

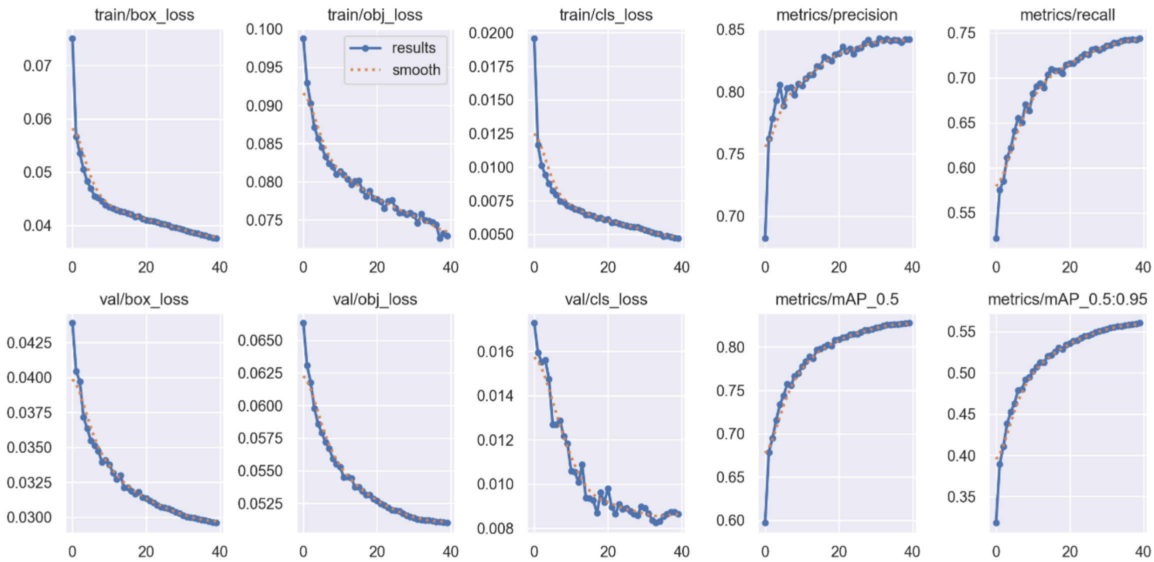


Figure 32: Training and Validation Losses and Metrics

The training and validation losses for bounding box (box), objectness (obj), and class (cls) loss steadily decrease over the epochs, indicating successful learning without significant overfitting. It is important to note that Class Loss nearly reaches zero in the train/cls_loss graph, showing effective learning in distinguishing between “weed” and “crop” classes. The precision and recall metrics indicate that the model achieves high precision stabilizing at around 0.85 and recall at around 0.8, indicating robust detection capabilities.

4.1.6 Conclusion

The YOLOv5 Small model has been successfully trained to detect “weed” and “crop” with high precision and recall. The model balances between minimizing false positives and maximizing detections, as shown by high F1 scores and an mAP of 0.828 or 82.8%. These results suggest that the model is well-suited for accurate weed detection applications with an optimal confidence threshold of around 0.4, effectively balancing precision and recall. Overall, the model indicates strong performance, and further evaluation will be detailed in the testing and validation section.

4.2 Development of Control System for Robotic Arm and Dynamic Herbicide Spraying Mechanism

4.2.1 Wiring Diagram

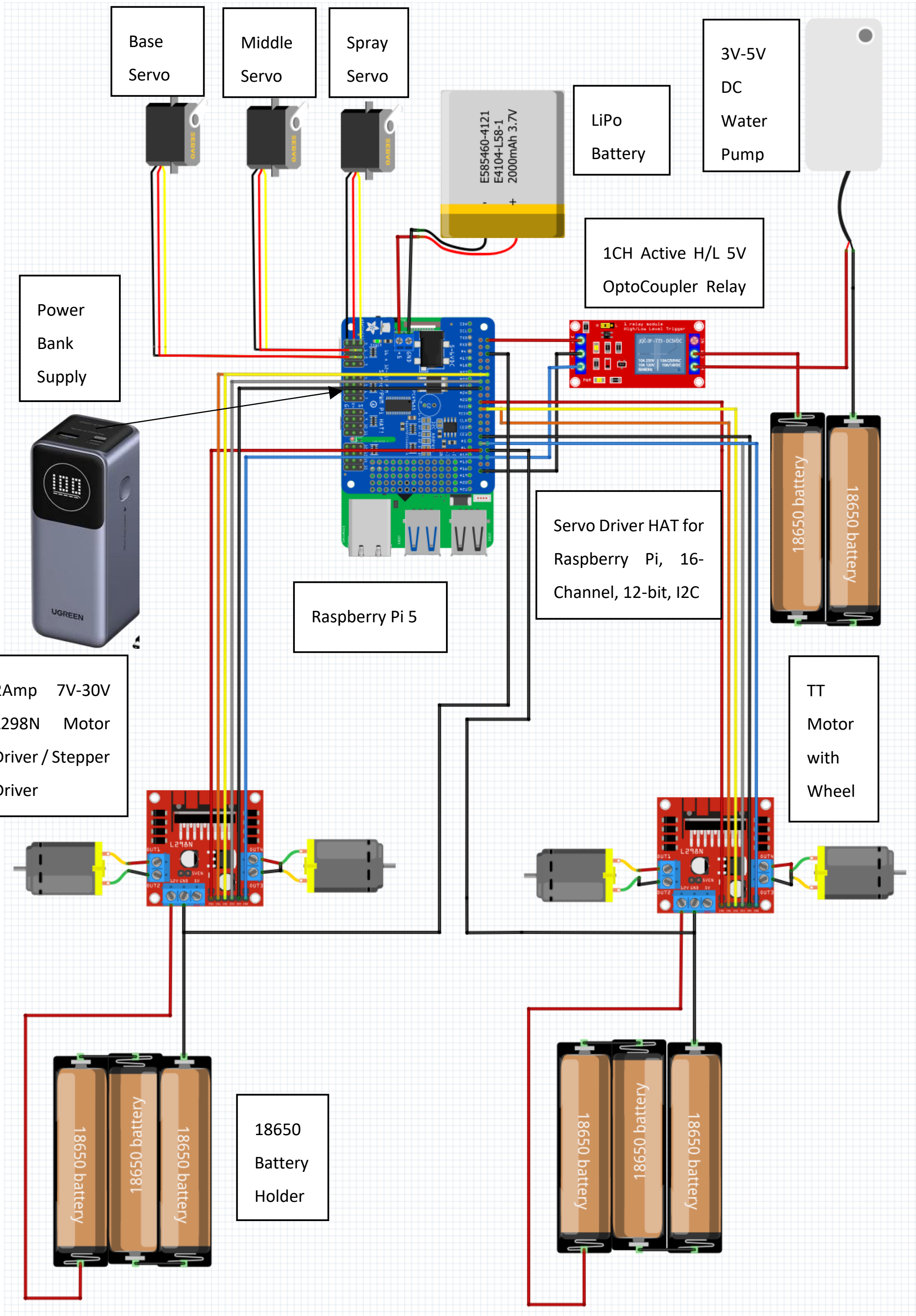


Figure 33: Wiring Diagram of Proposed Robot

4.2.2 Connections

- **Wheels**

Table 20: Wheel Wiring Connections

Component	**Motor Driver**	**Servo Driver HAT**
Left Back Wheel	ENA	GPIO 13
	IN1	GPIO 17
	IN2	GPIO 18
Right Back Wheel	ENB	GPIO 19
	IN3	GPIO 27
	IN4	GPIO18
Right Front Wheel	ENA	GPIO10
	IN1	GPIO9
	IN2	GPIO25
Left Front Wheel	ENB	GPIO12
	IN3	GPIO5
	IN4	GPIO6

- **Robotic Arm**

Table 21: Robotic arm Servo Motor Connections

Servo Motor	**Servo Driver HAT**
Base Servo	PWM 0
Middle Servo	PWM 1
Spray Servo	PWM 2

- **Water Pump**

Table 22: Water Pump Connection

1CH Active H/L 5V OptoCoupler Relay	GPIO16

- **Raspberry Pi 5**

Table 23: Raspberry Pi 5 Connections

Raspberry Pi Camera	CSI/DSI Connector
Power Bank (100W PD)	USB-C

4.2.3 Design

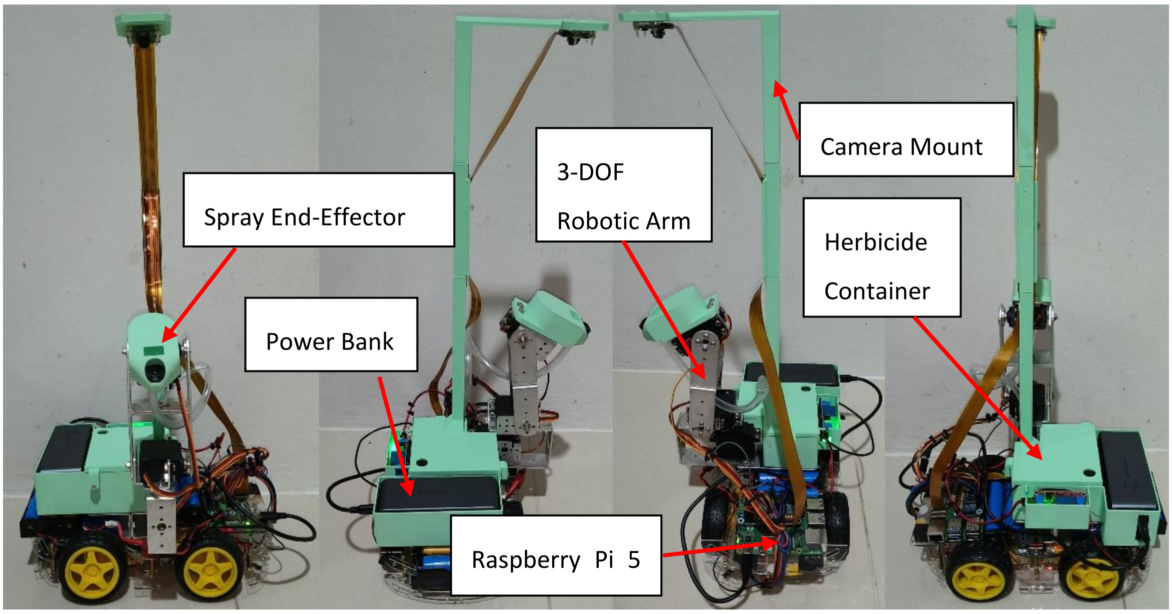


Figure 34: Final Robotic System Design

4.2.4 Upgrades

Table 24: Modifications Added to Robot

Modification	**Rationale**
Upgrade to Raspberry Pi 5	Initially, the provided robot was equipped with a Raspberry Pi 3 Model B V1.2. As a main processing unit, this model could not handle the increased computational demands of running the YOLOv5 object detection model. The newer model offers superior processing power and RAM.
Reduction to 3DOF Robotic Arm	The 6 Degree-of-Freedom (DOF) robotic arm was simplified to a 3 Degree-of-Freedom (DOF) robotic arm to reduce the complexity of the robotic arm movement overall, reduce end-effector weight, and increase operational area coverage.
Spray End-Effector	A herbicide sprayer was placed at the end-effector to directly apply herbicide onto the targeted weed. The DC Water Pump supplies this sprayer through a plastic tube.

Camera Mount	The Raspberry Pi Camera module is placed about 50cm above the body of the Robot to obtain a wide camera view of the operational area.

4.2.5 Robot Navigation System

The robot's navigation system is controlled by four independently operated motors configured with GPIOZero for efficient and precise movement. The motors are paired with PWM signals, enabling speed adjustments ranging from 0% to 100%, normalized for smooth acceleration and deceleration.

The robot uses a stop-and-go navigation approach to integrate the weed detection and spraying tasks. It moves forward for approximately 1 second at 25% speed and then stops to open the camera view for a detection and spraying cycle. This controlled movement is essential to avoid motion blur in camera frames, which could lead to incorrect weed detections during movement. The stop-and-go approach ensures that the system has clear and stable images to accurately detect weeds and determine their corresponding grid cell locations.

Furthermore, the robot must pause to aim at the detected weed, as the system is not fast enough to simultaneously detect weeds, identify grid cell locations, and move the robotic arm while the robot is in motion. Once a weed is detected, the grid cell containing the weed is determined based on the camera's field of view. However, if the robot continues moving, the grid cell associated with the detected weed would no longer be valid due to the change in the robot's position. To ensure precision, the robot stops during detection to maintain alignment between the weed's location and the robotic arm's spray mechanism, allowing accurate targeting and herbicide application.

4.2.6 Workflow Technical Overview

The video stream is initialized as soon as the script begins execution and continuously provides real-time frames at a resolution of **700x700 pixels** at an average of **30 Frames Per Second (FPS)** before any image inferencing.

- **Frame Capture and Preprocessing:** The system utilizes the stream to retrieve the latest frame from the video stream. However, not all captured frames are processed. To manage computational constraints, the script uses a frame_skip mechanism. Specifically, a frame_skip value of 2 ensures that the system only processes every second frame, skipping the rest. This reduces the computational load on the Raspberry Pi and keeps the FPS at around **5-6 FPS** while maintaining a smooth operation without compromising the detection quality.

- **Preprocessing:** Once a frame is retrieved, It undergoes preprocessing to prepare it for the YOLOv5 detection model. The frame is resized to a predefined input size of 704 x 704 pixels, and its dimensions are rearranged to align with the model's input requirements. During this process, the pixel values, originally ranging from 0 to 255, are normalized to a 0 to 1 range for consistency with the model's training data. Finally, the frame is converted into a tensor, a multi-dimensional array optimized for computations, with an additional batch dimension added to make it ready for YOLOv5 inference.

- **Weed Detection:** The weed detection process uses the trained YOLOv5 object detection model configured specifically to distinguish between "weed" and "crop." Once a preprocessed frame is passed to the YOLOv5 model, the detection pipeline begins by generating predictions that include bounding boxes, confidence scores, and class labels for any identified weed or crop.

    - **Confidence Threshold at 0.5:** Although the model training showed that a confidence threshold of 0.4 is recommended, testing showed that it could misclassify a crop as a weed. Thus, a confidence threshold of 0.5 was used instead to ensure only accurate detections were kept, and the results section showed good performance at this threshold.

    - **Intersection over Union (IoU) at 0.5:** The IoU threshold was set to 0.5 to prevent duplicates. This value is used during Non-Maximum Suppression (NMS) to consolidate overlapping bounding boxes that likely represent the same object. Bounding boxes with an IoU greater than 0.5 overlap, and only the one with the highest confidence score is retained.

    - **Output:** The script explicitly filters the output, retaining only objects classified as “weed.” Each weed detection is also given a unique bounding box, which is used to determine its location in the frame and map it to a specific grid cell for spraying.

    - **Detection Window:** The detections are processed during a fixed detection window of **4 seconds**. Once the robot stops, this detection window starts, and the system iteratively processes frames only during this period. This approach reduces computational load and ensures that, after the detection process, the system sprays all detected weeds in one cycle before the robot resumes moving. Additionally, it prevents the robot from continuously detecting and spraying the same weed over and over before deciding to continue moving forward.

- **Dynamic Spraying Mechanism:** The dynamic spraying mechanism initiates once the weed detection process identifies and maps weeds to specific grid cells. This mechanism ensures precise and efficient herbicide application based on the location and size of detected weeds. Through the grid mapping and a servo control system, it dynamically adjusts the spraying duration for each weed.

    - **Mapping Detection to Grid Cells:** The system employs an 11x11 grid mapped over the camera frame to accurately target weeds, aligning the grid cells with the robot's defined operational area. The bounding box of the detected weed is analyzed to determine its overlap with each grid cell. The system calculates the intersection area for each overlapping cell, identifying the grid cell with the largest overlap as the optimal target for spraying. This ensures that the robotic arm focuses on the precise location of the weed, typically its center, to maximize herbicide accuracy. If multiple cells have similar overlap areas, the system prioritizes the cell closest to the geometric center of the bounding box. Additionally, while the video stream visually shows an 11x11 grid, only grid cells within the robot's operational 7x6 map are considered, and weeds outside this map are ignored to align with the robot's physical spraying capabilities.

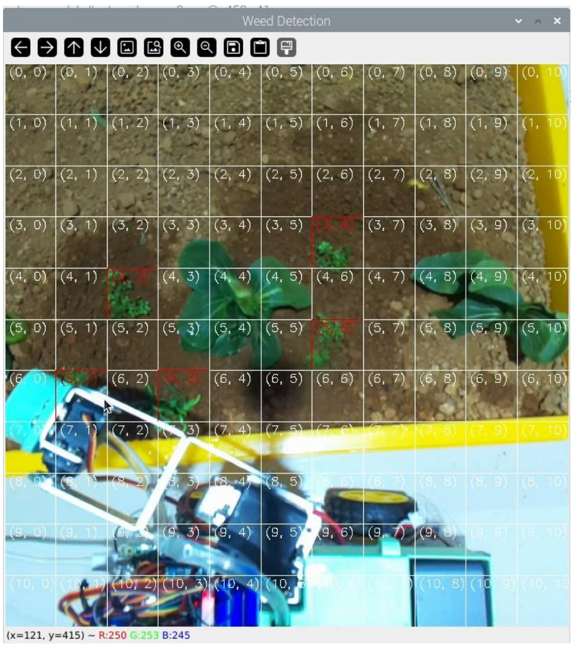


Figure 35: Chosen Grid Cell

- **Spraying Mechanism:** The spraying mechanism begins by calculating the servo angles required to position the robotic arm accurately over the identified grid cell, with each grid cell corresponding to predefined servo angles for the base, middle, and spray servos to ensure precise alignment. As this robot serves as a proof of concept, an assumption was made that the area of its bounding box could approximate the size of the detected weed: weeds with bounding boxes over 8,000 pixels are classified as large and require 3 seconds of spray, while those below this threshold are classified as small and require 1.5 seconds of spray. The pump is activated dynamically based on this classification to ensure efficient use of the "herbicide." The robotic arm sequentially sprays each detected weed, grid cell by grid cell, and after completing all tasks, it resets to its default position, preparing the system to move forward and begin the next detection cycle.

```
Starting detection window of 4 seconds...
Weed detected with bounding box area: 5440px, Spray duration: 1.5s
Weed detected in grid cell (3, 6) with 166 green pixels.
Weed detected with bounding box area: 7387px, Spray duration: 1.5s
Weed detected in grid cell (5, 6) with 251 green pixels.
Weed detected with bounding box area: 5850px, Spray duration: 1.5s
Weed detected in grid cell (6, 1) with 174 green pixels.
Weed detected with bounding box area: 8010px, Spray duration: 3s
Weed detected in grid cell (4, 2) with 186 green pixels.
Weed detected with bounding box area: 9860px, Spray duration: 3s
Weed detected in grid cell (6, 3) with 493 green pixels.
Detection window ended. 5 unique grid cells detected.
```

Figure 36: Weed was Detected along with the bounding box and spray duration.

```
Grid cell (3, 6) detected.
Targeting grid cell (3, 6) with Servo Angles -> Base: 64.64°, Middle: 153.06°, Spray: 142.62°
Activating pump...Spraying for 1.5 seconds

Pump deactivated.Grid cell (4, 2) detected.
Targeting grid cell (4, 2) with Servo Angles -> Base: 138.42°, Middle: 145.44°, Spray: 121.44°

Activating pump...Spraying for 3 seconds

Grid cell (5, 6) detected.Pump deactivated.

Targeting grid cell (5, 6) with Servo Angles -> Base: 56.44°, Middle: 131.98°, Spray: 59.95°
Activating pump...Spraying for 1.5 seconds

Grid cell (6, 3) detected.Pump deactivated.

Targeting grid cell (6, 3) with Servo Angles -> Base: 148.96°, Middle: 127.88°, Spray: 53.51°
Activating pump...Spraying for 3 seconds

Grid cell (6, 1) detected.Pump deactivated.

Targeting grid cell (6, 1) with Servo Angles -> Base: 170.63°, Middle: 135.49°, Spray: 95.67°
Activating pump...Spraying for 1.5 seconds
```

Figure 37: Sequential Spraying of all detected weeds.

- **Reset:** After completing the spraying process, the system resets and prepares for the next cycle. The robotic arm is returned to its default "home" position, minimizing the risk of collisions or misalignment during movement. Following the reset, the robot advances for 1 second to a new position where the detection and spraying cycle starts again. A brief delay is introduced after the movement to ensure stability, allowing the robot to stop moving completely before the detection window starts again. This reset and preparation process ensures a seamless transition between cycles and maintains consistent functionality.

4.3 Comprehensive Testing and Validation

This section details the assessment of the robotic system's weed detection and spraying mechanism functionalities. Five test sets were designed to evaluate the system's performance across varying crop arrangements, weed densities, and weed sizes. Key metrics focused on measuring weed spraying accuracy, reliably avoiding spraying crops, and the system's capacity to dynamically increase herbicide application for larger weeds.

4.3.1 Results and Observations

The results for each test set and subsequent test runs are summarized in the following table. It is important to note that the totals for weeds and crops are calculated by adding all instances across the individual test runs within each test set.

Table 25: Test Result

Test Set	Total Weeds	Total Crops	Test Runs	Weed			Crop	
				Sprayed	Missed	Long Spray	Sprayed	Skipped
1	8	6	1	6	2	NA	0	6
			2	8	0		0	6
			3	6	2		0	6
			4	5	3		0	6
			5	8	0		0	6
			6	8	0		0	6
			7	5	3		0	6
			8	5	3		0	6
			9	8	0		0	6
			10	7	1		0	6
			Total	**66**	**14**	**NA**	**0**	**60**
			Accuracy	**82.5%**				
			Reliability	**100%**				
			Spray Efficiency	**NA**				

2	8	6	1	6	2	NA	2	4
			2	5	3		0	6
			3	8	0		0	6
			4	7	1		0	6
			5	7	1		0	6
			6	7	1		0	6
			7	7	1		0	6
			8	8	0		0	6
			9	8	0		0	6
			10	8	0		0	6
			Total	**71**	**9**	**NA**	**2**	**58**
			Accuracy	**88.75%**				
			Reliability	**96.67%**				
			Spray Efficiency	**NA**				
3	7	5	1	6	1	2	0	5
			2	6	1	2	0	5
			3	6	1	2	0	5
			4	6	1	2	0	5
			5	5	2	2	1	4
			6	5	2	2	0	5
			7	6	1	2	0	5
			8	6	1	2	0	5
			9	7	0	2	0	5
			10	7	0	2	0	5
			Total	**60**	**10**	**20**	**1**	**49**
			Accuracy	**85.71%**				
			Reliability	**98%**				
			Spray Efficiency	**100%**				
4	7	7	1	5	0	2	0	7
			2	5	0	2	0	7
			3	5	0	2	0	7
			4	5	0	2	0	7
			5	5	0	2	0	7
			6	5	0	2	0	7
			7	5	0	2	0	7
			8	5	0	2	0	7
			9	4	1	2	0	7
			10	5	0	2	0	7
			Total	**49**	**1**	**20**	**0**	**70**
			Accuracy	**98%**				
			Reliability	**100%**				
			Spray Efficiency	**100%**				
5	6	5	1	5	1	2	0	5
			2	6	0	2	0	5

			3	5	1	2	0	5
			4	5	1	2	0	5
			5	6	0	2	0	5
			6	6	0	2	0	5
			7	5	1	2	0	5
			8	6	0	2	0	5
			9	5	1	2	0	5
			10	6	0	2	0	5
			Total	**55**	**5**	**20**	**0**	**50**
			Accuracy	**91.67%**				
			Reliability	**100%**				
			Spray Efficiency	**100%**				

Observations

Table 26: Test Observations

Test Set	**Performance Metrics**	**Results**	**Observations**
1	**Accuracy**	82.5%	The accuracy score of 82.5% reflects the system's ability to correctly detect and classify weeds; however, it struggled with consistently aiming the spray at the weeds. Most inaccuracies occurred because the robotic arm failed to precisely target the weeds, even though they were correctly identified in the correct grid cell. Despite this challenge, the system achieved a perfect reliability score of 100%, successfully avoiding all crops. This test highlights the need to further calibrate the robotic arm's targeting mechanism.
	Reliability	100%,	
	Spray Efficiency	NA	
2	**Accuracy**	88.75%	The accuracy score of 88.75% reflects an improvement over Test Set 1, partly due to the calibration of the robotic arm's targeting system, which reduced instances of missed sprays. Most of the remaining inaccuracies were caused by the system failing to detect certain weeds, likely due to overlapping features. Despite these challenges, the system successfully avoided spraying most crops, achieving a strong reliability score of 96.67%. The slight dip in
	Reliability	96.67%	

	Spray Efficiency	NA	reliability, caused by two mistakenly sprayed crops, highlights the need for further refinement in distinguishing crops from weeds in cluttered environments.
3	**Accuracy**	85.71%	The system maintained a perfect spray efficiency of 100%, demonstrating its ability to effectively differentiate between weeds of varying sizes and dynamically adjust the spraying duration for larger weeds. While the accuracy of 85.71% reflects the successful detection and spraying of most weeds, smaller weeds were occasionally missed. The reliability of 98% reinforces the system’s strong capability to avoid crops, with only one misclassification recorded.
	Reliability	98%	
	Spray Efficiency	100%	
4	**Accuracy**	98%	The system performed exceptionally well, achieving near-perfect accuracy and perfect reliability. The spray efficiency of 100% underscores its ability to differentiate between weeds of different sizes and dynamically adjust herbicide application accordingly. This test highlights the system's robustness in adapting to randomized layouts without compromising performance.
	Reliability	100%	
	Spray Efficiency	100%	
5	**Accuracy**	91.67%	The system performed well again, achieving high accuracy and perfect reliability while maintaining a spray efficiency of 100% again. The slight reduction in accuracy to 91.67% was primarily due to small weeds that were cramped together, making precise detection and targeting more challenging. This test shows that further refinement is needed to improve the detection of individual smaller weeds in a dense cluster.
	Reliability	100%	
	Spray Efficiency	100%	

4.4 Final Evaluation and Analysis

This section comprehensively evaluates the robotic weed detection and spraying system by analyzing results from all test sets. The analysis highlights key trends, strengths, and challenges observed during testing, offering insights into the system's overall performance and readiness for real-world agricultural applications.

4.4.1 Accuracy Analysis

The system achieved an overall accuracy score of **89.73%,** reflecting its strong capability to detect and spray weeds effectively across various scenarios. This result directly addresses **Research Question A** by demonstrating the efficacy of the YOLOv5 model for weed detection in controlled settings, with accuracy progressively improving from 82.5% in Test Set 1 to 91.67% in Test Set 5, largely due to the calibration of the robotic arm's targeting system, which reduced missed sprays and improved precision.

However, some weeds were still missed, possibly due to specific limitations in the robot's movement and detection process. The current workflow involves the robot moving forward, stopping, opening the camera view, detecting and spraying weeds within that field of view, and then moving forward again. In some cases, weeds exited the camera's view during movement or fell outside the range of the robotic arm, resulting in missed detections. Addressing these challenges would ideally require an improved navigation process with continuous camera scanning to eliminate blind spots. However, due to the performance limitations of the current hardware, implementing such a solution is not feasible at this stage.

To further increase accuracy, the system can benefit from improving the detection model and advanced image preprocessing. Methods to improve the detection model include increasing the training dataset with more images of small weeds, weeds in overlapping configurations, and weeds in complex backgrounds. Upgrading to a larger model, such as YOLOv5-medium, can also significantly enhance detection capabilities. A larger model offers improved feature extraction due to its increased layers and parameters, enabling it to better distinguish small or less distinct weeds, even in cluttered environments. However, implementing YOLOv5-medium on the current hardware is challenging due to its computational demands. When tested, the detection performance and video stream frame rate were halved, making real-time operation infeasible with the existing hardware. While this approach shows potential, it would require hardware upgrades to maintain system efficiency and performance. Advanced image preprocessing, including improved filtering, noise reduction, and adaptive segmentation, could enhance weed visibility and distinguish subtle features in complex or cluttered environments. Combined with future hardware upgrades, these refinements could significantly improve the system's ability to detect and spray weeds with even greater precision.

4.4.2 Reliability Analysis

The system demonstrated exceptional reliability across all test sets, achieving an average reliability score of **98.73%,** with near-perfect performance in most scenarios. This aligns with **Research Question B**, focusing on how the robotic arm's configuration and grid-mapping system ensure precise and reliable weed targeting. This consistency highlights the system's ability to distinguish crops from weeds, ensuring crops were accurately identified and skipped during herbicide application. In Test Sets 1, 4, and 5, the system achieved a perfect reliability score of 100%, avoiding any misclassification of crops.

The slight dip in reliability to 96.67% in Test Set 2 was caused by two crops being mistakenly sprayed in the scattered and irregular crop layout. This indicates that irregular planting patterns can occasionally challenge the system's classification algorithm, particularly when crop features overlap with weeds or are positioned near the edge of the camera's view. Addressing this challenge may involve refining the model's crop classification by introducing additional training data with varied crop arrangements and edge-case scenarios. Despite this minor limitation, the system's consistently high reliability suggests it is well-suited for real-world applications, minimizing crop damage and ensuring herbicide is applied only where necessary.

4.4.3 Spray Efficiency Analysis

The system achieved a perfect spray efficiency score of **100%** across all test sets involving large weeds (Test Sets 3, 4, and 5), demonstrating its ability to dynamically adjust herbicide application based on weed size, further supporting the reliability addressed in **Research Question B**. This indicates that the system detected large weeds and applied the appropriate spraying duration, ensuring effective herbicide coverage for larger targets. The consistent performance highlights the strength of the dynamic spraying mechanism in adapting to variations in weed size. This high level of spray efficiency underscores the system's ability to optimize herbicide usage by applying only the necessary amount for larger weeds while maintaining precision.

4.4.4 Strengths of the System

A few key factors can explain the system's good performance. First, the downward-facing camera placed directly above the working area helped achieve accurate results. This setup provided a clear and consistent view of weeds against the soil background, reducing errors caused by background noise. The system could perform effectively by ensuring the camera's view was similar to the data used to train the YOLOv5 detection model.

Another strength of the system is its use of a carefully designed 7x6 operational grid. This grid helped the robotic arm locate and spray weeds with high precision. The grid cells were small enough to place a weed in the center of each cell. Since the system's end-effector only needed to spray near the weed rather than touch it, it achieved accurate results while being efficient.

4.4.5 Limitations in Real-Life Applications

Despite its success under controlled testing conditions, several limitations were observed to address **Research Question C,** especially when transitioning to real-world agricultural test environments. While highly effective in structured settings, the fixed and predefined grid-based mapping system struggles with adaptability on uneven terrain or in fields with unpredictable weed growth patterns. Uneven or soft soil can misalign the robot's grid map, leading to targeting errors or missed weeds, while varying soil types may affect the robot's mobility due to its reliance on a wheeled design prone to sinking or slipping in muddy or loose ground. Furthermore, inconsistent lighting conditions caused by shadows, weather variations, or direct sunlight can compromise the YOLOv5 detection model's accuracy, especially in scenarios where the lighting differs significantly from the conditions present during training. The fixed grid also limits the system's scalability, requiring frequent manual repositioning to cover large agricultural fields, which reduces efficiency. These factors collectively highlight the need for further improvements, particularly in adaptive navigation, real-time grid recalibration, and robust detection models capable of handling diverse environmental conditions.

Figure 38: Testing in an external environment.

4.4.6 Suitability of the System

However, the robotic weed detection and spraying system can be suited for structured and less harsh agricultural environments, such as small farms, greenhouses, or high-value crop fields. This is because its reliance on a predefined and calibrated 7x6 operational grid allows precise targeting but only within a limited area, making it ideal for applications where consistent terrain and predictable field layouts are maintained. Furthermore, Its cost-effective design and accessible technology make it an appealing solution for farmers with limited resources, addressing the need for affordable automation in smaller agricultural operations. By targeting high-value crops and environments where manual weed management is labor-intensive, the system offers a practical and sustainable approach to modernizing agricultural practices.

4.4.7 Novelty and Implications

The proposed system represents a novel integration of YOLOv5 object detection and grid-based targeting, creating a cost-effective and efficient approach to weed management. Unlike traditional systems, it minimizes herbicide use and environmental impact while addressing the resource constraints of small-scale farming. The Grid-based mapping simplifies spatial localization, eliminating the need for expensive depth sensors or complex navigation and making the system accessible to farmers with limited resources. The demonstrated accuracy of 89.73% and reliability of 98.73% highlight its potential to transform structured agricultural settings like greenhouses and high-value crop fields. The system tackles challenges like herbicide resistance and resource waste by selectively targeting weeds and dynamically adjusting herbicide dosage.

Compared to existing solutions, it offers precision with reduced hardware complexity, making it ideal for real-world applications in constrained environments. This system also lays the groundwork for broader agricultural applications, including pest management and crop health monitoring, showcasing the scalability of grid-based targeting and AI-driven detection. The findings underline the potential for robotics and AI to modernize farming practices while ensuring accessibility and sustainability, contributing meaningfully to global precision agriculture and food security initiatives.

Chapter 5: **Conclusion**

This project successfully developed an autonomous robotic system capable of precise weed detection and targeted herbicide application in a controlled laboratory environment. Implementing the YOLOv5 Small object detection model enabled the system to accurately distinguish between crops and weeds. Training the model on a comprehensive dataset of over 22,000 images resulted in a mean average precision (mAP) of 82.8% and balanced F1 scores for both classes. The system demonstrated an overall weed detection and spraying accuracy of 89.73% across five test scenarios, reflecting its robustness in different planting patterns and weed densities. The system's reliability was highlighted by its ability to avoid spraying crops, achieving a high average reliability score of 98.73%.

The dynamic herbicide spraying mechanism proved effective, with the system adjusting the spraying duration based on weed size, achieving a perfect spray efficiency score of 100%. This adaptability ensures optimal herbicide use, reducing environmental impact and operational costs. The grid mapping strategy allowed the robotic arm to accurately target weeds within its operational area using predefined servo angles for each grid cell.

Despite these successes, the project identified areas for improvement. The system occasionally missed smaller weeds, particularly those in dense clusters or at the edges of the camera's field of view. Limitations in the robotic arm's range and the processing capabilities of the Raspberry Pi 5 affected the detection and targeting of some weeds.

Future Work

- **Navigation System:** Future work should focus on developing a more sophisticated navigation system to improve the system's practicality and effectiveness. Instead of the current hardcoded forward movement, implementing a navigation algorithm that allows the robot to actively move toward detected weeds would increase operational efficiency and ensure comprehensive field coverage. Path planning and obstacle avoidance could be integrated to navigate complex agricultural environments effectively.

- **Robotic Arm:** Improving the robotic arm's movement through inverse kinematics calculations is another critical area for development. Implementing inverse kinematics would enable the robotic arm to reach any position within its workspace more precisely, allowing it to target weeds outside the predefined grid cells. This would enhance the system's flexibility and adaptability to different field layouts and weed distributions.

- **Processing Unit:** Upgrading the processing unit from a Raspberry Pi and refining the weed detection model could significantly address current performance limitations. Utilizing a more powerful processor would enable larger models like YOLOv5-medium, which improves detection accuracy, especially for smaller weeds and those in cluttered environments.

- **Dataset:** Expanding the training dataset to include more diverse images of specifically smaller weeds under various environmental conditions would improve the model's generalization capabilities. Further, incorporating advanced image preprocessing techniques could improve weed visibility and aid in detecting small or obscured weeds.

In conclusion, the project's outcomes validate the hypothesis that an AI-powered robotic system can reliably identify weeds and precisely apply targeted herbicide applications, enhancing efficiency and reducing herbicide use. Future iterations can offer even greater precision and adaptability by focusing on advanced navigation systems and implementing inverse kinematics for robotic arm control, contributing significantly to the precision agriculture industry.

Chapter 6: **Appendix**

- **Test Set Recordings (Google Drive)**

  https://drive.google.com/file/d/1RA0uKrPaAc4KZmtzRJj8uEKczlVYKFo-/view?usp=sharing

- **Fusion360 Designs (Google Drive)**

  https://drive.google.com/file/d/1Gsz6m2vrVPNPvgA_dOQDenYQncXzYVUM/view?usp=sharing

- **Training Dataset (Google Drive)**

  https://drive.google.com/file/d/1_FTWLxmFMxcu-_6GTmoKIc4tJ7raFZf9/view?usp=sharing

- **Raspberry Pi Script (Google Drive)**

  https://drive.google.com/file/d/1Q1Hn9yJq8I6WiScB2npbojd8tJUy5O0_/view?usp=sharing

Chapter 7: **References**

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