2026 ASABE Robotics Competition
Standard Division
Robot Design Report

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Table of Acronyms, Initialisms, Abbreviations, Units

%	Percent
“	Inches
°	Degrees
USDA	United States Department of Agriculture
UAV	Unmanned Aerial Vehicles
ASABE	American Society of Agricultural and Biosystems Engineers
3D	Three Dimensional
PWM	Pulse Width Modulation
YOLO	You Only Look Once Object Detection Model

ROS2	Robot Operating System 2

1. Establishment of Need and Benefit to Agriculture

The major feed grain in this United States include corn, sorghum, and oats, with corn accounting for more than 95% of total production and use (USDA Economic Research Service, 2023). Annually farms plant about 90 million acres of corn, making the country the largest global producer, consumer, and exported of the crop (USDA Economic Research Service, 2023). Strong domestic demand is driven by livestock feed, which accounts for approximately 40% of domestic use, with food, seed, and industrial applications comprising the other 60%. Producing high-quality corn is important, as modern research demonstrates that specific cultivation techniques and early-stage crop management strategies directly alter grain quality indicators, including starch, protein, and crude fat content (Drobitko et al., 2024).

Current agricultural operations rely on several methods, including traditional manual labor and mechanization to establish, monitor, and harvest crops. Traditional manual techniques involve field workers utilizing basic tools such as sickles or their bare hands to complete grain harvesting along with early season stand monitoring. Alternatively, to accommodate large scale production efficiency, producers utilize high-end technology, such as combine harvesters, to process large crop areas efficiently, while medium grade reapers are implemented to lower production costs and increase profit (Kaur et al., 2023).

While manual methods have historical backing, traditional manual harvesting and monitoring are both labor-intensive and inefficient. Manual labor allows for meticulous plant handling and minimizes the need for high-cost capital investments. However, manual crop establishment and harvesting demand strenuous physical exertion and require up to 33 man days per hectare, yielding a timeliness rate of exactly 0.04 hectares per day (Madzivanzira et al., 2024). This heavy reliance on manual labor makes agricultural operations vulnerable to shortages of seasonal workers. Conversely, conventional machine harvesting resolves many throughput issues by drastically reducing the time required to clear fields. Despite this advantage, the integration of bulk machinery lacks the fine precision required for selective, individual plant tasks and requires high initial capital costs, which farmers often rank as their primary operational concern (De Jesus et al., 2025). Furthermore, heavy conventional machinery often contributes to soil compaction and increased environmental impact.

The operational limitations of manual labor and the imprecision of bulk machinery highlight the need for automation within modern agriculture. While large-scale mechanization has drastically improved field throughput, these heavy systems lack the dexterity required for selective, individual plant management, often leading to input waste and environmental issues like soil compaction (Boutheina et al., 2024). In addition, the cost allocated to manual labor frequently accounts for more than 30% of total agricultural production costs (Marani et al., 2022). As labor availability decreases and its cost rises, traditional manual harvesting and field scouting become progressively more expensive, reducing profit margins. Automation and robotics present a solution to this. Autonomous systems bridge the gap between slow manual precision and fast, imprecise bulk machinery by executing repetitive, labor-intensive tasks with high accuracy, which alleviates the physical burden on human workers allowing for continuous production (Wang et al., 2024).

Specifically, automation has already demonstrated significant benefits in crop management and harvesting. For example, Unmanned Aerial Vehicles (UAVs) integrated with artificial intelligence are actively used for precision field mapping and monitoring, reducing water and fertilizer use by up to 96% and 40%, respectively, through targeted management (Raj & Prahadeeswaran, 2025). Furthermore, in delicate crop harvesting, modular autonomous systems utilizing sophisticated computer vision and robotic manipulation can successfully harvest crops like strawberries within dense clusters with high accuracy, eliminating the human induced damage to the fruit flesh (Parsa et al., 2023).

2. Design Objectives

The following objectives are crucial for the successful execution of the robot in competition. They function as key milestones throughout the design of the robot to maximize points earned, robustness, and minimize complexity. Objectives are categorized through the three main tasks of navigation, vision, and actuation.

2.1 Navigation Goals

The objectives for navigation involve moving the robot through the playing field. To do this, the robot must be able to follow a black line, keep track of which row the robot is in, and know when to stop so it can remove bad plants. To achieve all these goals, the robot must have fine motor control to accurately position itself, the ability to move forward in a consistent pattern, the ability to turn, and the ability to give real-time updates from the vision system.

2.2 Vision Goals

The design objectives for vision include the ability to detect and differentiate between plants. This is achieved by first detecting the plant bases, then differentiating between the good and bad plants. The plants are differentiated only by color with good being green and bad yellow. The vision system must be able to perform real-time identification for both the vision specific task and the main challenge. In addition to just detecting, the robot must be able to keep track of the number of bases and which lines to know its location on the playing field in real-time.

2.3 Actuation Goals

The last task is actuation which is governed by consistency and accuracy. The actuating system must be consistent in removing the plant every time by allowing for a simple system with a large margin of error. The system should also be accurate to only remove bad stems without interacting with the good ones.

3. Design Constraints

The robotic design is governed by the physical and operational parameters established by the 2026 ASABE Student Robotics Challenge. These constraints dictate the physical footprint, navigation requirements, and task performance necessary for successful field deployment.

For the physical footprint, the maximum dimension of the robot is 12” x 12” x 12” before stating any task. Additionally, the layout of the field impacts both the footprint and navigational requirements. This is visualized in Figure 1, where the robot must weave 5 lanes of plants within a 96” x 96” field.

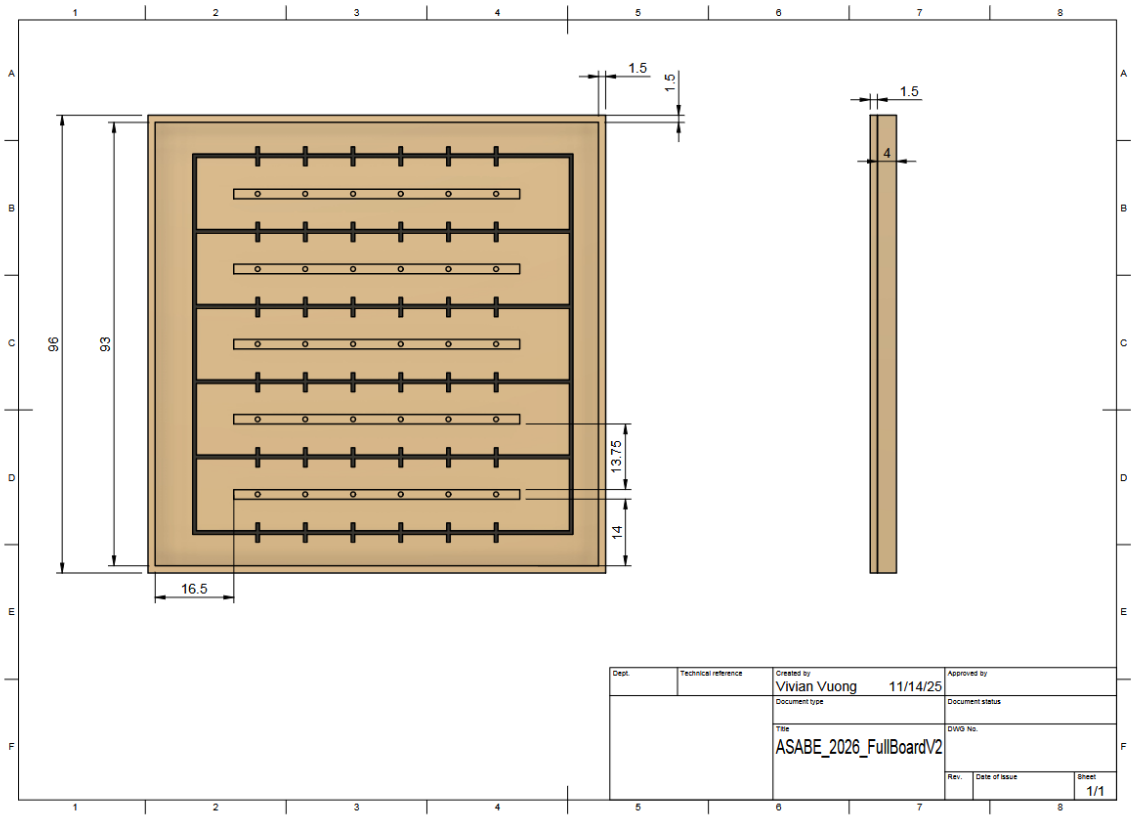


Figure 1: Top view and side view of the playing field with dimensions

The dimensions of these lanes alter how the actuation task and visual identification can be completed. The lanes control plant height and distance between plants, as shown in Figure 2. Furthermore, the plants are 3D printed and separated into 3 main components. The base, collar, and plant itself. Figure 3 shows how the base and collar are connected and the 3 locations for plants to rest. These plants are connected by magnets placed at the bottom of the plant, and within the 3 available slots of the plant base. The design of the robot actuation must consider the geometry of the plant based plus collar along with the magnetic force created from the magnets.

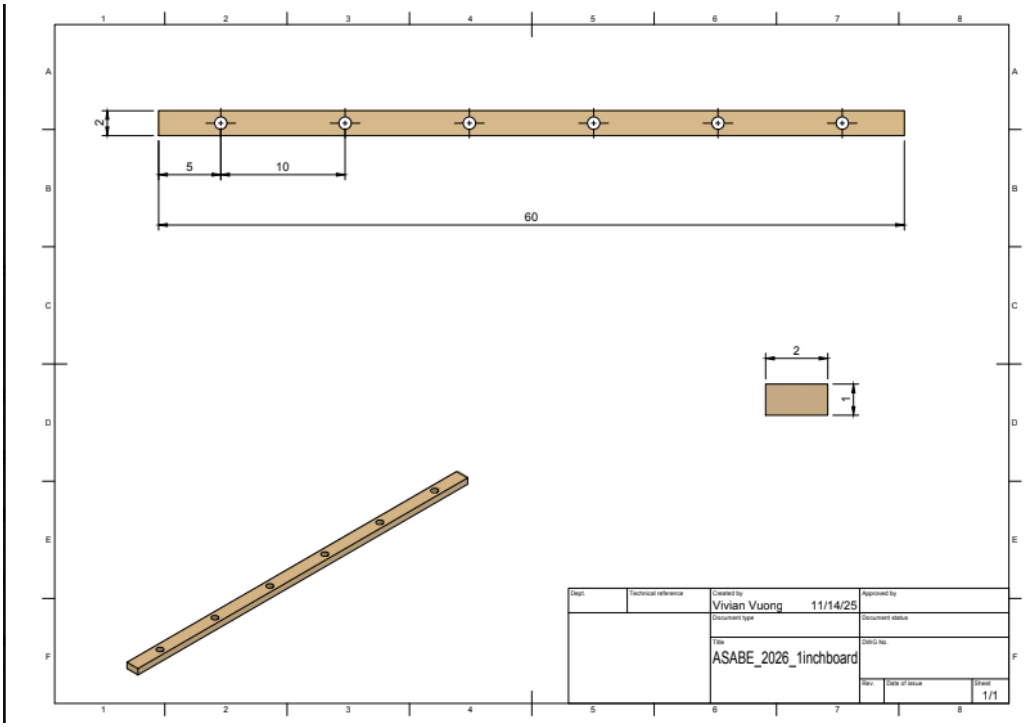


Figure 2: Drawing of an individual lane in the playing field with dimensions

Figure 3: Photo of single plant base with good (green) and bad (yellow) plants attached

In the design and construction of the robot, the team ran into several resource constraints. Operationally, access to 3D printers was limited, which delayed the ability to recreate playing field materials. Additionally, the 3D printing space was limited to 10” x 10” x 10”. This made larger pieces for the robot had to be designed around this constraint

For construction of the playing field, the team had to use commercially available materials. The plant beds are listed as 1” x 2” pieced of wood, indicated in Figure 2. The actual size of 1” x 2” boards that are available at most hardware stores is 0.75” x 1.5” boards. While the difference is small when trying to design and test accurate systems, the difference may have a noticeable effect that must be taken into consideration during testing.

4. Overview of Design

The design of this robot has been optimized to account for all objectives and constraints. RGB cameras are used for line and plant detection, a jetson nano orin to process all video and motor information, Mecanum wheels for omni-directional movement, an Arduino along with the nano GPIO board for motor control, a two-sided actuator for plant removal, and all necessary chassis components and batteries for support of necessary components. Table 1 displays all parts purchased in the design of the robot.

Table 1: Parts table with quantities and MSRP prices.

Part	Specification	Quantity	Total Price (MSRP)
Microcomputer	Jetson Orin Nano Super Developer Kit	1	$249.00
Cameras	Waveshare IMX219-160 Camera	2	
	HBVCAM-V2101 V11O	2	$78.02

Cables	CSI FPC Flexible Cable (B)	2	$9.59
Gear Rack	100mm Metal Gear Rack	2	$43.08
Pinion Gear	Brass Pinion Gear	1	$9.30
Wheels	60mm Mecanum Wheels	4	$77.35
Arduino	Arduino Mega R3	1	$20.99
Motors	DC Brushless Motor	5	$99.50
	MG90S Servo	2	$6.44
Display Screen	3.2in HDMI Screen	1	$29.99
Pin connectors	Male to female pin connectors	80	
	Female to female pin connectors	80	
	Male to male pin connectors	80	$12.95
Generic PLA	3D Printing	1	$11.87
PLA +	3D Printing	3	$50.97
Battery	12V 5200mAh Lithium-ion Battery	1	$32.89
	V-Mount Battery	1	$86.39
Bus Connectors	Power and GND Buses	2	$9.99
Total			$828.32

The robot's design philosophy is centered on consistency and reliability in all moving parts. A simple actuation system is adopted to reduce potential error, and movement is limited by fewer degrees of freedom to allow a more consistent pattern. Motor Control is designed to prioritize high levels of precision and accuracy within these constraints. By increasing these performance metrics, both navigation and actuation are improved to ensure reliable execution of tasks.

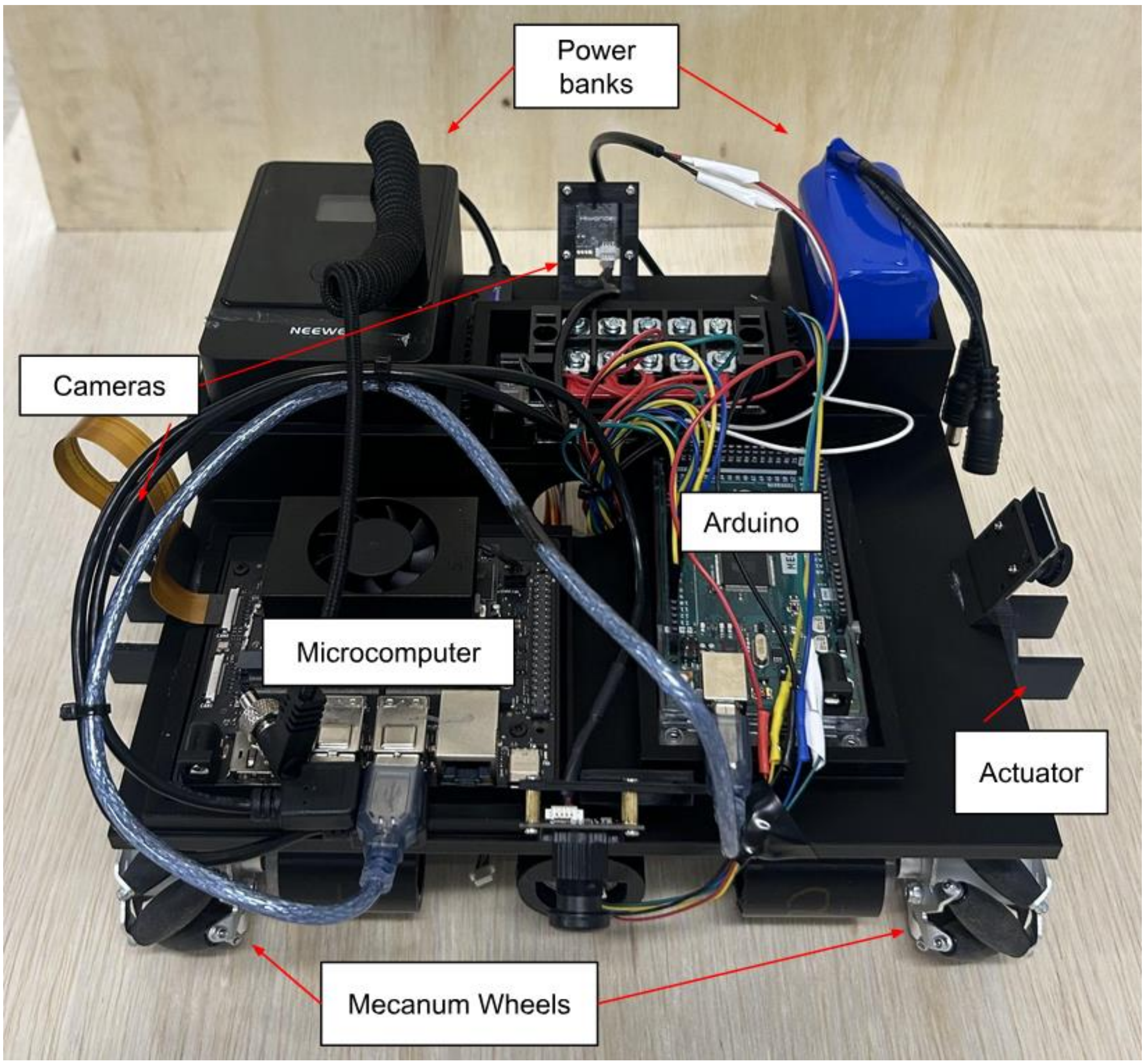


Figure 4: Top and Front facing view of completed robot with main components location indicated

5. Mechanical Systems

The mechanical systems of the robot can be split into two categories: chassis and drivetrain, and the end effector.

5.1 Chassis and Drivetrain:

The chassis for our robot (Figure 4) was designed using Fusion 360 software, then printed with a Bambu Labs P2S 3D printer using PLA+ filament. The choice to use a 3D printed chassis was motivated through the freedom of design it allowed so it could be custom built around the constraints presented by other parts. The chassis is square in shape. On the top side it features walls, creating sections, which securely hold a Jetson Nano Orin, Arduino Mega, power and ground busses, and the 2 batteries that power everything. The bottom side of the chassis features 5 motor holders and housing for the actuation system. 4 of the motor holders are for the wheels, with the last one for the actuation system. The chassis also features camera mounts that were printed separately, and a center hole used as a wire pass-through.

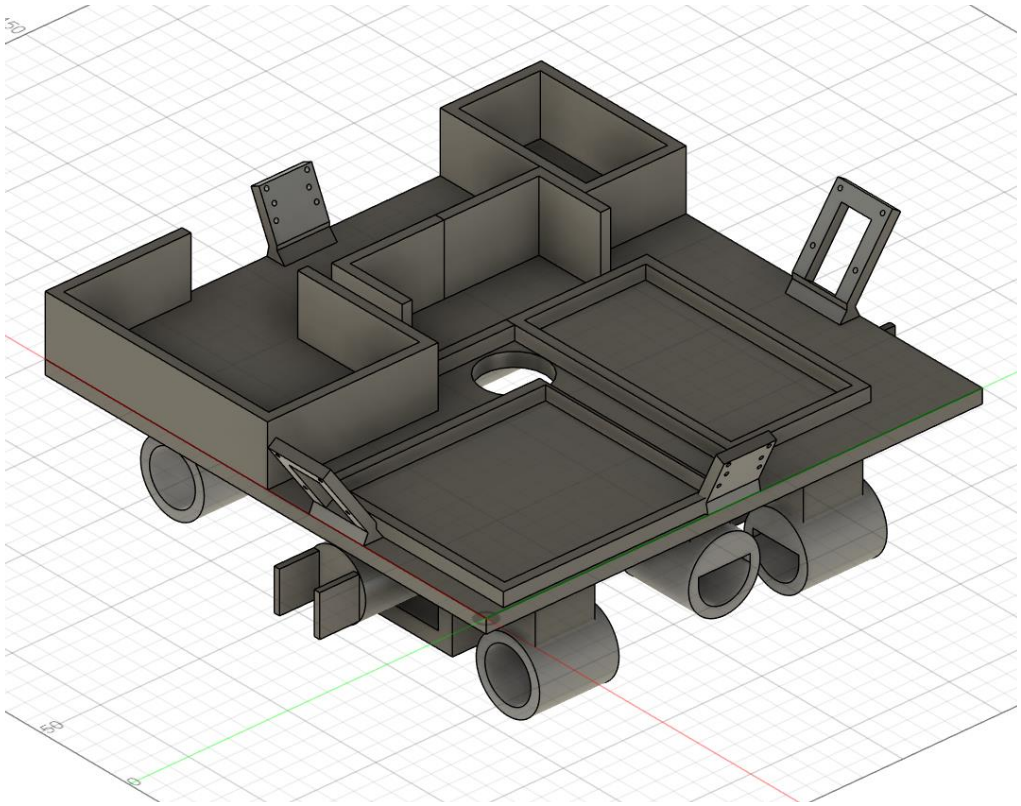


Figure 5: The Top view of chassis from Fusion 360 software

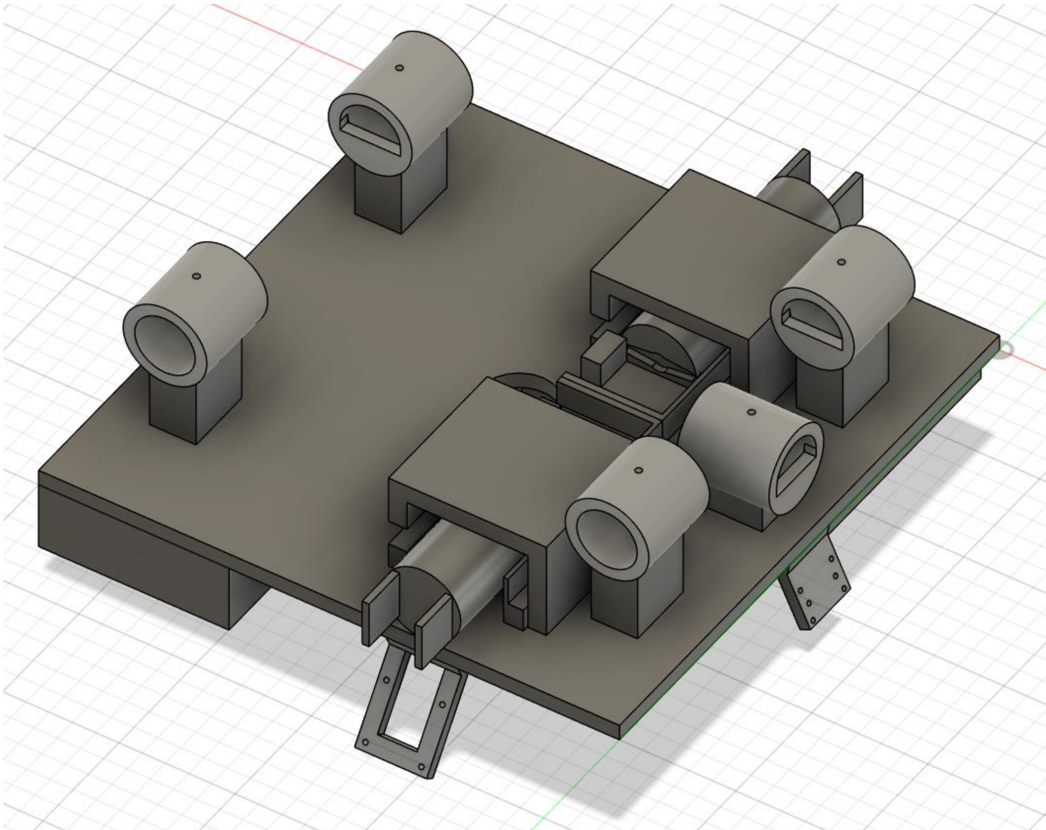


Figure 6: The underside view of the chassis from Fusion 360 software

The drivetrain is comprised of 4 FIT0441 DC Gearmotors (Figure 7). Each motor is attached to a 60mm Mecanum wheel which has a wide variety of movements (roboteq.com) as seen in Figure 8. Figure 9 describes how omnidirectional movement can be achieved when wheels are oriented correctly. Each motor is connected to the Arduino Mega via PWM, direction, and frequency generator signals. With these connections, each motor can be set in any direction and a range of strengths which allows for small corrections of movement.

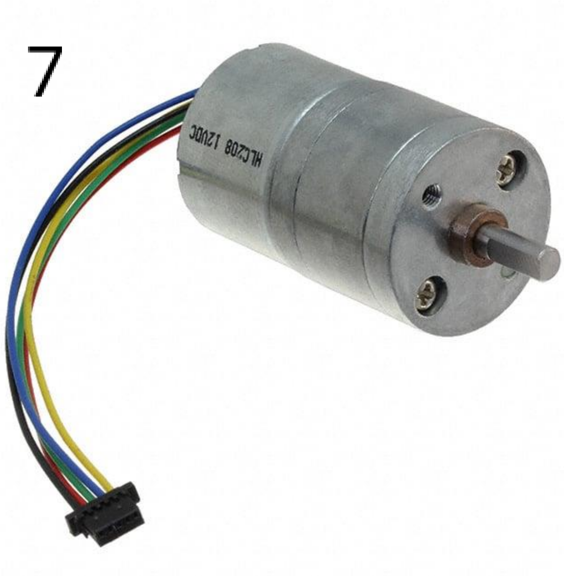


Figure 7: DC Brushless Motor

Figure 8: 60mm Mecanum Wheels

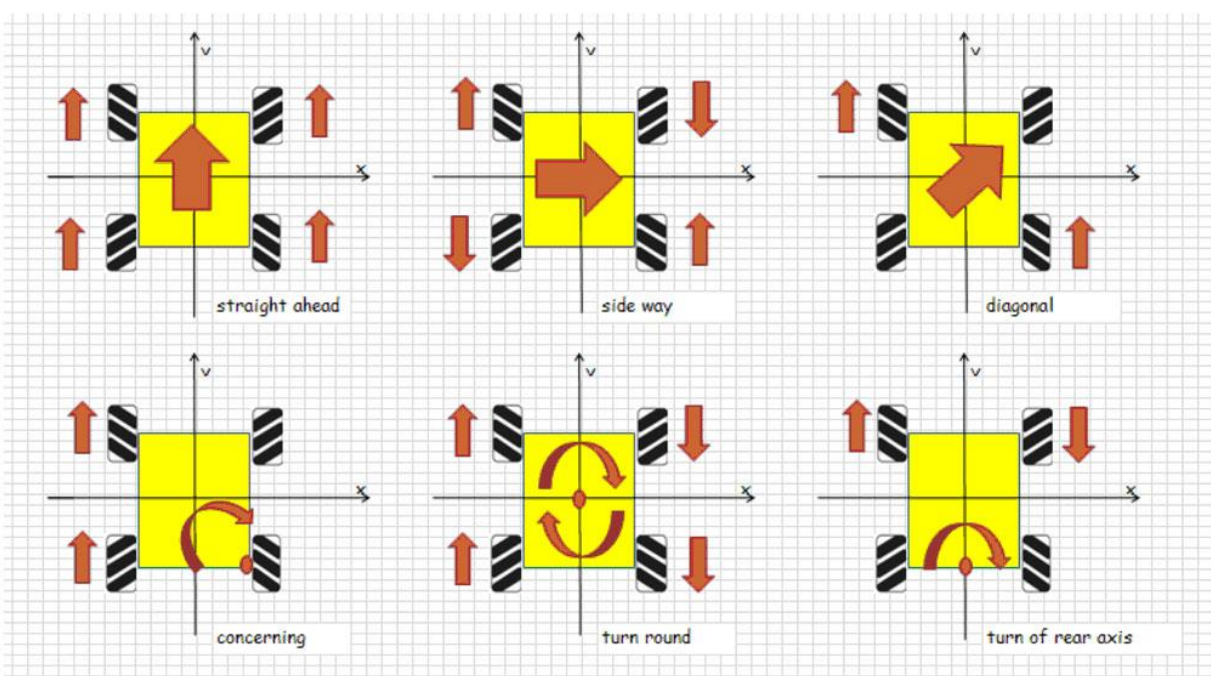


Figure 9: Movement Options with the Mecanum Wheels

5.2 Actuator

The actuator is comprised of multiple components, as detailed in Table 2 with visualization in Figure 10. Adhering to objectives, the full system was designed with the fewest possible degrees of freedom. The total system moves along one axis which is horizontal and perpendicular to those lanes on the field. A rack and pinion mechanism, shown in Figure 11, moves the actuation system so that one side will be close to the lanes which out move the robot. A rotational motor rotates the end effector 360° about that axis.

To complete the actuation component, the complete system operates in conjunction. Once a bad plant is identified, the robot will stop, so the center of the end effector is aligned with the center of the plant. The actuation system will move horizontally, so the plant is in line with the prongs of the end effector, described in Figure 12. When that occurs, the rotational motors will rotate the end effector 90° lifting the plant off the magnet and out of the base. Lastly, the actuation system will move back into the resting position in preparation for the next plant removal.

Table 2: Part List for Plant Removal System

Part	Label	Material
End Effector	A	PLA
Motor/Gear Rack Holder	B	PLA+
Gear Rack	C	Aluminum
Lateral Motor	D	Mix
Rotation Motor	E	Mix
Pinion	F	Brass

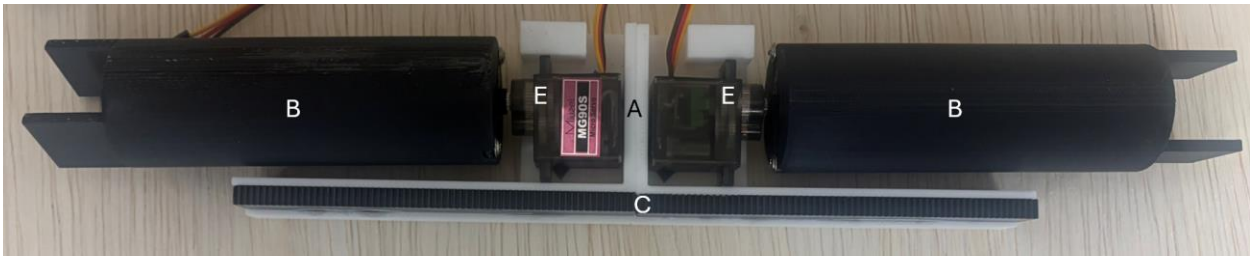
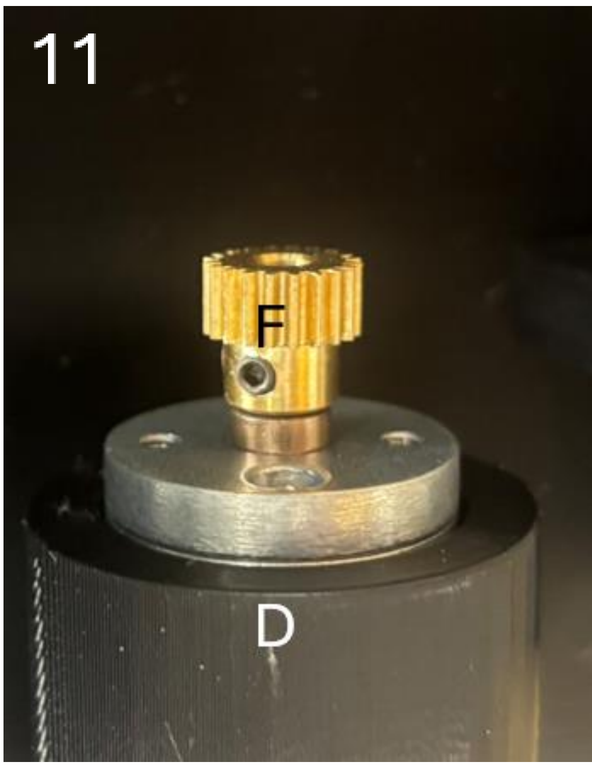


Figure 10: Full Assembly of Plant Removal System



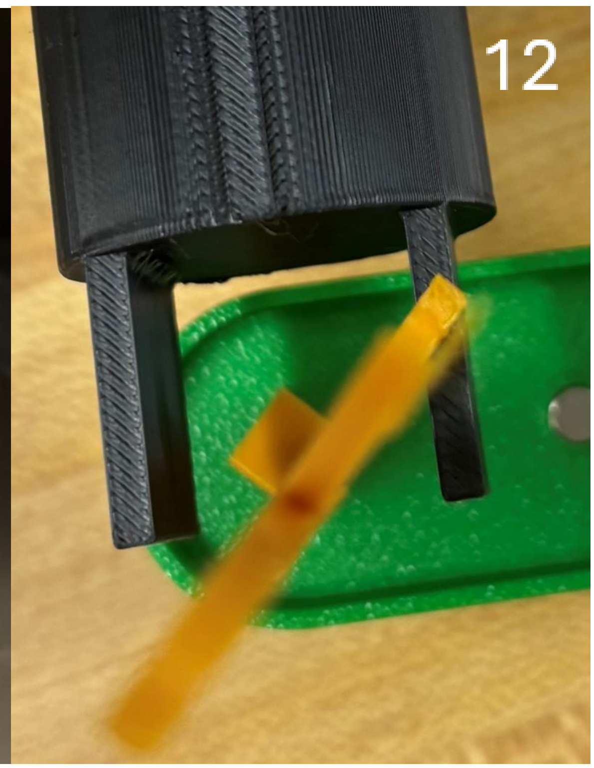


Figure 11: Motor and Gear Pinion for Lateral Movement of Plant Removal System

Figure 12: End Effector Prongs Around Bad Plant

The design is effective as it can only move and rotate around 1 axis. Because of this, the opportunity for error in the system is much lower and more reliable when compared to something that has more freedom, such as a robotic arm.

6. Electrical Architecture and Computer Systems

The electrical system for the robot must be able to provide power and communication for 7 motors, a Jetson Nano Orin, an Arduino Mega, and 4 cameras. Powering the wheel motors and the motor for the lateral movement of the end effector, a 12V battery 5200mAh Li-ion battery is used. This battery provides enough power to run the motors for a minimum of 1 hour. Simple bus connectors connect all the motors to the power and ground of the battery (Figure 13).

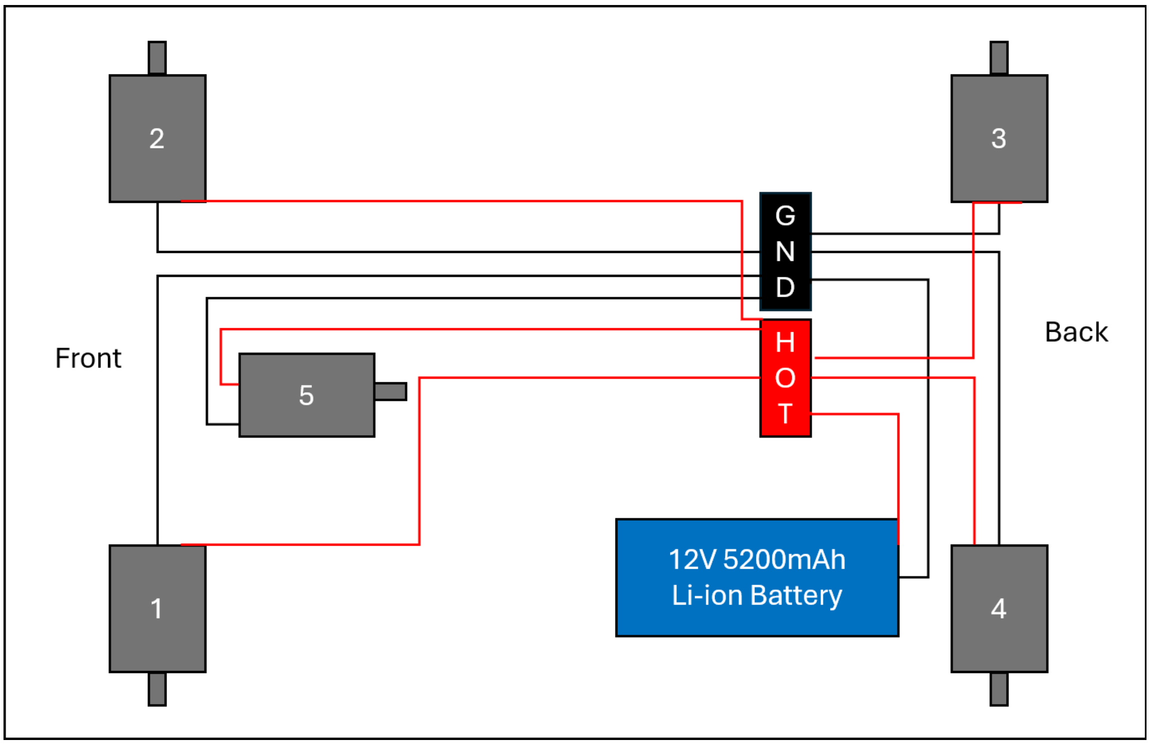


Figure 13: Diagram of Power Circuit for Motors 1-5

A 14.54 V 6800 mAh 99 Wh V-Mount battery is used to power both the Jetson Nano Orin and the display screen. The last 2 motors, the cameras, and the Arduino Mega are all powered via their connection to the Jetson Nano Orin (Figure 14).

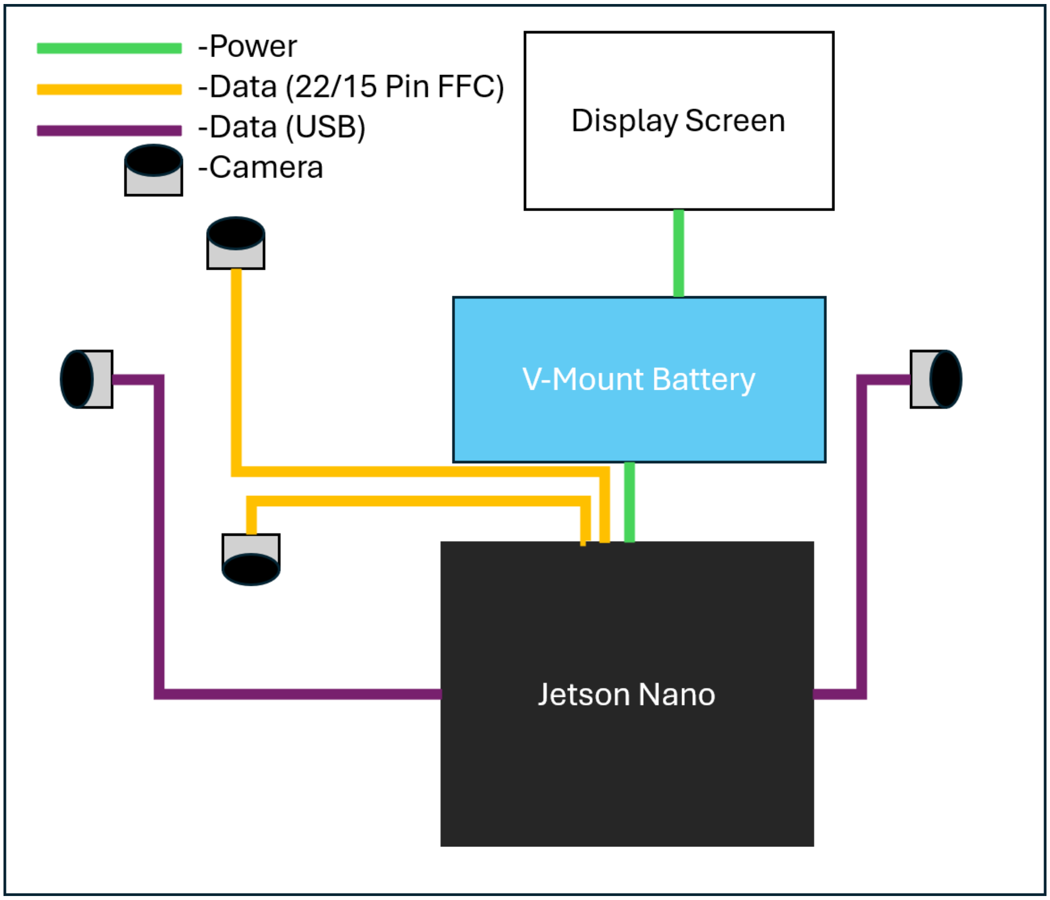


Figure 14: Power and Data connections for camera, Jetson Nano Orin, and Display

The other aspect of the robot's electrical design involves data connections. 5 motors are connected directly to and controlled by the Arduino Mega. The remaining 2 motors are connected to the 40-pin GPIO header on the Jetson Nano Orin. All other hardware is connected with the Jetson Nano Orin, which serves as the robot's central computer (Figure 15)

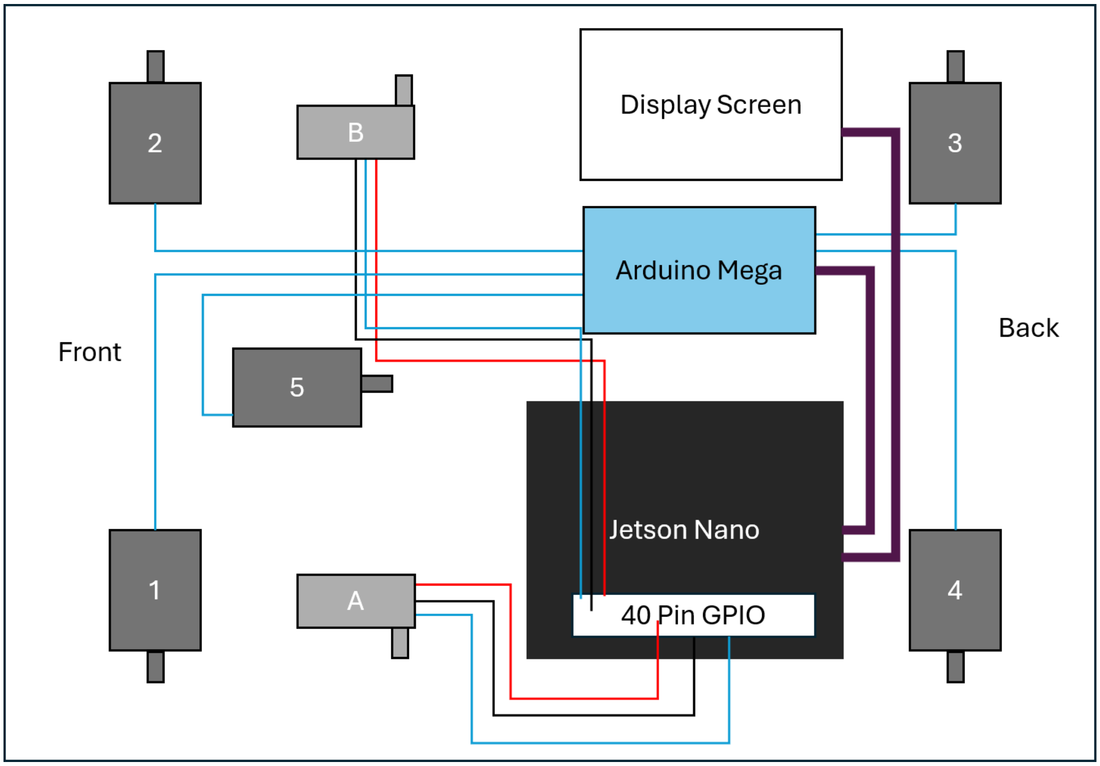


Figure 15: Data Connections for all motors and display screen

7. Software

To achieve a smooth workflow between the navigation, vision, and actuation modules, we used ROS2 as it is a flexible framework used to build complex robotic applications. The publish-subscribe architecture allows multiple nodes to function and communicate concurrently, which makes this software the ideal choice for our robot.

7.1 Navigation

The navigation system's purpose is to traverse throughout the field by identifying the guide lines and making the appropriate navigation decision. The drive_node is the main node controlling this system described in Figure 16. The conduct line following, this node relies on information from the two HBVCAM-V2101 V11 cameras. At the start operation, only one camera is publishing frames, upon detecting the end of a row, the system switches to the second camera to transition to the next line.

The detect_node handles the camera switching as well as color detection, publishing the detected line state to the drive_node. The drive_node processes this input to command the motors accordingly, utilizing a basic PID controller to minimize pixel based tracking errors.

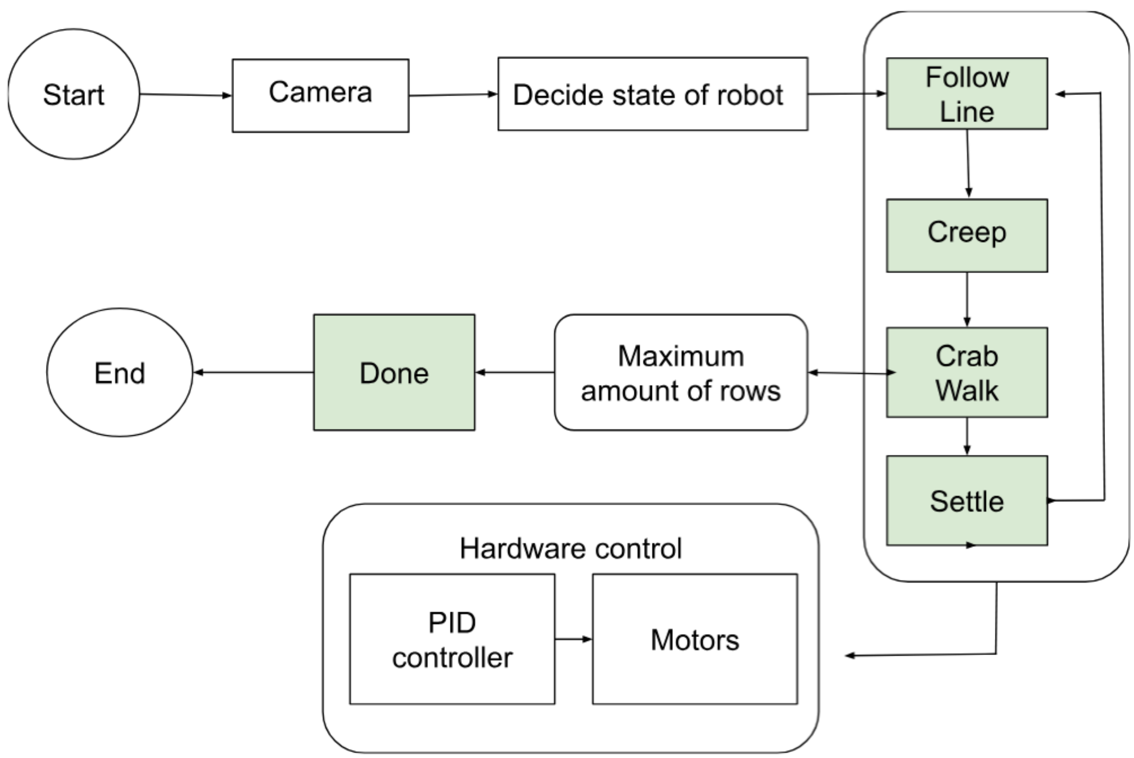


Figure 16: Flowchart of Drive Node

7.2 Vision

The detection system was built for the purpose of processing and classifying the plants. This system was built using simple image detection using a YOLO model. The YOLO (You Only Look Once) model works by processing an image in a single forward pass through a neural network. It divides the image into a grid, and for each grid cell, predicts bounding boxes and the confidence score of each box being a part of one of the given classes. In our case, we had 3 different classes: Base, Green Corn, and Yellow Corn. Based on the confidence score for each bounding box, we can decide which color the stand is, or whether there are none. The reasons we chose YOLO as our Object detection model were for the following reasons:

1. YOLO handles all predictions simultaneously by processing the entire image in a single pass. This makes it favorable to other object detections models such as R-CNN, as it processes instantly, which provides a significant speed advantage without compromising accuracy.

2. The combination of predicting bounding boxes and class probabilities at once leaves a small room for independent error correction.

3. Training the model is relatively straightforward, as YOLO's label format only requires labels images with bounding boxes around our classes.

To train the model, 255 images were collected and annotated using Roboflow. Roboflow is a platform for annotating images using bounding boxes and labeling to use in image datasets for training models. We used Roboflow because of the efficient conversion from images with bounding boxes to datasets ready for YOLO training. The YOLO model was then used in the detection nodes to identify the type of plant (green or yellow corn) and the base, by using these classifiers we are able to detect the count of plants and display the appropriate color and live count of single, double, and empty. Figure 17 displays the object detection in action with the confidence score at the top of each bounding box, while Figure 18 describes the step-by-step process of the detection system.

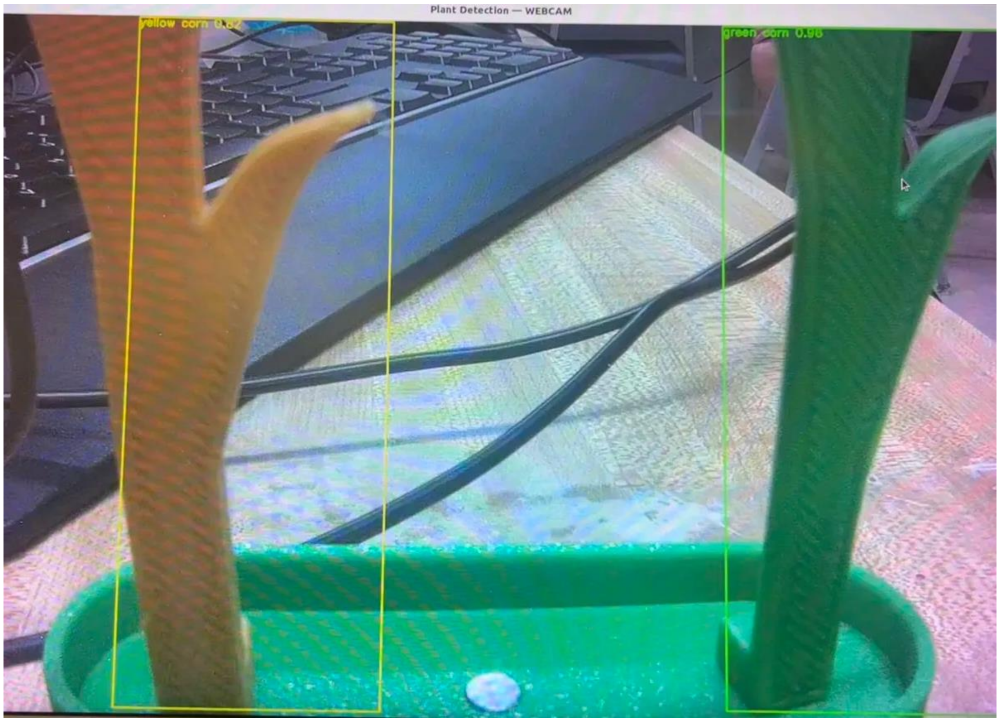


Figure 17: Live Object Detection with bounding boxes around the green plant and yellow plant.

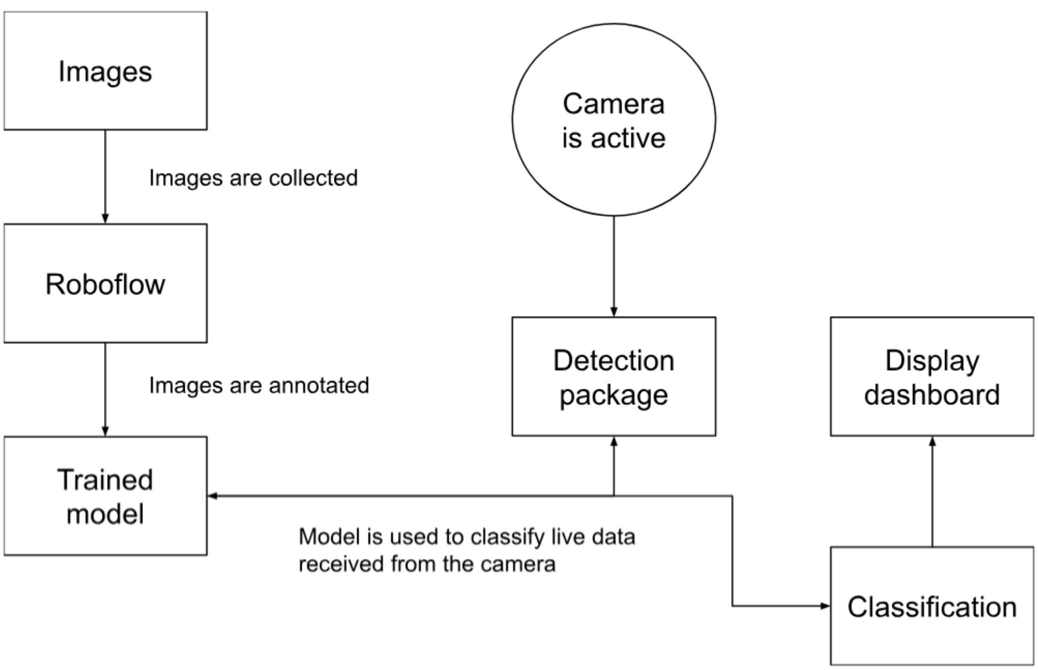


Figure *18: A diagram of the detection system and how it works while the camera is active.*

7.3 Main Task

The main task logic uses both the navigation and detection software along with simple commands for actuation. The biggest thing added to the main task logic is the workflow of the robot. Due to our robot's ability to remove plants on either side, it follows the path as shown by the red line in Figure 19. As the robot traverses each row, it follows the logic map as seen in Figure 20.

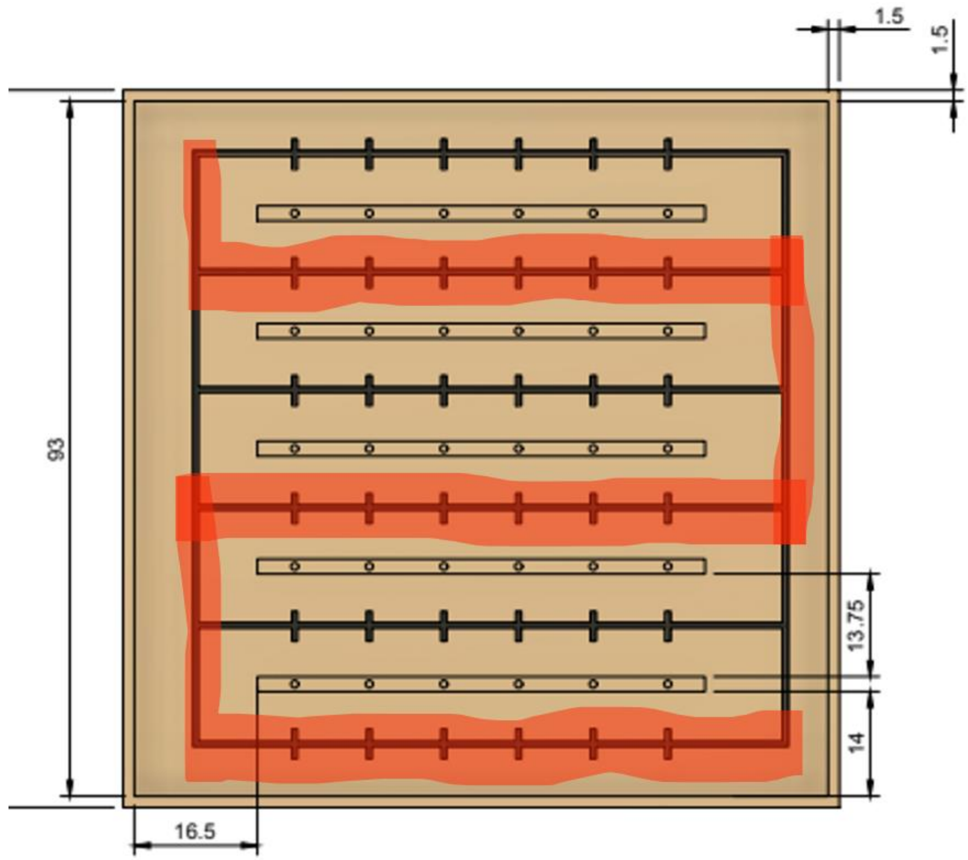


Figure 19: Robot path for main task in red

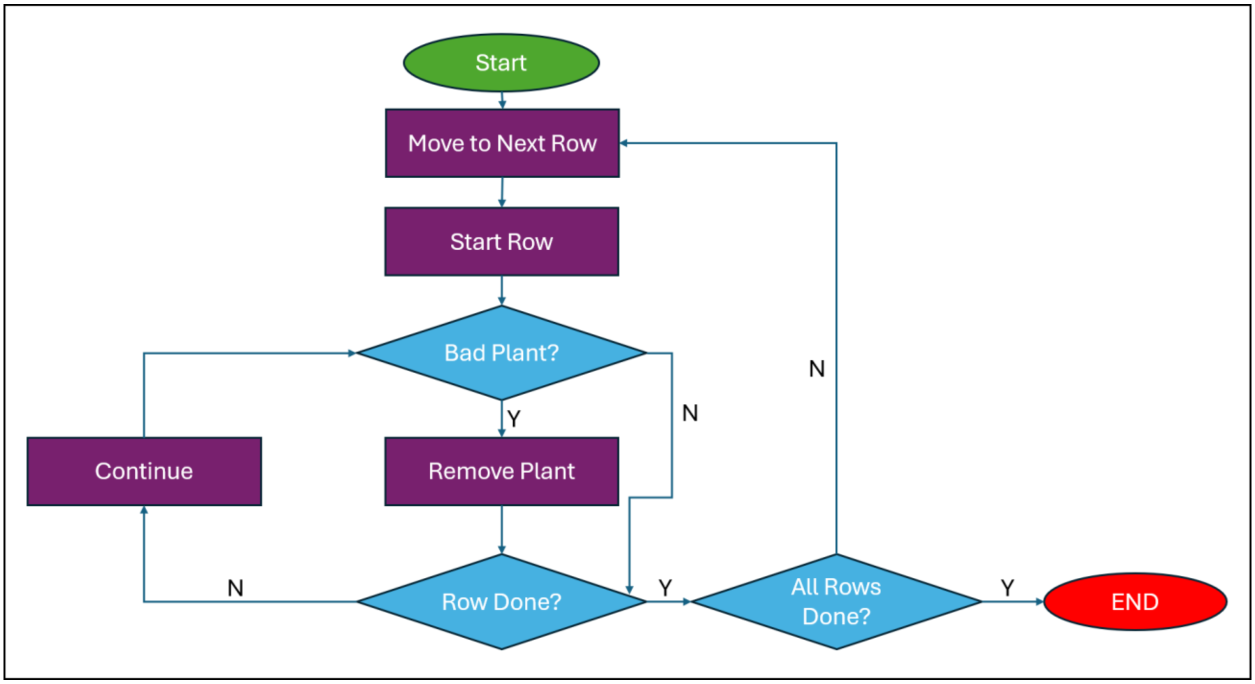


Figure 20: Logic Flow for Main Task

8. Testing, Results, and Performance Data:

For the testing of the robot, a recreation of the arena was made according to the specification outlined in the 2026 ASABE Student Robotics Challenge. The recreation is shown in Figure 21

Figure 21: Full-scale replica of competition board

8.1 Navigation

The navigation system was tested under numerous runs where it traveled through an accurate to size remake of the competition arena. With the runs that were documented, the fastest run that was achieved was 62.63 seconds, just over a minute, with the average time per row being 11.37 seconds. The tests were done on a full-scale replica of the playing field. The positive results obtained from the tests demonstrate the reliability and steadiness of the line following system.

8.2 Vision and Actuation

The detection system was tested under a run of live plant detection over 5 minutes to simulate the plant identification task. The highest number of true positives for all three classes were 22, while the false positives were 4. Based on the scoring table for the Real Time Report, we would have had 100% score for singles, 90% score for doubles, and 70% score for empty. Based on the results, we intend to update the class for empty bases to better reflect a true empty base.

Figure 22 shows the Precision-Recall curve for each class which was auto generated by YOLO during the training of the model. The average precision values of 0.995 for the base, 0.984 for the green corn, and 0.995 for the yellow corn, resulting in an overall value of 0.991. These results validate YOLO as an effective choice for this detection task, achieving high accuracy across all plant classes with minimal confusion between them. The live precision and recall that were calculated did differ from the results achieved during the training run, this was likely due to how the model was being used in the code by having it due live camera detection rather than being tested on still images that were all taken in the same lighting conditions all in one go.

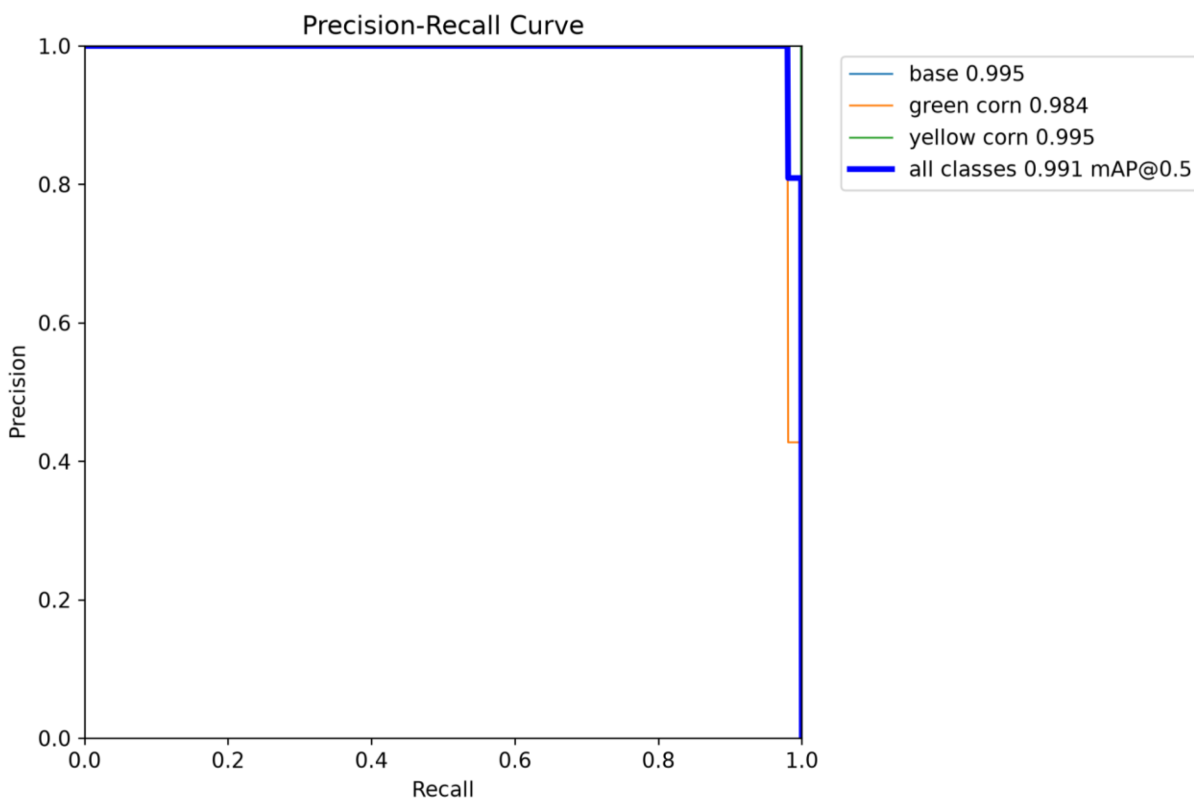


Figure 22: Precision-Recall for each Plant Class

The actuation system was tested during live detection practices. Testing allowed us to change how we were calculating the location of the plants in relation to the robot.

9. Conclusion

The robot that was created for the ASABE Student Robotics Challenge meets all design and performance requirements outlined by both the ruleset and our team's design goals. It has basic functionality for Navigation, Actuation, and Identification tasks, as well as the ability to combine these functionalities to be able to complete the main task of traversing a cornfield and removing unhealthy plants. Additionally, this robot meets the 12" x 12" x 12" size requirement outlined in the ruleset. The robot achieves this with simple movement and actuation mechanics all packaged in a custom 3D printed chassis. ROS2 is also utilized for the code base, and this allows the robot to work together to create a fully autonomous corn pruning robot. The completion of the objectives is a testimony to the hard work, perseverance, and dedication the team has put into the robot. While this robot is a scaled-down prototype of real-world agricultural robots, we believe that agricultural robots will be essential in the future for crop production, reducing manual labor, and improving crop monitoring.

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