Automatic Weeding Arm

Spring 2020 ECE 445 Senior Design

Design Document

Team 9

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Contents

1 Introduction

1.1 Objective

For generations, humans have used manual labor to curb aggressive weeds, which leech nutrients and resources from staple crops. As agricultural demands and farm sizes grew, the industry started to heavily rely on chemical herbicides to ensure maximum yields. Herbicide use, however, has not been as harmless as originally believed. Long-term exposure to chemical runoffs has been linked to kidney, liver and spleen complications in humans [1]. Recent developments have also shown that the most commonly used herbicide contributes to a host of developmental problems in pregnancies, leading to disruption of sex hormones and even miscarriages [2]. Still, it is hard for the agricultural industry to eliminate this practice, as there are no cost- and labor-effective, fully chemical-free alternatives. To reduce herbicide's use in crops, we propose a solution of an automatic robotic weeding arm that can identify post-emergent weeds and cut them with an attached blunted sheer. Automated weeders do exist in the industry, but they still rely on herbicides and just promise localized exposure [3]. This does not mitigate the risks of the herbicides themselves as repeated exposure to these specific chemicals is still harmful. Since there are existing agricultural robots in the market that can navigate the difficult terrain of crop fields, such as the TerraSentia [4], we are not focusing on the robotic base. Rather, we consider the arm as a potential extension of a robotic base, allowing us to target the specific problem of chemical-free weed removal.

Our arm focuses on the identification of various seedling species and automization of the weeding process. The arm is fitted with a camera that can detect different seedlings through neural network training and can enable real-time video monitoring from a connected computer screen. Once the arm can detect the unwanted plant, it can maneuver and cut the weed with its motorized sheer. We decided to cut instead of pulling the weeds because cutting requires less force and it is more efficient when treating tall plants. To accomplish this function, the arm will have four motorized joints with 180 degrees of freedom, allowing the arm to trim weeds on either side. The flexibility of the arm allows it to attack hard-to-reach plants effectively. With the arm's trainability it can also be easily repurposed to perform many different agricultural functions. For example, once the arm can learn from various plant databases, it could easily be used to pick fruit or trim foliage just by switching out the shear-hand attachment for other applicable tools.

1.2 Background

Weed control through herbicide has recently become controversial for its carcinogenic potential [5] and environmental-contamination concerns [6]. Currently, farms use about 44 gallons of herbicide per acre to kill unwanted weeds [7]. This practice comes with risks. Runoff from the herbicide sprays threatens the natural ecosystem such as groundwater and soil. Herbicide use has also affected human lives, as research has linked an increase in cancer with the use of glyphosate, a popular weed killer used in the industry [5]. In terms of economics, chemical crop control has been slowly bleeding farmers dry. Agrochemical companies have been selling genetically modified seeds that can resist the herbicide, but this action only boosts their herbicide sales over time as weeds have evolved into "superweeds" which require higher and stronger doses of chemicals to kill [8]. This ballooning effect can be clearly noted in the soy industry, where, as of 2008, 92% of soy plants had become glyphosate-resistant [9], requiring the industry to begin using genetically modified crops with herbicide and liquid herbicide in tandem. Meanwhile, agrochemical companies have quietly quintupled their prices for both genetically modified seeds and chemical herbicide within the last two decades [10]. Ethically, herbicide use must be phased out, but regressing to the use of human labor is not a realistic solution. Modern agriculture requires a solution to streamline the repetitive act of finding and destroying specific plants while keeping the desired crops safe and healthy. Naturally, robotics can provide an answer which is both ethical and cost-effective in the long run.

1.3 Visual Aid

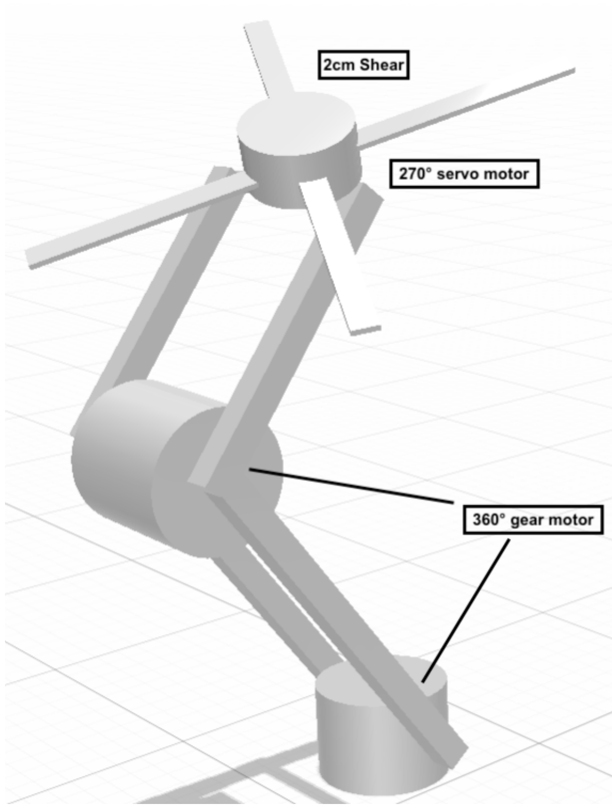

Figure 1: Physical Design

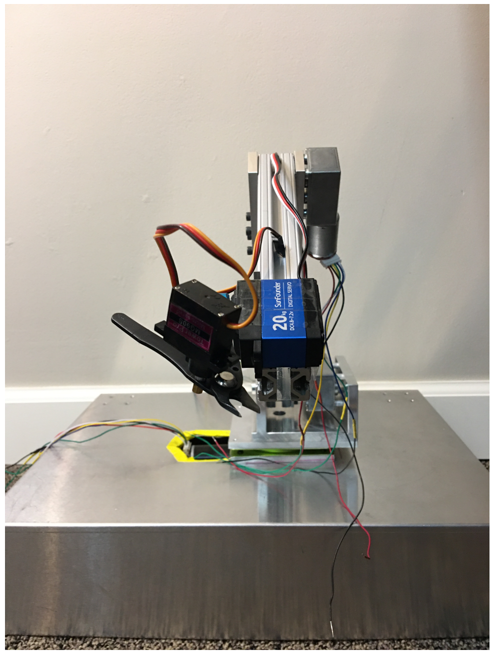

Figure 2: Robot - Front View

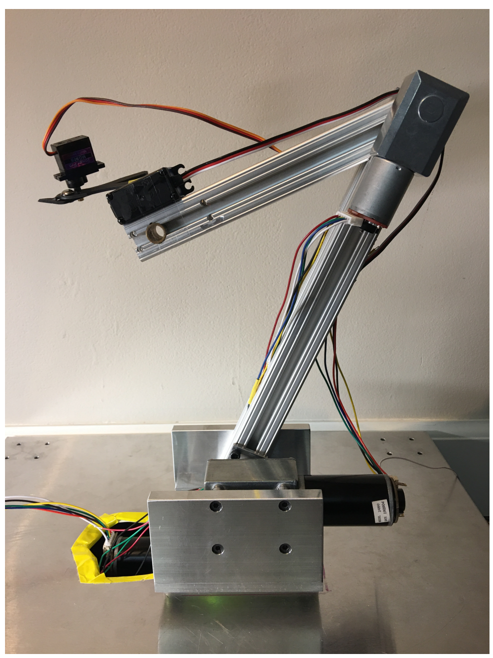

Figure 3: Robot - Side View

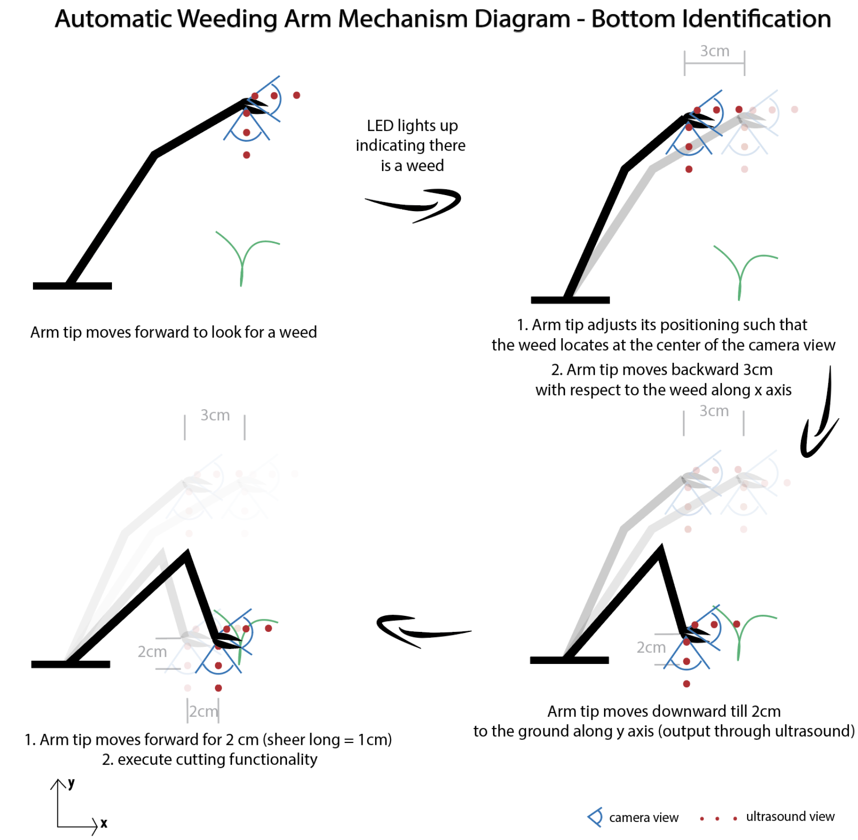

Figure 4: Primary Cutting Mechanism

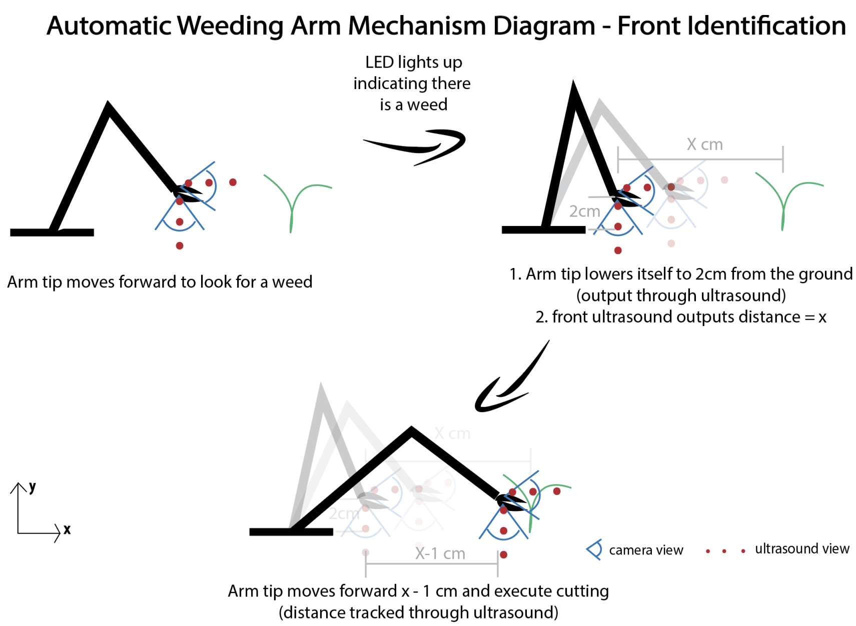

Figure 5: Complementary Cutting Mechanism

1.4 High-Level Requirements

- The recognition unit, including camera and the neural network model trained by V2 Plant Seedlings Dataset [11], can successfully detect and differentiate weeds (e.g. black-grass, loose silky-bent, etc.) from other crop seedlings (e.g. wheat, maize, sugar beet), with a classification accuracy over 75%.
- The location of weeds (with respect to ground and homing position) can be successfully determined by camera and ultrasound modules within ± 2 cm errors.
- Assuming no failures in mechanical and software systems, the robotic arm can successfully cut off weeds (5-20 cm tall) through the flexible yet torque-sufficient motors, with an over 75% successful rate.

2 Design

2.1 Block Diagram

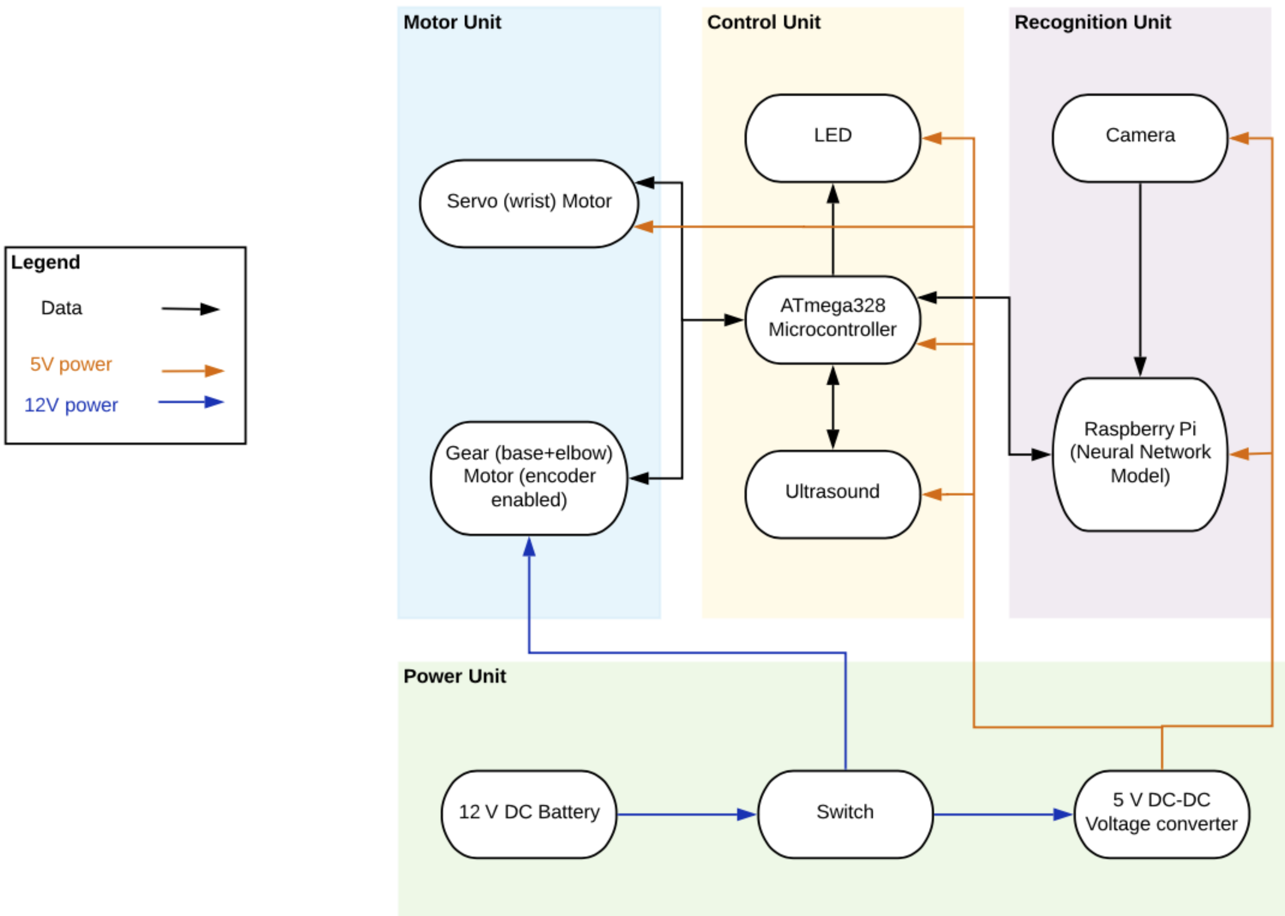

Figure 6: High-level Block Diagram

2.2 Functional Overview and Block Descriptions

2.2.1 Control Unit

1. **Microcontroller**
   The input/output of the robotic arm is mainly handled by a microcontroller. It communicates with 3 motors, Raspberry Pi, ultrasound module and LED. We chose ATmega328 because it is affordable, widely commercialized and compatible with many programming approaches. In order to fully control 3 motors for homing mechanism, we will connect the motors with SPI bus in series, with 3kΩ pull-up resistor to ensure the signal to not interfere. It will follow daisy chain configuration, since speed of operation is a minor factor to determine the success of our project. The SDA, SCL will be connected to raspberry Pi (I2C). Since ATmega328 only has one SPI bus, I2C is the option left for Raspberry Pi, which can also optimize the speed. The UART bus will be connected to the ultrasound module as the ultrasound unit should not have significant delay which impairs the sensitivity of the arm (UART is slower). Furthermore, the ultrasound module only sends data to the microcontroller and does not receive any feedback. The PWM bus will be connected to the LED since LED is doing a simple response of lighting up if weed is detected.

Requirement	*Verification*
The microcontroller must be able to receive electrical signal	To test the microcontroller can receive electrical signal: (1) Connect the microcontroller to a battery-voltage converter and verify with a multimeter to ensure current flows through
The signal transmission between microcontroller and the recognition unit can be indicated by the LED	To test LED can indicate detecting status: (1) Check the LED remains on when running pictures from weed databases through neural network, and off when running pictures from non-weed databases through neural network (2) Mix weed and non-weed pictures. Run the pictures through neural network one-by-one (3) Record true positive, false positive, true negative and false negative rates

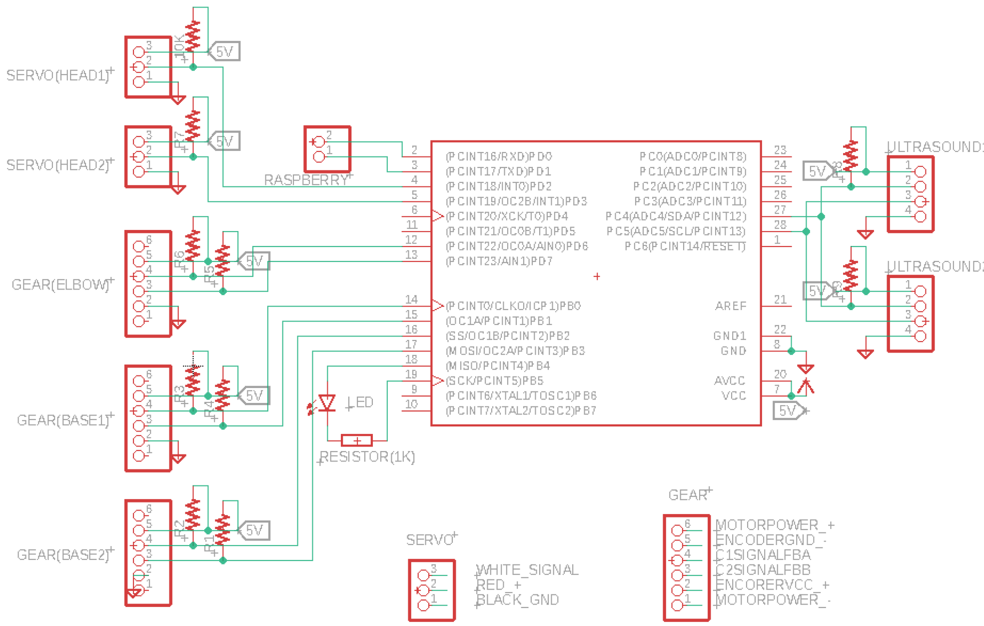

Figure 7: PCB Schematics

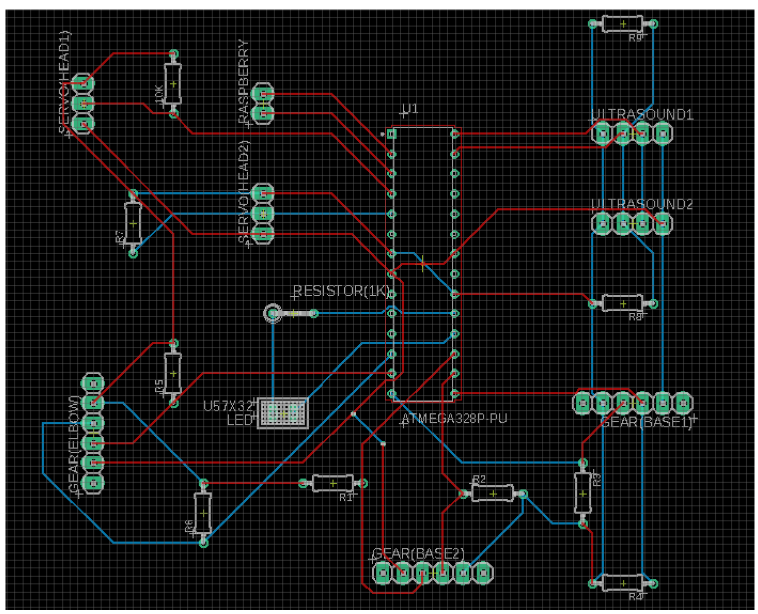

Figure 8: PCB Board

2. **Ultrasound**

The second component of the control unit is ultrasound, which helps to locate plants and to control the position of the arm. We plan to use two HC-SR04 ultrasonic modules to assist plant locating. The modules can be controlled through either Raspberry Pi or microcontroller. We chose this ultrasound module because it has a working distance 2cm to 4m, which is sufficient for locating [14]. Its maximum repetition rate of 50us is fast enough to prevent crashing [14]. HC-SR04 ultrasonic module is also affordable and compatible with control devices such as Raspberry Pi and microcontroller, and this gives us more flexibility in terms of designing and troubleshooting. The first module will be installed at the bottom of the blade to detect the distance between the arm tip and the ground, as part of the robot's weeding mechanism. The second module will be installed on the top of the blade to detect the distance from the blade to the plant, when the arm tip moves forward to reach the plant.

Requirement	*Verification*
The ultrasound must be able to detect the distance to an obstacle with an error margin within ±3mm	To test distance detection: (1) Microcontroller code for ultrasound module is free of bugs. (2) Experiment each ultrasound module by drawing a line on the table, which is 3cm away from a wall. Hand-hold each module (connected to Raspberry Pi and power), and move it from a distance larger than 3cm to the line (3) If Raspberry Pi successfully output 3cm±3mm at the line, the ultrasound module is working properly

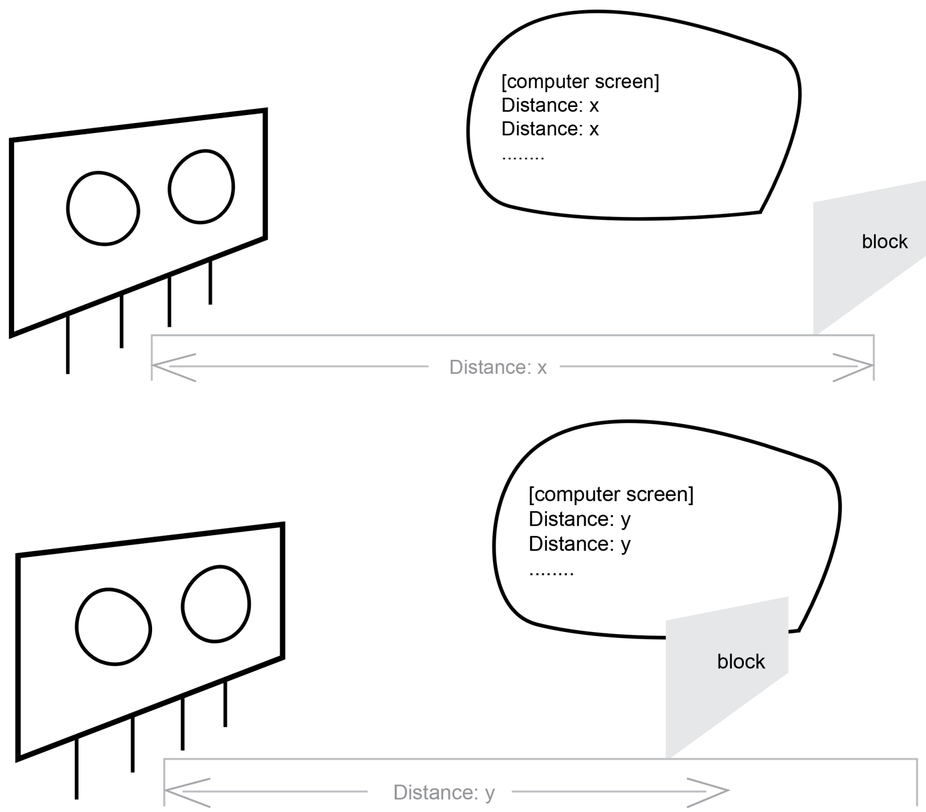

Figure 9: Ultrasonic Unit Testing Setup

2.2.2 Recognition Unit

1. **Camera**

   The Arducam 5MP OV5647 Raspberry Pi camera module is connected to the Raspberry Pi series board for image detection and real-time video monitoring. The recognition will be assisted by a trained neural network model. The camera was chosen to maximize cost efficiency with motorized focus lens, IR and sufficient resolution (still picture resolution 2592×1944 and max video resolution 1080p). The motorized focus lens aids in detecting the distance from arm tip to plant by focal plane distance calculation. The IR feature enables vision at night or darkness for real world application. The resolution can aid to improve neural network accuracy. Arducam 5MP OV5647 has rolling shutter, which scans across the scene rapidly. The camera provides several options for frame rates, 592×1944 (15fps), 1920×1080 (30fps) and 1280×720 (60fps), which determine the video resolution for a real-time monitoring system.

Requirement	*Verification*
The camera must be able to capture clear images with a resolution greater than 625×625 to be qualified for the neural network dataset images	To test the camera vision: (1) Connect the camera to Raspberry pi through ribbon cable (2) Take 50 pictures with the camera with default resolution (3) Verify that at least 95% of the pictures have resolution over 625×625
The camera must be able to capture the image in 6 seconds.	To test the speed of photo capturing: (1) Connect the camera to Raspberry pi through ribbon cable (2) Calculate the time of taking a single image

```
camera_time1 = time.time()
camera = PiCamera()
# camera.resolution = (625, 625)
camera.start_preview()
sleep(5) # >2 to capture an image
camera.capture('example_img1.png')
camera.stop_preview()
camera_time2 = time.time()
print('Time used to take photo: %.2f sec' % (camera_time2-camera_time1))
```

Figure 10: Testing Code of Camera Resolution/Speed

2. **Raspberry Pi Board**
   A Raspberry Pi 3B+ with a 64-bit quad core processor running at 1.4GHz is chosen to control the camera module and ultrasound sensors. The 1GB SDRAM memory storage and an additional SD card support are sufficient to store a relative complex trained neural network model. The Raspberry Pi is responsible for communicating with the microcontroller, controlling the camera module through the 15-pin MIPI Camera Serial Interface (CSI) connector and ultrasound sensors through I/O ports.

Requirement	*Verification*
Raspberry Pi can connect the camera module to the computer screen for testing and streaming within a delay $\leq$ 1s	To test the signal delay: (1) After connecting the Raspberry Pi to computer through USB port, enable camera module through Python Record the monitor screen to measure the time needed for view shifting by adjusting camera orientation
The ethernet communication speed is above 10MB/s	To test ethernet speed: (1) Test the communication speed through terminal by transferring large files (1GB) through USB port

3. **Neural Network**

We will start with a two-layer neural network model and increase the complexity to achieve higher detection accuracy. The training dataset will be based on the V2 Plant Seedlings Dataset [11] and Weed Detection in Soybean Crops [15] from Kaggle. These contain images of 3 kinds of crops (i.e. wheat, maize, sugar beet) and 9 kinds of weeds (i.e. black-grass, loose silky bent, etc.) seedlings. We will expand the dataset through basic data augmentation techniques including rotation, flipping, and saturation/brightness adjustment. We may take images by the camera module to expand the training dataset.

Requirement	*Verification*
The model must reach a classification accuracy above 75%	To test classification accuracy: (1) Verify that prediction loss$<$ 0.8, classification accuracy$>$75% by the end of the training
The size of the neural net model is reasonable to be transferred to Raspberry Pi	To test neural network size: (1) The size of neural network model is less than size of the Raspberry Pi SDRAM storage (1GB)

2.2.3 Power Unit

1. **12 Volts Rechargeable Lithium Iron Phosphate Battery**
   A 12 V rechargeable Lithium Iron Phosphate Battery was chosen to power the gear motors. We chose the 12 V battery to be compatible with higher voltage components because the gear motors have heavier loads due to the aluminum frame and electronics components. They would require sufficient power to run at their optimum speeds (30rpm max and 7rpm max, respectively). We plan on using a rechargeable battery to better simulate the real-world application of having a free-roaming robot. The Lithium-Ion Phosphate battery also has a higher maximum recharging cycle (1000-3000) than a Lead battery (200-1000), and it's more environmentally friendly [16].

Requirement	*Verification*
The battery must be able to distribute 12V of power to motors	To test the battery output (1) Fully charge the battery (2) Disconnect from charger (3) Connect to a multimeter and measure voltage output (4) Connect the multimeter to LabView and monitor the voltage for 3hrs to verify a constant output of 12V with a margin of error of 5%

2. **DC-DC Buck Step Down Voltage Converter**
   Since most of the electrical components run on 5 V, we incorporated a DC-DC Buck Step Down 12V to 5V Voltage Converter to drive the rest of the circuit. We chose a voltage converter instead of a regulator because it has a superior power efficiency.

Requirement	*Verification*
The converter must be able to convert 12V to 5V	To test the functionality of DC converter: (1) Connect the converter to 12V battery (2) Use a multimeter to measure whether the output voltage equals to 5V

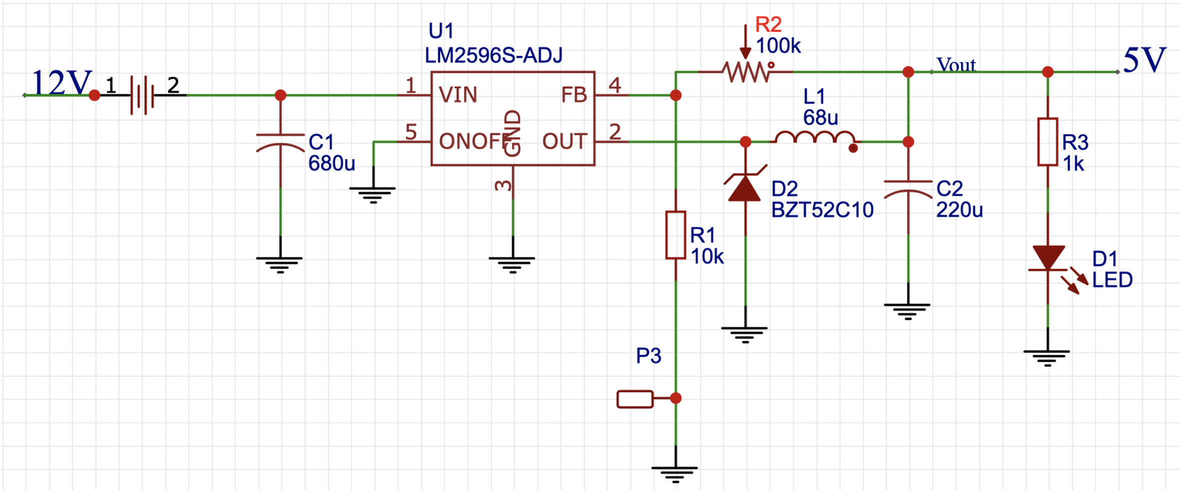

Figure 11: Voltage Converter Schematics

2.2.4 Motor Unit

1. **Gear Motors**

   In our design, we use two gear motors to drive the robot base and elbow. Compared to a servo motor, the shaft on gear motor can provide the respective joints with better mechanical support. We chose a DC 12V 7rpm (torque = 30kgcm) gear motor for the base, which is sufficient to drive the arm (after we consulted a technician in ECEB machine shop). Because we are not building the mechanical parts, we were only able to estimate the required torque based on limited information. As such, our estimate is mainly based on the weight of the Aluminum body. The elbow motor is a DC 12V 30rpm (max torque = 25kgcm; rated torque = 7.4kgcm) gear motor. We chose this motor due to its higher speed, compared to the base. The two motors were selected out of 20+ options, as we looked to optimize specifications, cost, shipping dates. These two motors also have mounted encoders, enabling us to smoothly control the joints and implement a "homing" mechanism.

Requirement	*Verification*
The motors must be able to achieve "homing"	To test whether the motors can implement "homing" mechanism: (1) Program and compile code specifying a "homing" position (2) Load the code to microcontroller (3) Connect the microcontroller to each motor (4) Connect battery to motor and battery-voltage converter to microcontroller (5) Verify whether the motor-driven-arm moves to the "homing" position
The motors must be controlled by microcontroller to achieve "cutting" mechanism.	To test "cutting" mechanism: (1) Program code to conduct "cutting" mechanism (2) Load the code to microcontroller (3) Connect the microcontroller to each motor (4) Run the program to cut the weed

2. **Servo Motor**
   We chose a servo motor with 20kgcm torque to drive the wrist. This was chosen to balance the cost and the performance, as servo motors are usually cheaper. The lightweight of the wrist ensures the arm to not tip forward during cutting motions. This servo motor has a control angle of 270 degrees, enabling sufficient flexibility for cutting. Its torque of 20kgcm is sufficient to execute cutting. In terms of the rotating pivot's stability, this motor is sufficient to drive the shear. The servo runs on 4.8-7.2V, which can be driven by the same voltage as other 5V electrical components.

Requirement	*Verification*
The motors must be able to achieve "homing"	To test whether the motors can implement "homing" mechanism: (1) Program and compile code specifying a "homing" position (2) Load the code to microcontroller (3) Connect the microcontroller to each motor (4) Connect battery to motor and battery-voltage converter to microcontroller (5) Verify whether the motor-driven-arm moves to the "homing" position
The motors must be controlled by microcontroller to achieve "cutting" mechanism.	To test "cutting" mechanism: (1) Program code to conduct "cutting" mechanism (2) Load the code to microcontroller (3) Connect the microcontroller to each motor (4) Run the program to cut the weed

2.3 Tolerance Analysis

The camera module and ultrasonic distance detection/reaction speed are critical to the movement of the robotic arm.

To achieve accurate cutting function, the camera needs to first capture clear images and detect the weed species on the focal plane. According to the datasheet of Arducam 5MP OV5647 Raspberry Pi camera [17] , the sensor size of the camera is 3.67×2.74 mm (1/4" format). The camera has an angle of view (AoV) of 54×41 degrees, and a field of view(FoV) of 2.0×1.33m at 2m. For any camera lens, AoV and FoV are defined in the following image and equations:

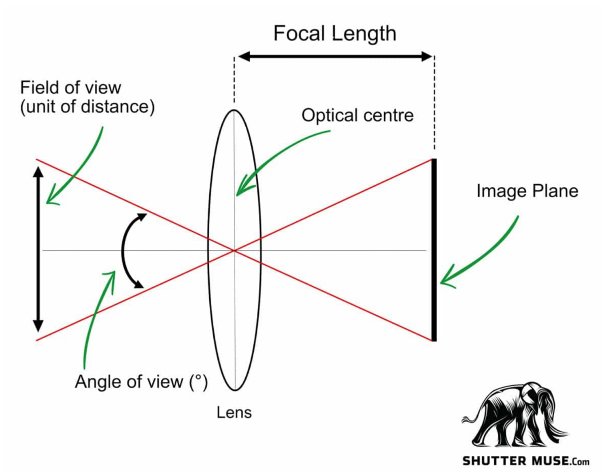

Figure 12: Definition of FoV and AoV [18]

$$AoV = 2 \times \arctan(\frac{\text{sensor width}}{2 \times \text{focal length}}) \tag{1}$$

$$FoV = 2 \times \tan(\frac{\text{AoV}}{2}) \times \text{distance to object} \tag{2}$$

Therefore, the focal length of the camera can be calculated as

$$\frac{0.003672}{2 \times \tan(54°/2)} \approx \frac{0.274}{2 \times \tan(41°/2)} \approx 0.0036\text{m} \tag{3}$$

As the Raspberry Pi camera lens falls into the standard lens range, it ensures images to not have any kind of distortion. In order to capture weed and crop images similar to the images from neural network model training dataset, the ideal images captured by the camera should have objects take up > 80% of the frame. As all types of weeds are relatively small objects, we approximate a field of view to be about 0.5m×0.35m. Then the distance of the lens to the weed needs to be

$$\frac{FoV}{2 \times \tan(\mathrm{AoV}/2)} = \frac{0.5}{2 \times \tan(54°/2)} \approx \frac{0.35}{2 \times \tan(41°/2)} \approx 0.5\mathrm{m} \tag{4}$$

to ensure the camera produces focused clear images. As the camera is attached to the arm, the motion could possibly cause instability that affects the quality of the images.

Ultrasonic distance detection-reaction speed is the last defense to prevent the arm tip from crashing into plants or ground. Therefore, the arm tip should move at a speed of micro-controller's full-cycle computing speed. The start of a full cycle is defined when ultrasound module outputs alert distance 3cm. The end of a full cycle is defined when the two gear motors stop moving. Considering the length of the shear (2cm), the tolerant dislocation is 1cm (3cm $\rightarrow$ 2cm). Using equation

$$L = vt \tag{5}$$

1cm $>$ v(arm tip) $\times$ t(full cycle). Therefore, the arm tip, based on 3D kinematics calculation, should move at the speed lower than 1cm/t(full cycle). In other words, if a full cycle takes 1s, the arm tip should not move more than 1cm/s.

3 Cost and Schedule

3.1 Cost Analysis

Physical Parts	Unit Cost	Quantity	Subtotal Cost
SunFounder 20KG Servo Motor Waterproof High Torque Servo, SF3218MG Metal Gear Digital Servo	$14.99	1	$14.99
Yosoo High Torques Worm Geared Motor DC 12V Reduction Motor with Encoder Strong Self-locking	$29.17	1	$29.17
uxcell DC 12V 7RPM 30Kg.cm Self-Locking Worm Gear Motor with Encoder and Cable, High Torque Speed Reduction Motor	$34.99	1	$34.99
Arducam 5 Megapixels 1080p Sensor OV5647 Mini Camera Video Module for Raspberry Pi Model	$12.99	2	$25.98
Shear from ECE Supply Shop	$10	1	$10
Element14 Raspberry Pi 3 B+ Motherboard	$49.98	1	$49.98
TMS320F28335 control card	$69	1	$69
HiLetgo 5pcs DC-DC Buck Step Down Voltage Module 6-24V 12V/24V to 5V 3A	$7.59	1	$7.59
SainSmart HC-SR04 Ranging Detector Mod Distance Sensor	$4.95	1	$4.95
Mighty Max Battery ML9-12 12V 9Ah Rechargeable SLA Battery	$21.99	1	$21.99
			Subtotal: $273.59

Table 1. Physical Parts Cost

Labor Type	Number of Workers	Hourly Cost	Total Hours	Subtotal Cost
ECE Machine Shop Machinist	1	$19 [19]	35 hrs	$665
Team 9 ECE Engineers	3	$50	8 hrs × 15 weeks	$18,000
				Subtotal: $18,665

Table 2. Labor Cost

Combining the physical parts cost and the labor cost, the grand cost for the entire project is **$18938.59**.

3.2 Schedule

Week	Sophie & Sowji	Lucia
1/20/20	Brainstorm ideas and create project scoping. Literature review and research on potential hardware and software components.	
1/27/20	Finish early RFA. Refine projects with TAs to improve hardware design.	
2/3/20	Design block diagram. Create physical model with AutoDesk. Draft project proposal.	
2/10/20	Edit and submit project proposal.	
2/17/20	Communicate with ECE Machine Shop and obtain feedback on the mechanical design. Start order physical parts for the project.	Start image processing and data augmentation to expand training dataset.
2/24/20	Start PCB design. Verify the requirements of individual parts, i.e. battery, motor, sensors, etc.	Finish image processing and data augmentation.
3/2/20	Finalize PCB design. Electrical/mechanical parts assembly and connection.	Complete the baseline neural network model.
3/9/20	Order PCB. Continue electrical/mechanical parts assembly and connection. Create motor motion control through kinematics.	Improve neural net model performance to meet >75% requirement.
3/23/20	Design homing system. Connect ultrasound to Raspberry Pi. Combine PCB and the electrical system.	Transfer neural net model to Raspberry Pi. Test camera and Raspberry Pi connection. Improve camera module detection accuracy.
3/30/20	Test the mechanical and electrical parts of the arm.	Work on the real-time monitoring system. Expand training dataset by taking pictures with the camera module.
4/6/20	Unit test individual subsystems.	

4/13/20	Final round of testing and debugging the whole project. Prepare for the demo.
4/20/20	Mock demo. Improve the whole project based on feedback.
4/27/20	Final demo.
5/4/20	Complete final project report.

Table 3. Project Plan Time Table

4 Safety and Ethics

Following the IEEE Code of Ethics #1, we aim "to hold paramount the safety, health, and welfare of the public, to strive to comply with ethical design and sustainable development practices, and to disclose promptly factors that might endanger the public or the environment" [20].

There are several potential concerns regarding the safety and ethics related to our project. One main safety concern is the usage of rechargeable lithium batteries. The batteries are central to the project as it is the main component of the power unit and intended to supply power to all other units. While our robotic arm is designed to fit for an outdoor environment, it needs to function well under direct sunlight or high temperatures. We will carefully check the datasheet of the chosen battery and ensure it is safe to use in the target environment. In addition, we will conduct circuit implementation and testing in the lab, which is equipped with a fire extinguisher and sand bucket. We will also constantly monitor the battery voltage to avoid over-discharging.

Since the weeding arm is an autonomous system, another potential safety risk is that the system could unexpectedly get out of control and cause damage to the surrounding environment. As indicated by the IEEE Code of Ethics #9, we understand it is our responsibility to "avoid injuring others [and] their properties" [20]. Not only will we carefully check each step when implementing our system, but we will also design a switch particularly for the weeding arm that can stop the whole system immediately in case of any emergency. According to the IEEE Code of Ethics #5, we also strive "to improve the understanding by individuals and society of the capabilities and societal implications of conventional and emerging technologies, including intelligent systems." Hence, we would provide a detailed description of our robotic design to all of the users for both safety and education purposes.

The blades are important components of the weeding arm to ensure cutting efficiency and efficacy. They, however, pose a potential safety concern. Sharp blades can easily cause accidental cuts if not handled with enough care. To prevent any injuries to the users, we choose to adopt small, blunted shears to trim the weeds in our design. This precaution to avoid sharp shears will drastically reduce the risk of accidental cuts.

An ethical concern is the source of data used for the neural net model. In order to obtain a neural net model that can perform accurate detection and classification, we need a relatively large plant seedling dataset for training. While we do not have access to the field to take in plant seedling images to construct our dataset, we will mainly rely on online resources.

Based on the IEEE Code of Ethics #5, we will "be honest and realistic in stating claims or estimates based on available data" [20]. We will clearly state the datasets we decide to use for training and honestly report obtained accuracy for classification.

We will only use open-source datasets that are free to share and adapt for non-commercial use. We have checked the license of V2 Plant Seedlings Dataset [11] to be CC BY-SA 4.0 and Weed Detection in Soybean Crops [15] to be CC BY NC 3.0. In addition, we will also carefully examine the permission of any additional data, code, and information before using it. We will ensure "to credit properly the contributions of others" [20] as stated in the IEEE Code of Ethics #7 to avoid violating the code of ethics.

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