# AUTOMATED WEED REMOVER FOR ROW CROPS

*A Project Report Submitted By*


| | |
|---|---|
| **ADITHYA ALEWOORAYA** | **4NM17EC006** |
| **DHANUSH M S** | **4NM17EC040** |
| **SOURABH SHANBHOGUE** | **4NM17EC158** |
| **S SATHWIK PAWAR** | **4NM17EC191** |

*Under the Guidance of*

**Mr. Anil Kumar Bhat**

**Assistant Professor Gd. II**


*in partial fulfillment of the requirements for the award of the Degree of*

**Bachelor of Engineering**

**in**

***Electronics and Communication Engineering***

**from**

**Visvesvaraya Technological University, Belagavi**

NITTE EDUCATION TRUST | NMAM INSTITUTE OF TECHNOLOGY

**Nitte-574110, Karnataka, India**

**June-2021**

**N.M.A.M. INSTITUTE OF TECHNOLOGY**
(An Autonomous Institution affiliated to Visvesvaraya Technological University, Belagavi)
Nitte – 574 110, Karnataka, India
ISO 9001:2015 Certified, Accredited with 'A' Grade by NAAC
☎:08258 - 281039 – 281263, Fax: 08258 – 281265

**Department of Electronics and Communication Engineering**

---

# *Certificate*

*Certified that the project work entitled* ***Automated Weed Remover for Row Crops*** *is a bonafide work carried out by* ***Adithya Alewooraya (4NM17EC006), Dhanush M S (4NM17EC040), Sourabh Shanbhogue (4NM17EC158) & S Sathwik Pawar (4NM17EC191)*** *in partial fulfillment of the requirements for the award of* ***Bachelor of Engineering Degree in Electronics and Communication Engineering*** *prescribed by Visvesvaraya Technological University, Belagavi during the year 2020-2021. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the Bachelor of Engineering Degree.*

**Signature of the Guide** | **Signature of the HOD**

**Signature of the Principal**

## Semester End Viva Voce Examination

| **Name of the Examiners** | **Signature With Date** |
|---|---|
| 1. ______________________ | ______________________ |
| 2. ______________________ | ______________________ |

# Abstract

Weeds are a major problem in the farming industry. They are a major biotic constraint to food production. They invade crops, smother pastures, and can also harm livestock. Weeds compete with crops for the same resources, basically water, nutrients, light and carbon dioxide. Furthermore, they are alternate hosts for crop pests and pathogens. Some of them lack autotrophy and fully develop only by parasitizing crops or wild hosts. Weed competition with crops reduces agricultural yield and also results in decrease in the quality of crops. It is also a major constraint to increased farmers' productivity. The removal of such weeds is generally done manually, but this is very time-consuming and inefficient.

This project is aimed at finding these weeds and removing them without manual labor. We achieve this using a Rover that is fitted with a camera. The rover navigates through the field by exploiting the regular row structure of the field crops. It detects the crop rows and aligns itself to move along the crop rows. The weed detection is carried out using the video feed from the camera. A machine learning model is used for the purpose of weed detection. Once the weed is detected, it is neutralized by selective spraying of weedicide or herbicide.

This system of weed removal reduces the physical work involved in the weed removal process. It also reduces the use of herbicides. This project provides several benefits to the farmers as it reduces the amount of money that is spent on herbicides, increases the agricultural output (quality and quantity) and increases the efficiency of the weed removal process.

# Acknowledgement

Our project would not have been successful without the encouragement, guidance and support by various personalities. First and foremost, we would like to express our sincere gratitude towards our project guide **Mr. Anil Kumar Bhat**, Assistant Professor Gd. II, Department of Electronics and Communication Engineering, N. M. A. M. Institute of Technology, Nitte, for his guidance, encouragement and inspiration throughout the project work.

We extend our gratitude to **Dr. Rekha Bhandarkar**, Professor and Head, Department of Electronics and Communication Engineering, N. M. A. M. Institute of Technology, Nitte, for her encouragement and providing necessary facilities in the department.

We wish to acknowledge the support of **Dr. Niranjan N. Chiplunkar,** Principal, N. M. A. M. Institute of Technology, Nitte, for providing motivational academic environment.

We would like to express our sincere thanks to all the teaching and non-teaching staff of the department of Electronics and Communication Engineering, N. M. A. M. Institute of Technology, Nitte, for their patience and help during our project work.

Finally, we would like to thank all our friends and well-wishers who have helped us whenever needed and supported us.

Adithya Alewooraya
Dhanush M S
Sourabh Shanbhogue
S Sathwik Pawar

# Table of Contents

# List of Figures

# List of Tables

# Chapter 1
# Introduction

## 1.1 General Introduction

Farmers are often concerned that weeds may reduce crop yields. Weeds use the same nutrients that crop plants use, often in very similar proportions. The more similar the weed and crop requirements, the more they will compete for those resources. Weeds that compete aggressively with crops reduce their yield. Herbicides and other agro-chemicals are often used in farming but they can have adverse effects on the plants and the environment. Hence it is necessary to minimize the usage of these agro-chemicals.

Furthermore, the removal of weeds is usually carried out manually, which is a tedious and inefficient process. The process can be automated and thus efficiency can be increased.

## 1.2 Aim

The project aims to automate and optimize the weed removal process by using a rover for weed detection and reducing the use of herbicides and agro-chemicals by performing the herbicide treatment at a per-plant level.

## 1.3 Objectives

1. To automate the weed removal process.
2. To design a system to detect weeds in a row of plants.
3. To effectively neutralize weeds by herbicide treatment.
4. To reduce the usage of herbicides and agro-chemicals in farming.

## 1.4 Problem Formulation

To design and develop a prototype for an automated weed detection and removal system for removing weeds that grow among row crops in agricultural fields by optimized, per-plant level herbicide treatment.

## 1.5 Methodology

The project has three major sections. Movement, Detection and Treatment. The brain of the system is a Raspberry Pi board.

- Movement: A rover is designed in such a way that easy scaling of the field is possible. The rover moves across the field by employing the technique of Visual-Servoing [1]. The rover camera looks forward to see if there are crops ahead and follows the path over the crops. If there are no crops visible i.e., the rover is at the end of the crop row, it turns itself to switch over to the next row of crops.

- Detection: The camera attached below the rover takes images constantly as the rover scales the field. The images are then processed in real-time. A Convolutional Neural Networks (CNN) model is pre-trained using a synthetic dataset created using the images of weeds and crops.

- Treatment: When a weed is detected, the rover stops and the positional information of the weed is taken from segmented image and mapped to the herbicide spray system. A single burst spray is shot at the weed to neutralize it.

## 1.6 Literature Survey

Andres Milioto et.al. [2] provide an approach for semantic segmentation of field crops, weeds and soil solely based on RGB data. The system was thoroughly tested on a real robot using data from 3 different fields in Germany and Switzerland. It was found that the system generalizes well, can operate at around 20 Hz and is suitable for online operation in fields.

Sebastian Haug et.al. [3] present a method for crop/weed discrimination without the use of segmentation. To analyze the system a dataset of images was captured in an organic carrot farm under commercial field conditions. Applying cross-validation using a leave-one-out scheme an accuracy of 93.8% was achieved.

Chris McCool et.al. [4] propose a method in which a complex, pre-trained model is used to train a lighter model. A mixture of K-lightweight models is used to enhance the performance of lightweight models. A model with a combined accuracy of above 90% and frame rate between 1.07 and 1.83 is obtained.

Maurilio Di Cicco et.al. [5] present a method for generating a large synthetic training dataset by randomizing the key features of the target environment (i.e., crop and weed species, type of soil, light conditions).

AlirezaAhmadi et.al. [1] propose a method for automatic robot navigation through the field by exploiting the regular row structure of the field crops. Two cameras at the front and back are used for this purpose.

Chris McCool et.al. [6] explores mechanical weed removal methods, using robots as opposed to the application of herbicides. The results show that weeding activities carried out after six weeks of planting were found to be ineffective with a survival probability of 0.54 ± 0.08 whereas weeding action carried out before week four showed a weed survival probability of 0.24 ± 0.18.

DaniloAlves de Lima and Alessandro Correa Victorino [7] explore the use of visual servoing for car-like robots in urban environment, combining an Image-Based Visual Servoing with an Image-Based Dynamic Window Approach in a hybrid controller calledVS+IDWA. The hybrid VS+IDWA controller was validated in simulation, performing the road lane following with obstacles avoidance in different scenarios. A full-sized car-like robot experiment also showed the viability of the proposed methodology.

Henrik S. Midtiby et.al. [8] present a system for automated plant stem emerging point(PSEP) estimation of sugar beet plants based on leaf detection. From testing the system, PSEP estimates based on a single leaf have an average error of approximately 3 mm. When several leaves are detected the average error decreases to less than 2 mm. The stem locations can be used for navigation.

### 1.6.1 Summary

Different methods for discriminating crops and weeds were studied and it was found that the semantic segmentation method used by Andres Milioto et.al. [2] gives the best results. The method presented in the paper by Maurilio Di Cicco et.al. [5] for dataset generation is employed to generate a dataset for our project. The system of Visual Servoing discussed in the paper by Alireza Ahmadi et.al. [1] is used as the basis for the navigation of the rover in or project. The validation for this method is provided by Danilo Alves de Lima and Alessandro Correa Victorino [7] in their paper on Visual Servoing for car-like robots.

## 1.7 Organization of the Report

Chapter 1 provides a general introduction and gives a basic idea of the project.
Chapter 2 briefs about the system architecture and working of different aspects of the project.
Chapter 3 outlines the hardware and software requirements of the project.
Chapter 4 presents the implementation details of the project.
Chapter 5 describes the testing and analysis aspect of the project.
Chapter 6 provides the concluding remarks.

# Chapter 2
# System Architecture

## 2.1 Block Diagram and Working

A camera is mounted at the bottom of the rover is the primary source of input to the system.The camera feed is used for both lane detection and weed detection. The crops are detected continuously and this information is processed and the signal information of the path to be taken is sent to the wheels of the rover. When weeds are detected, signal is sent to the herbicide spray system to selectively spray at the weed. A block diagram of the Automated Weed Remover for Row Crops is shown in 2.1

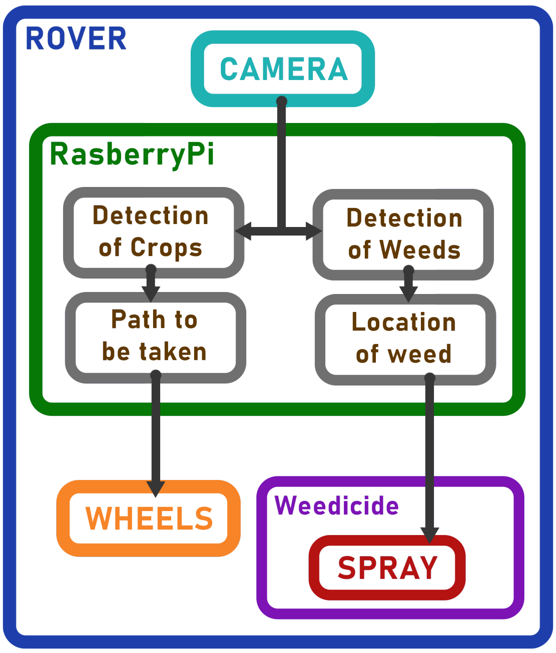


Figure 2.1: Block diagram of Automated Weed Remover for Row Crops

## 2.2 Hardware Design

### 2.2.1 Structural Frame

Research on locally grown crops has been conducted and shrub level crops like carrots and cabbages are chosen as the target crops.

Table 2.1: Crop Height and Row Separation Table

| **Types of Row Crops** | **Max Crop height at 4-6 weeks** | **Distance between each row** | **Area in which they grow** | **Season in which they grow** |
|---|---|---|---|---|
| Corn | 14-20 inches | 2.5-3 feet apart | 6 states including Karnataka | Jun-Jul, Sep-Oct, Jan-Feb |
| Tomato | 3 inches | 1-2 feet apart | 10 states including Karnataka | Mar-Jun |
| Cabbage | 4-5 inches | 1-2 feet apart | 6 states including Karnataka | Jul-Nov, Apr-Aug |

The dimensions of the rover are set to an optimal size to avoid damaging the crops and also be small enough to be mobile. The average maximum height of a crop at the time of weeding does not cross 40cm for shrub level crops. Considering the target crops and the data mentioned in 2.1, the rover is designed to be 40x40x40cm in dimension. This is shown in 2.2

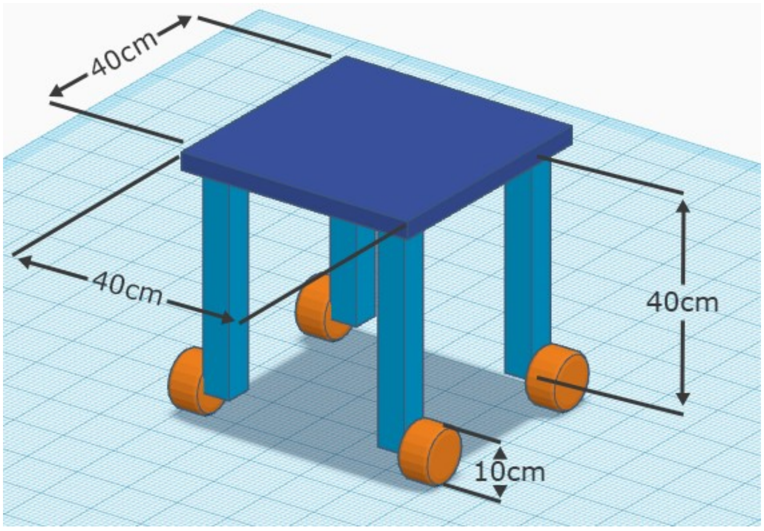


Figure 2.2: Rover Frame Design

### 2.2.2 Motor Specifications

The rover needs to navigate through the field easily. This requires a DC motor which efficiently consumes power while also carrying the load. The calculation for selection of motor is mentioned below.

1. The total weight of the rover is 5.15kgs $\approx$ 5kg

    - Weight of Motors : 400g x 4 = 1.6Kg
    - Weight of Battery Pack : 500g

- Weight of RasberryPi : 300g
- Weight of Tank : 500g
- Weight of Frame : 750g
- Weight of Miscellaneous parts : 500g
- Additional weight as Buffer : 1kg

2. Weight acting on each leg of the rover is : 5kg ÷ 4 = 1.25kg
3. Minimum speed of rover movement 0.3 m/s
4. With a wheel diameter of 10cm the rotational speed of the motor = 60 RPM

With these conditions, a 10kg-cm motor is chosen to be optimal. This is further verified using a torque test. The test bench used is shown in 2.3 and the tabulated values are as shown in 2.2

Figure 2.3: Test Bench for Torque Test of Motor

Table 2.2: Torque Testing of Motor

| Voltage Applied (V) | Trial 1 (Kg) | Trial 2 (Kg) | Trial 3 (Kg) |
|---|---|---|---|
| 4.8 | 1.415 | 1.241 | 1.518 |
| 6 | 1.565 | 1.565 | 1.560 |
| 9 | 1.875 | 2.225 | 1.935 |

### 2.2.3 Power Management

The calculations for rover power management were carried out. The power requirements are mentioned below.

1. Power consumed by RasberryPi = 15W
2. Power consumed by 4 motors = 72W
3. Power consumed by other devices = 10W

4. Total power consumed : 15W + 72W + 10W $\approx$ 100W

5. Energy consumed by rover after 1 hour of use = 100Wh

6. Voltage required to power the rover = 12V

With these conditions, an 8Ah battery is chosen to be optimal.

To meet these requirements, a battery pack consisting of 14 single cell 18650 Li-ion batteries are used. It is interconnected in a way that provides approximately 12V and 15A in total. It is charged using a 3S charger connected to the battery pack. This approach to power management is better as it is modular and easy to recharge when compared to the conventional lead-acid batteries. A simplified version of the charging system is shown in 2.4

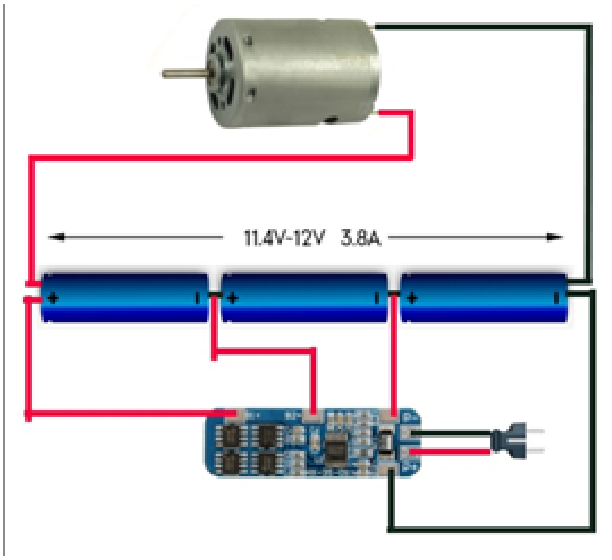


Figure 2.4: Li-ion Battery Charging System

### 2.2.4 Spray System

The liquid weedicide is sprayed onto the weeds using a spray system. It consists of a DC water pump fitted into a tank containing the liquid. The liquid is pump into a tube connected to a solenoid valve and full-cone nozzle. When the weeds are detected, the solenoid valve opens and a uniform jet of weedicide is sprayed onto the weeds. A simplified version of this system is shown in 2.5

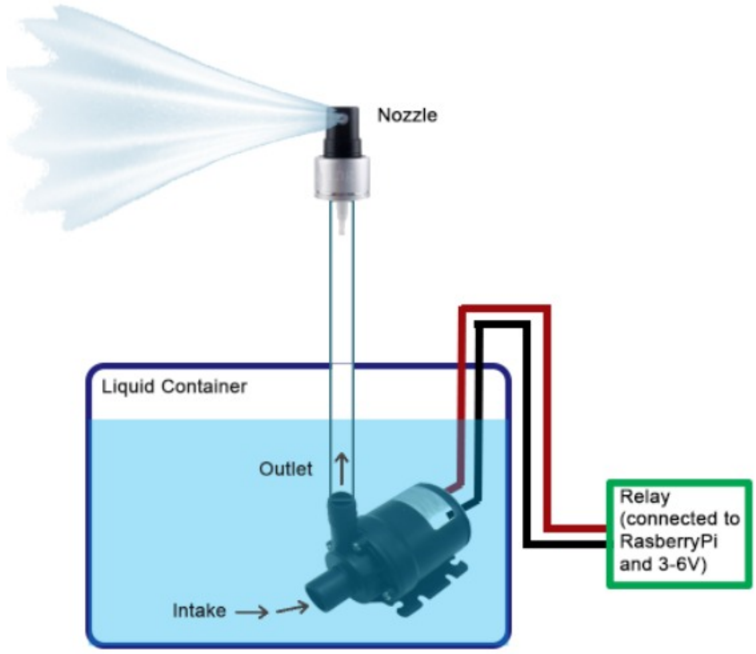


Figure 2.5: Spray System with DC Water Pump

## 2.3 Detection of Crops and Navigation

### 2.3.1 Canny Edge Detection

Canny Edge Detection is a popular edge detection algorithm. It uses a multi-stage algorithm to detect a wide range of edges in images. The general criteria for edge detection include:

1. Detection of edge with low error rate, which means that the detection should accurately catch as many edges shown in the image as possible.

2. The edge point detected from the operator should accurately localize on the center of the edge.

3. A given edge in the image should only be marked once, and where possible, image noise should not create false edges.

The Process of Canny edge detection algorithm can be broken down to 5 different steps:

1. Apply Gaussian filter to smooth the image in order to remove the noise.

2. Find the intensity gradients of the image.

3. Apply gradient magnitude thresholding or lower bound cut-off suppression to get rid of spurious response to edge detection.

4. Apply double threshold to determine potential edges.

5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

The Canny algorithm is adaptable to various environments. Its parameters allow it to be tailored to recognition of edges of differing characteristics depending on the particular requirements of a given implementation. An aerial image of a crop field is taken and canny edge detection is applied to detect the paths of crop rows as shown in 2.6.

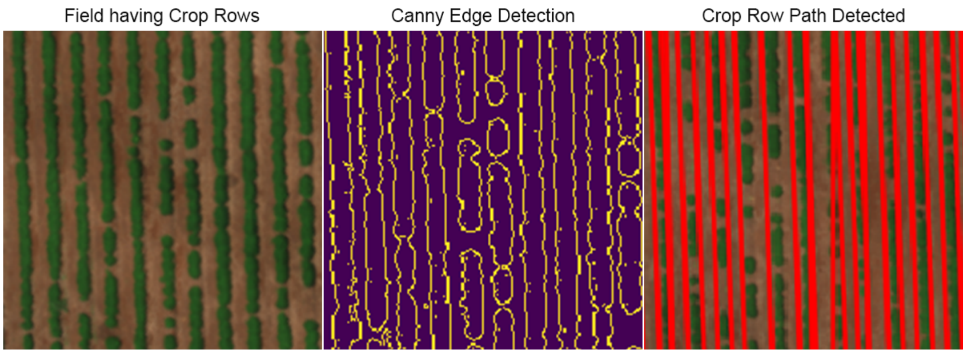


Figure 2.6: Canny Edge Detection on Aerial View of Crop Field

### 2.3.2 Navigating the Crop field

Row crops are crops that are planted in rows parallel to each other on the agricultural fields. The rover exploits these parallel row structure to steer through the field. The rover moves over the crops. This does not affect the crops as the wheels of the rover moves in the gaps between each parallel row. After successful navigation of the first row of crops, the rover moves on to the next crop row by turning clockwise or counter-clockwise. It checks if another crop row is present, if yes, then the rover aligns itself to the crop rows and starts moving over the crop rows. If no, then the rover has completed navigating the entire field. 2.7 shows how the rover navigates the crop rows. The flow of control during crop row detection and navigation is shown in 2.8

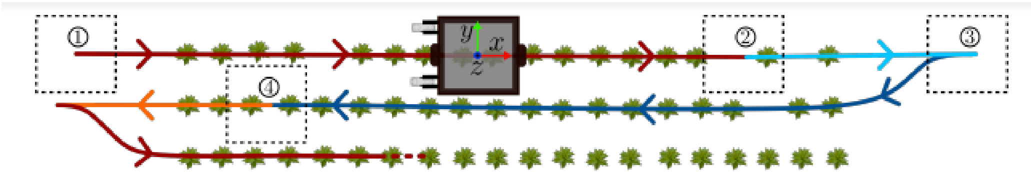


Figure 2.7: Crop Row Navigation
(1) shows the rover entering the first crop row, (2) exits the first crop row, (3) transitions to the next crop row, (4) exits the row on the opposite side.

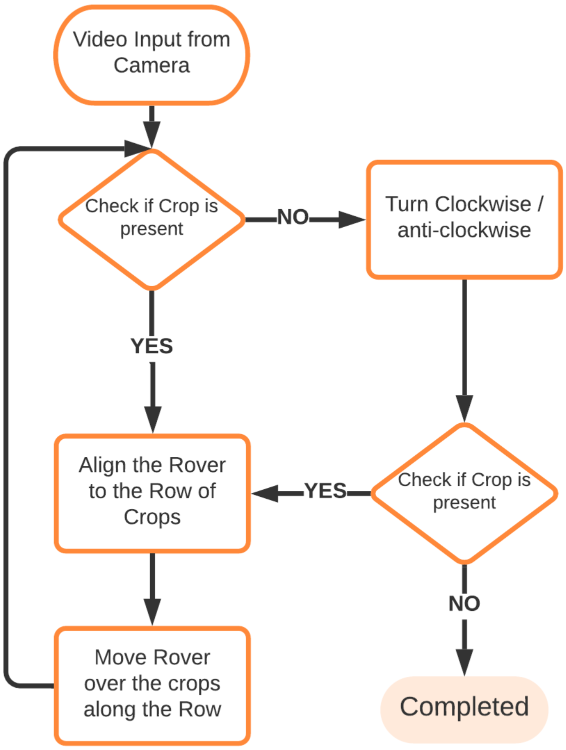


Figure 2.8: Flowchart of Crop Lane Detection

## 2.4 Detection and Treatment of Weeds

### 2.4.1 Object Detection

Object detection is a method in which an object's location in an image is made known by means of bounding boxes. Image classification is used to classify the image as to whether the image consists of a particular class Eg: dog, cat, apple, orange by extracting features from the image. If more than one class is present then the class with the highest score is taken up as the detected class. On the other hand by using object detection, the objects of interest can be identified and localized in the images. It can also localize more than one class in an image. The usual procedure in object detection framework is as follows:

1. Region proposals or Region of interest is generated for an image. These region proposals consist of large number of bounding boxes.

2. Feature extraction is performed on the generated region proposals to obtain the required visual features.

3. In the last step overlapping boxes are combined to a single bounding box. This is known as non-maximum suppression.

### 2.4.2 Weed Treatment

A liquid selective or non-selective weedicide is used to neutralize the weeds. This liqiud is filled in the tank of the spray system and is sprayed onto the weeds when detected. Targeted application of such weedicides reduces the overall usage of herbicides in the field, thus minimizing crop damage while also cutting down herbicides costs. The flow of control during weed detection and treatment is shown in 2.9

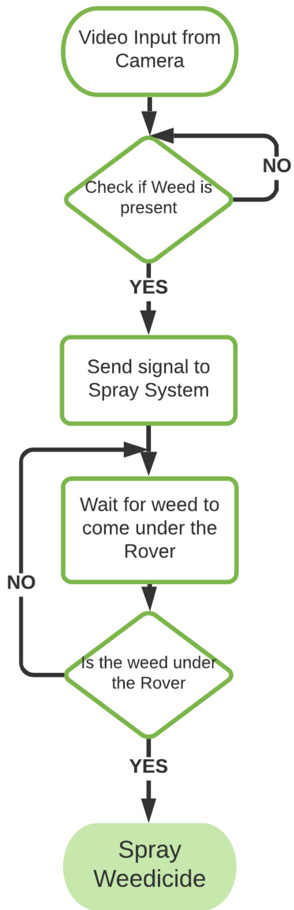


Figure 2.9: Flowchart of Weed Treatment

# Chapter 3
# Hardware and Software Description

## 3.1 Hardware Requirements

### 3.1.1 RasberryPi 4

Rasberry Pi 4 as shown in 3.1 is a development board in PI series. It can be considered as a single board computer that works on LINUX operating system. The board not only has tons of features it also has terrific processing speed making it suitable for advanced applications. PI board is specifically designed for hobbyist and engineers who are interested in LINUX systems and IoT (Internet of Things).

Figure 3.1: Rasberry Pi 4 Board

### 3.1.2 PiCamera

The Raspberry Pi Camera v2 as shown in 3.2 is a high quality 8 megapixel Sony IMX219 image sensor custom designed add-on board for Raspberry Pi, featuring a fixed focus lens. It's capable of 3280 x 2464 pixel static images, and also supports 1080p30, 720p60 and 640x480p60/90 video.

Figure 3.2: Pi Camera

### 3.1.3 DC Motor

A single shaft dc motor is shown in 3.3 These motors are simple DC Motors featuring gears for the shaft for obtaining the optimal performance characteristics. They are known as Center Shaft DC Geared Motors because their shaft extends through the center of their gearbox assembly.

Figure 3.3: DC Motor

### 3.1.4 Wheels

This wheel has two degrees of freedom and can traverse Front or Reverse. The center of the wheel is fixed to the robot chassis. The angle between the robot chassis and wheel plane is constant. A generic wheel used for robotic projects is shown in 3.4

Figure 3.4: Wheels

### 3.1.5 Motor Driver

The L298N Dual H Bridge DC/Stepper Motor Driver Controller Module as shown in 3.55 is for driving two robot motors. It uses the popular L298N Dual H-Bridge Motor Driver chip and is powerful enough to drive motors from 5-35 Volts at up to 2 Amps per channel. The flexible digital input controls allow each motor to be fully independent with complete control over speed direction and braking action.

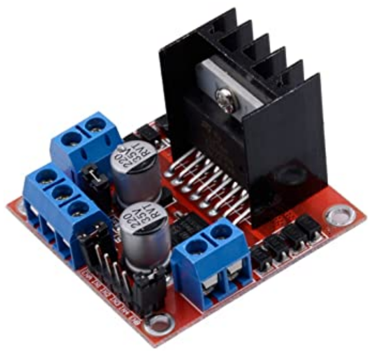

Figure 3.5: Motor Driver

### 3.1.6 Solenoid Valve

A solenoid valve is an electrically controlled valve. The valve features a solenoid, which is an electric coil with a movable ferromagnetic core (plunger) in its center. In the rest position, the plunger closes off a small orifice. An electric current through the coil creates a magnetic field. The magnetic field exerts an upwards force on the plunger opening the orifice. This is the basic principle that is used to open and close solenoid valves. A simple solenoid valve is shown in 3.6

Figure 3.6: Solenoid Valve

### 3.1.7 DC Water Pump

A solenoid valve is an electrically controlled valve. The valve features a solenoid, which is an electric coil with a movable ferromagnetic core (plunger) in its center. In the rest position, the plunger closes off a small orifice. An electric current through the coil creates a magnetic field. The magnetic field exerts an upwards force on the plunger opening the orifice. This is the basic principle that is used to open and close solenoid valves. A simple solenoid valve is shown in 3.7

Figure 3.7: DC Water Pump

### 3.1.8 Li-ion Battery

A lithium-ion battery or Li-ion battery as shown in 3.8 is a type of rechargeable battery. Lithium-ion batteries are commonly used for portable electronics and electric vehicles and are growing in popularity for military and aerospace applications.

Figure 3.8: Li-ion Battery Cells

### 3.1.9 Battery Charger

The 18650 Lithium Battery Charging and Protection Board shown in 3.9 works for 11.1V 12.6V. It provides a continuous discharge of current, 100mA balanced current, for electric drill/sprayer/LED lights/low power inverter. The Scope of Nominal voltage of 3.6V, 3.7V lithium battery where Charging voltage can be range between 16.8V to 18.1V.

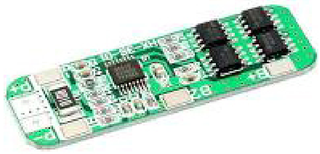

Figure 3.9: Li-ion Battery Charger

## 3.2 Software Requirements

### 3.2.1 Open CV

OpenCV is a library of programming functions mainly aimed at real-time computer vision. Originally developed by Intel, it was later supported by Willow Garage then Itseez. The library is cross-platform and free for use under the open-source Apache 2 License.

### 3.2.2 Microsoft Lobe

A machine learning tool which helps people apply deep learning and AI models quickly - without the need of writing code - into tools they are developing, is now available with image classification support. This essentially means that people can import images of the things they want Lobe to recognize, and the free app automatically selects the right machine learning architecture to begin training a machine learning model.

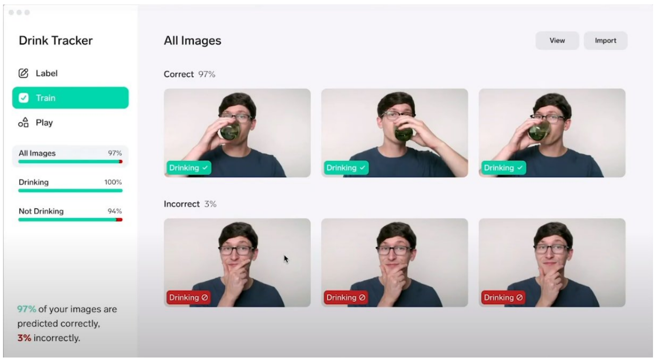


Figure 3.10: Microsoft Lobe UI

## 3.3 Image Dataset

A large set of images generated by superimposing background (soil or ground) and object (weed and or crops) images is created. These are termed as synthetic images. After the successful working of the system using synthetic images, real plants and weeds must be photographed and collected and the model is to be retrained with this dataset.

# Chapter 4
# Implementation

## 4.1 Hardware

### 4.1.1 Frame

The rover frame is built using rectangular aluminium channels. A platform is created on top using a flat, sturdy board. The motors are mounted to the legs of the frame using saddles and the wheels are directly mounted to the motors. The speed of the motor is varied using the motor driver attached to the motor. The RasberryPi, motor driver, battery pack, charger and tank of the spray system are all mounted on top of the flat board. The components above the rover are arranged in way that the weight distribution is spread even.

### 4.1.2 Mounting Parts

The camera is mounted infront of the rover, tilted downwards. This configuration is chosen as the video feed from the camera has better visuals of the crop layouts and also helps in lane switching. A pictorial representation of the camera placement is shown in 4.1.The Nozzle of the spray system is mounted directly under the flat board. This makes the effective spray area to be right under the rover. This configuration is shown in 4.2

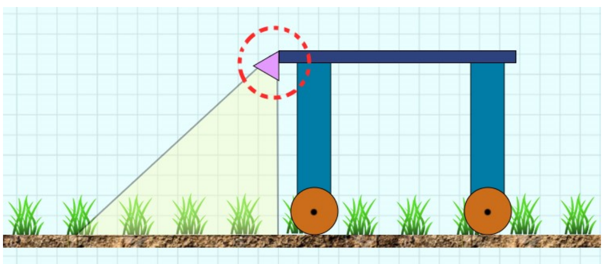

Figure 4.1: Camera Placement in the Rover

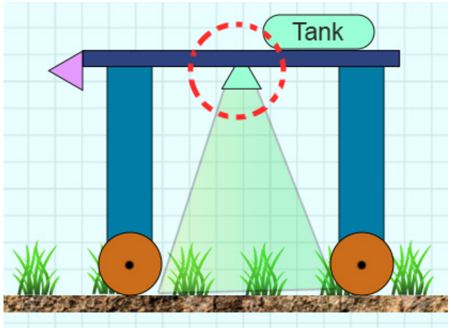


Figure 4.2: Spray Nozzle Placement in the Rover

## 4.2 Software

### 4.2.1 Dataset

A synthetic dataset 1,000 images of weeds among the crops are created. This was done by collecting a small batch of object images, i.e. images of weeds, segmenting the images, applying random alterations to it and compiling it on top of the background images of crops and crop fields. The working of this method is shown in 4.3

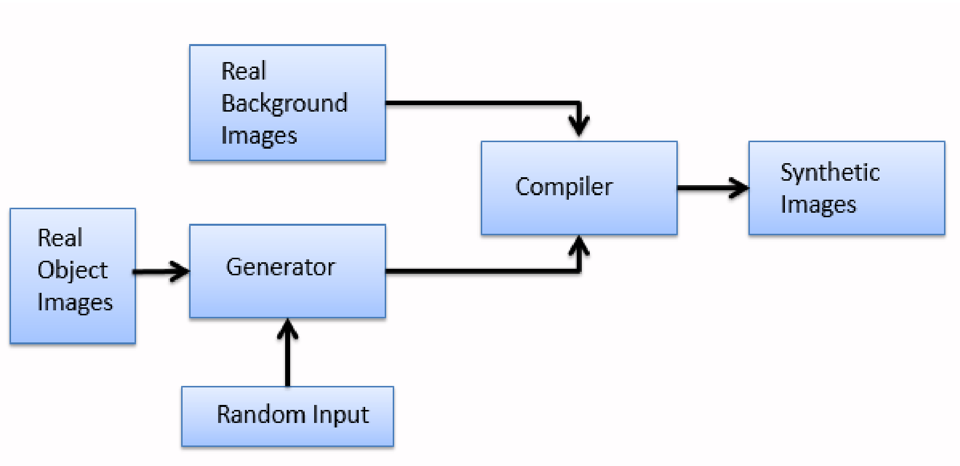


Figure 4.3: Synthetic Dataset Generation

### 4.2.2 Weed Detection Model

Microsoft Lobe is used for training the machine learning model for weed detection as it allows users to train their own machine learning and AI models without writing a single line of code. Users only have to import their images into Lobe and label them in order to create a machine learning dataset. Lobe automatically selects the best machine learning model and starts training immediately without any complicated configuration or setup. Users can also evaluate the model and offer feedback in order to boost performance. The trained models can be easily exported to run on any platform and it works on many applications, websites and devices.

In this project, the images are uploaded onto Lobe and are divided into two fields, namely 'Weed Detected' and 'No Weed Detected', by assigning one of these two labels to every image. The images used include images of plain ground with no weed, plain ground with weed, plant rows with no weeds and plant rows with weeds between them. A large dataset of images which accounts for all possible locations of weeds in or around the plants is used to train a model that has a very high level of accuracy. Once all the images are labeled Lobe automatically trains the model and also gives the accuracy of the model. After the model is trained and tested, it is exported as a TensorFlow model. The TensorFlow and Lobe packages are installed in the RaspberryPi board and the model can be imported and used as required.

### 4.2.3 Path Detection

In 4.4, path detection using Canny Edge detection is shown on a test ground. This test ground is created with markers used to represent crops and the placement of these markers are made in such a way that it represents the actual placements of crop rows in the agricultural fields. This same detection model is then deployed onto the rover, which uses this to navigate the path of crop rows.

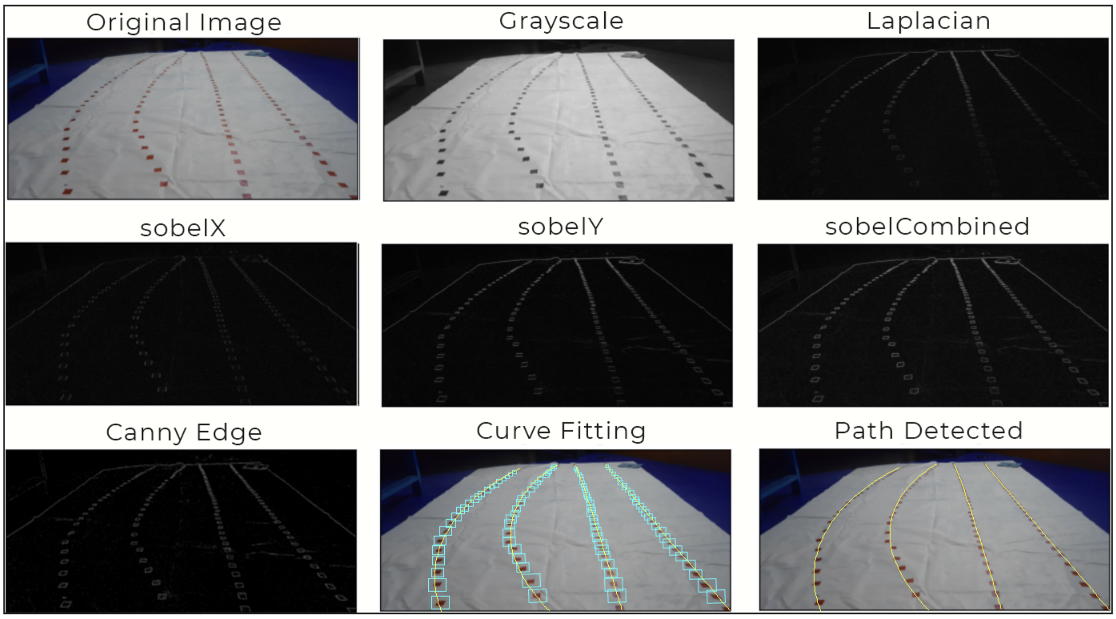


Figure 4.4: Path Detection using Canny Edge Detection

# Chapter 5
# Testing and Results

- The rover frame made using aluminium channels i sturdy and could withstand a load of 5Kg. The frame build is shown in 5.1

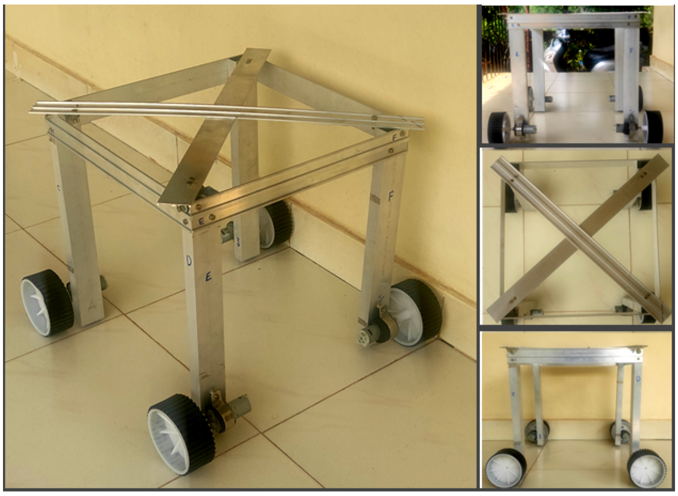

Figure 5.1: Skeletal Frame of the Rover

- The motors are tested with different supply voltages to check the current consumed in no-load conditions and operating temperatures are also tabulated as shown in 5.1

Table 5.1: Temperature testing of motor

| Voltage(V) | Current(mA) | $T$ - 30s(°f) | $T$ - 2min(°f) | $T$ - 5min(°f) | $T$ - 10min(°f) |
|---|---|---|---|---|---|
| 5 | 380 | 95.7 | 95.8 | 95.8 | 95.9 |
| 6 | 390 | 96.1 | 96.2 | 96.4 | 96.9 |
| 9 | 430 | 97 | 97.2 | 97.5 | 98 |
| 12 | 642 | 98.6 | 99.3 | 100.5 | 101.7 |
| 15 | 751 | 101.6 | 102.3 | 104.4 | 106.1 |

$T$ refers to Temperature

- The synthetic dataset created was imported into Microsoft lobe to train the machine learning model for weed detection. After training, the model was tested and it detected the presence of weeds in the images with 96% accuracy. The result window of the weed detector model is shown in 5.2

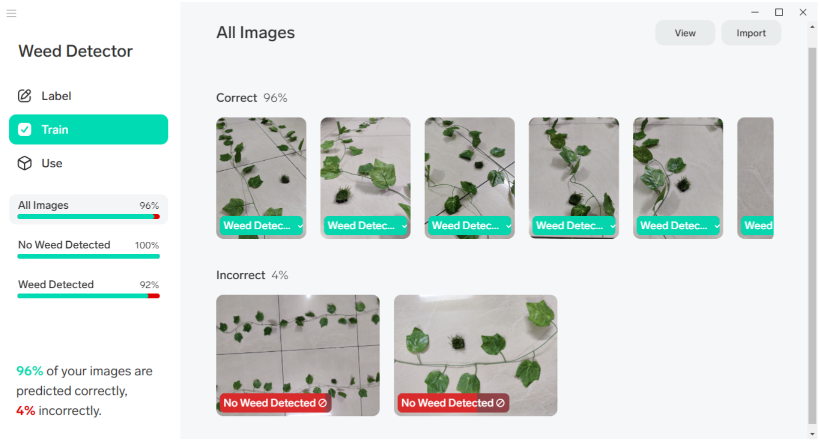


Figure 5.2: Result Window of Weed Detector Model

- A mini-rover is built to test the path detection and navigation system. This is done by creating a test ground with markers used to represent crops. These markers are placed in a way to mimic the actual placements of crop rows in the agricultural fields. The mini-rover programmed with Canny Edge Detection is placed on the test ground and navigation accuracy is tested by checking the correctness of the path followed.

# Chapter 6
# Conclusions and Future Work

## 6.1 Conclusion

The functioning of individual systems in the rover is working perfectly. The mini-rover successfully navigated the test ground using Canny Edge Detection method. The machine learning model trained using Microsoft Lobe, was able to correctly predict the presence of weed with an accuracy of more than 95%. However the final product, i.e. the rover with all the functioning part integrated into it is yet to be tested. Assuming the proper working of the final product, this system of weed removal is very advantageous to the farmer as it reduces the physical labour of manually searching and plucking the weeds. It reduces the total herbicide use in the field which decreases the amount spent on herbicides, reduces crop damage and increases the effective yield of a crop field. Hence this system saves both time and money for the farmers.

## 6.2 Scope of Improvement

1. Even though this project greatly reduces the use of herbicides it does not eliminate it entirely. The herbicides can still be harmful to plant growth. Methods other than herbicide spraying for weed treatment could be explored.

2. Solar panels can be integrated to charge and power this system. This greatly reduces operation costs.

3. Reduce overall cost of the Rover by finding better quality of products for lesser price, this makes it easy for the Rover to be marketed as a viable solution for farmers.

# Bibliography

[1] A. Ahmadi, L. Nardi, N. Chebrolu, and C. Stachniss, “Visual servoing-based navigation for monitoring row-crop fields,” in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 4920–4926.

[2] A. Milioto, P. Lottes, and C. Stachniss, “Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in cnns,” in *2018 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2018, pp. 2229–2235.

[3] S. Haug, A. Michaels, P. Biber, and J. Ostermann, “Plant classification system for crop/weed discrimination without segmentation,” in *IEEE winter conference on applications of computer vision*. IEEE, 2014, pp. 1142–1149.

[4] C. McCool, T. Perez, and B. Upcroft, “Mixtures of lightweight deep convolutional neural networks: Applied to agricultural robotics,” *IEEE Robotics and Automation Letters*, vol. 2, no. 3, pp. 1344–1351, 2017.

[5] M. Cicco, C. Potena, G. Grisetti, and A. Pretto, “Automatic model based dataset generation for fast and accurate crop and weeds detection, corr abs/1612.03019,” 2016.

[6] C. McCool, J. Beattie, J. Firn, C. Lehnert, J. Kulk, O. Bawden, R. Russell, and T. Perez, “Efficacy of mechanical weeding tools: A study into alternative weed management strategies enabled by robotics,” *IEEE Robotics and Automation Letters*, vol. 3, no. 2, pp. 1184–1190, 2018.

[7] D. A. de Lima and A. C. Victorino, “A visual servoing approach for road lane following with obstacle avoidance,” in *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2014, pp. 412–417.

[8] H. S. Midtiby, T. M. Giselsson, and R. N. Jørgensen, “Estimating the plant stem emerging points (pseps) of sugar beets at early growth stages,” *Biosystems engineering*, vol. 111, no. 1, pp. 83–90, 2012.