

Department of Electronics & Instrumentation Engineering

A Project Report on

Automatic Weed Detection Robot

Submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Engineering in Electronics & Instrumentation Engineering

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ABSTRACT

Automated processes in the field of agriculture have become increasingly reliable and efficient. Farmers face many difficulties due shortage of manpower since it is a time-consuming and tedious task. Robotic systems integrated with various control methods can be very useful in doing repetitive work, such as the seed-sowing process where the same movement is continuous.

This project utilizes a robot that acts as a cost-effective system to detect weeds in agricultural fields. An automated system is to develop a trainable-automatic robot that helps in removing unwanted weeds on agricultural fields using gestures to control a three-axis robotic arm to do the necessary work using Raspberry Pi. The arm is placed on a rover and an optical sensor of low resolution is placed on it to detect the difference between plants and weeds using Machine Learning. The arm is designed to perform repetitive motions to do the necessary work. If a plant is detected, the robot will treat as a plant and not harm it, the system provides an indication of a plant, or else it would display that a weed has been detected. The arms of the rover are activated and hence the weeds will be removed from the field. The robotic arm present on the rover would be tested and evaluated under normal environmental conditions. The Raspberry Pi transmits signals to control location as well as detect the presence or absence of weed, it is also used to ensure proper movement of a robot. This type of robot is used in the crop field to cut the weeds as per the user's command.

Keywords: Weed Identification, Raspberry Pi 4, Machine Learning, Robotic Arm, Accuracy, Convolutional Neural Networks, Robotic Movement, Training Model, Dataset.

CHAPTER 1 INTRODUCTION

Farmers today spend a lot of money on machinery that helps them reduce labor and increase yields. Mowing, mowing, spraying etc. There are many machines for the jobs, but these machines have to be operated manually to do the jobs that need to be done, and a separate machine is used for each job. Profits and profits return from using less equipment than on investment. Another problem is the increasing needs of the world's population. The World Health Organization estimates that the world population will reach 9 billion in 35 years, increasing the demand for food crops. Automation is the best solution to increase production on a large scale by creating and working on multitasking machines to overcome all the disadvantages mentioned above. Agriculture is humanity's oldest and most important form of trade, providing the food, feed, fiber and fuel we need to survive. The current trend in the development of agricultural robots is to create a smarter and more efficient machine to provide more and better services while reducing the farmer's expenses, which is exactly what we are doing in this article. Build robots that can work and keep the soil in the environment using plants and seeds that can be manually manipulated by farmers. Robotics and automation can play an important role in increasing the demand for agriculture. Pruning, thinning, harvesting, mowing, spraying and weeding are all automated by humans. We can also use it through improvements in sensors and control systems for optimum and pest control. When the concept of automation and Action Farms is adopted, the options will be high and the cost of technology will decrease. Autonomous machines will be safe, similar to many agrology facilities. Finding something else along with the image processing facility, it also provides automatic control of the robotic arm. The main component here is the Raspberry Pi microcontroller, which takes care of the whole process. Initially, the robot reaches all the fields, then the plants are found and cut. For robot control, the robot uses ultrasonic sensors to control the equipment and help the robot navigate the field. It controls these levels using a humidity sensor and informs the farmer. The alarm mechanism is a buzzer module that makes a sound to detect plants.

Today's Internet of Things (IoT) era has allowed billions of connected devices to be connected to provide valuable services. Agriculture is a rapidly growing industry with many IoT applications. The production of good and healthy food should increase by 70% by 2050. Many problems are looming: the dwindling supply of natural resources has resulted in sustained yields of several major crops. This has led to a drastic shift in the agricultural workforce, which is facing decline. These problems have led to the use of integrated technologies to predict crop losses, identify weeds and other spoiled crops, and reduce overall labor. The main applications of IoT in agriculture are precision agriculture, drones, livestock monitoring and surveillance, and predictive analytics. Precision farming uses sensor data to monitor various parameters such as detecting defects/diseases in the agro ecosystem, crop planning, personnel and job performance. The current ecosystem includes high-performance devices, control systems for robots and autonomous vehicles, and mobile devices with high-speed internet and satellite imagery. The second application of IoT is the use of ground and aerial drones for medium to large scale analytics. The drone approach includes crop health monitoring, spraying, planting and initial research. Animal care is another practice where information is collected and analyzed against health to prevent the spread of disease. Finally, predictive analytics are incorporated into smart agriculture to predict crop yields, develop logistical strategies and make risk assessments. This is done from data collected by various sensors. The main data used include soil health, temperature, humidity, and precipitation. An important aspect of precision agriculture is the ability to obtain detailed information from planting, one of the identifications of plants in crops. Plants absorb large amounts of nutrients, water and sunlight, which affects crop yield and quality. They also account for 45% of annual crop losses.

> Literature Survey:

In the paper [1], the plan includes capturing images of the area and then using a convolutional neural network (CNN) to determine the presence of vegetation. For training and testing of the CNN model, data from planted and plant less farm images were collected. They first used the VGG16 model for video extraction and studied the neural network to classify the images. Experimental results show that the method provides 96.3% accuracy in plant detection. The study also evaluated the performance of the proposed method against traditional machine learning methods and found that the CNN method outperformed them.

In the paper [2], a real-time plant detection and identification system using machine learning and voice recognition is developed. The system uses two cameras to capture stereoscopic images that are processed using a convolutional neural network (CNN) to identify vegetation. The different stages of building the system include image acquisition, stereo editing, image processing and plant classification. It provides an overview of the data used to train and test CNN models. Experimental results show that the system can successfully detect and identify plants in real time and with high accuracy. The system can be used in agricultural applications to improve crop and crop management.

In the paper [3], the performance of three different algorithms for vegetation detection was compared. The three algorithms compared in the article are K-means clustering algorithm, expectation maximization (EM) algorithm, and fuzzy C-mean clustering algorithm. The performance of the algorithms on vegetation and crop image data shows that the fuzzy C-means algorithm outperforms the other two algorithms in terms of accuracy, precision, and recall. This article also examines the computational complexity and execution time of these algorithms and concludes that the fuzzy C-means algorithm is more efficient than the other two algorithms. The fuzzy C-means algorithm can be integrated into a plant detection system, which can reduce pesticide use and increase crop yields.

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In the paper [4], a facility detection based on the Support Vector Machine (SVM) algorithm is proposed. The proposed system consists of a camera mounted on a mobile platform that captures images of crops and plants in the field. Images are preprocessed using image processing techniques and features are extracted from images. The SVM algorithm learned these features to classify plants as crops and weeds. This article discusses various techniques for detecting vegetation such as RGB cameras, hyperspectral sensors, and lidar sensors. The authors also describe different insecticide sprays such as nozzle-based sprayers, electrostatic sprayers, and laser-based sprayers.

In the paper [5] examines the latest technology for classifying crops and plants using deep learning in agriculture. This article provides an overview of various deep learning techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs) for classifying plants and plants. The authors describe various ways to train these models, including adaptive learning, remediation, and knowledge support. This article provides a comprehensive review of recent research in plant breeding and plant classification. The authors compare the performance of different methods and highlight their strengths and limitations. Overall, this article gives a good insight into the cutting-edge technology in deep learning-based plant breeding and classification and demonstrates the potential of the techniques in precision agriculture. The authors also discuss future research directions and suggest ways to increase the efficiency and effectiveness of deep learning-based plant breeding and classification.

In the paper [6], the design and development of a solar-powered autonomous agricultural robot capable of performing multiple tasks including soil moisture, crop monitoring toilet, weed removal and seeding. The robot is controlled using a Bluetooth-enabled Android app, which allows users to monitor and control the robot remotely. The authors describe the hardware and software components of the Raspberry Pi, including sensors, motors, and power supplies. They also discussed the design of the Android app and its features such as real-time monitoring of the robot's activities and manual control options. The article concludes with a discussion of the advantages of solar farm robots such as efficiency and cost reduction, as well as recommendations and teaching research for future development.

In paper [7], this article describes the development of an autonomous weeding robot that uses computer vision techniques to identify and remove weeds in agricultural fields. The robot is designed for effortless use and can be controlled using a mobile app. The authors discuss the robot's hardware and software components, including cameras, motors, and microcontrollers. They also describe the imaging techniques used to identify plants and the algorithms used to control the robot's movements. The article ends with the results of field tests to evaluate the robot's performance. The results showed that the robot was able to detect and remove weeds with a success rate of over 90%.

In the article [8], this article presents a low-cost robot designed for facility management in a narrow-gauge space. Equipped with a support and guidance system, the robot can identify and remove plants using a nozzle. The robot is designed for use in fields up to 30 cm row spacing, which is common for many crops. The robot uses stereo vision and deep learning algorithms to identify plants and distinguish crops. It also has a nozzle that detects and destroys weeds while reducing pesticide use. The robot's self-charging and navigation system allows it to work for a long time without human intervention. The robot can navigate the area using a GPS system and return to the charging station when the battery is low. The charging station is equipped with a wireless charging system to charge the robot without human intervention.

In paper [9], this paper presents the identification and removal of weeds in agriculture using machine vision and robotics. The system includes a camera that captures images of the field and then processes it using computer vision to identify plants. Identified weeds are then targeted for removal by a robotic arm that uses special tools to remove weeds without damaging the crop's environment. The experimental results presented in this paper demonstrate the effectiveness of the proposed method in the identification and removal of weeds. The authors also discuss the benefits of the system, including improved facility management and reduced labor costs.

Objectives of the Project Work:

- The main objective is to propose a novel approach for weed detection in agricultural fields using a robot that can be controlled through mobile applications. We also aim to develop a low-cost, efficient, and user-friendly system that can help farmers in identifying and removing weeds from their crops.
- The proposed system uses a camera mounted on the robot to capture images of the crop fields, which are then processed using image processing techniques to identify the presence of weeds. The robot is controlled using mobile application, which eliminates the need for complex programming or manual control systems.
- The ultimate goal is to provide a practical solution for weed detection that can significantly reduce the time, effort, and cost involved in manual weed removal. The proposed system can potentially increase crop yield and reduce the use of harmful herbicides, making it a sustainable solution for agriculture.

CHAPTER 2 WEED DETECTION ROBOT

> Block Diagram:

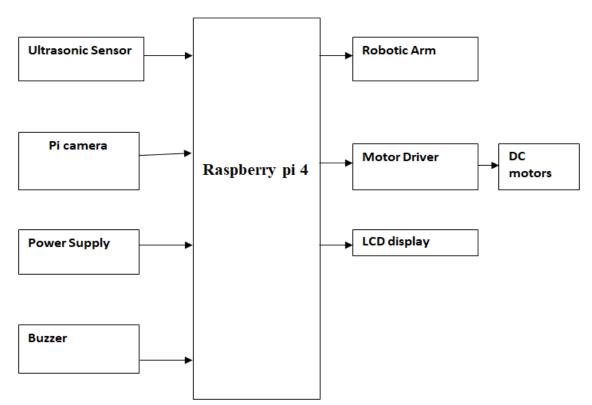


Fig 1 Block diagram of Weed Detection Process where the Left Part shows the Ultrasonic Sensor, Pi Camera, Power Supply, and Buzzer are Connected with Raspberry Pi 4 as Inputs to the System and the Right Part shows the Robotic Arm, Motor Drivers, DC Motors, and LCD Display Acting as Outputs when the Image Processing is Completed

> Hardware Setup:

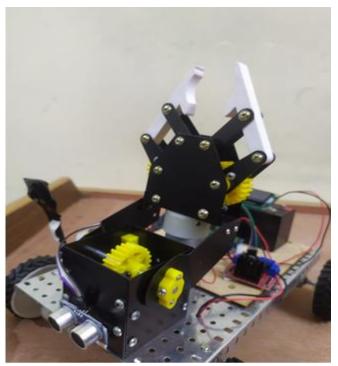


Fig 2 Hardware Realization of the Weed Detection Robot

Subsystem Explanation:

• Raspberry Pi:

One of the small-scale computers (SBCs) developed by the Raspberry Pi Foundation in partnership with Broadcom in the UK. The Raspberry Pi project was originally intended to support computer science teaching in schools and developing countries. The original model became more popular than expected and was sold outside of their stores for applications such as robotics. Due to its low cost, modularity and open design, it is widely used in many fields such as weather monitoring. It is often used by computer and electronics enthusiasts because of the HDMI and USB standards.



Fig 3 Raspberry Pi 4

After the second board was released, the Raspberry Pi Foundation established a new organization called Raspberry Pi Trading and appointed Eben Upton as CEO to be responsible for the development machine. The Foundation is re-committed to being a supporter of education that supports computer science teaching in schools and developing countries. Most Raspberry Pi are manufactured at Sony's factory in Pencord, Wales while others are manufactured in China and Japan.

• Pi Camera:

Used to capture images of crops. It connects directly to the Raspberry Pi model. There are two ways Raspberry pi can be like a mini computer. The images captured by the camera are sent to the Raspberry Pi. Image processed using tensorflow and detected by raspberry pi.



Fig 4 Pi Camera

• LCD Display:

LCD (Liquid Crystal Display) is a type of flat panel display which uses liquid crystals in its primary form of operation. LEDs have a large and varying set of use cases for consumers and businesses, as they can be commonly found in smartphones, televisions, computer monitors and instrument panels.

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LCDs were a big leap in terms of the technology they replaced, which include light-emitting diode (LED) and gas-plasma displays. LCDs allowed displays to be much thinner than cathode ray tube (<u>CRT</u>) technology. LCDs consume much less power than LED and gas-display displays because they work on the principle of blocking light rather than emitting it. Where an LED emits light, the liquid crystals in an LCD produces an image using a backlight.

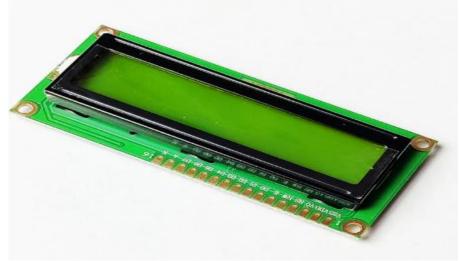


Fig 5 LCD Display

• Buzzer:

A buzzer or buzzer is an audio signal that can be mechanical, electromechanical or piezoelectric. Common ring and bell applications include alarms, timers, and recognition of user input such as mouse clicks or pulses. The piezo element can be driven by vibrating electronic or other audio signals driven by a piezo audio amplifier. A sound is often used to indicate that a button has been pressed, such as a click, bell, or beep.



Fig 6 Buzzer

Robotic Arm:

A robotic arm is a type of generally programmable robotic arm that has the same functionality as a human arm; The arm can be the equivalent of a mechanical device or a large part of a robot. Connections between such clients are articulated to allow rotation (as in robot speech) or translational (linear) displacement. The link between the components can be thought of as forming a kinematic chain. The end of the kinematic chain of the robot arm is called the end effector, which resembles a human hand. However, the use of the term "manipulator" as a definition of a robotic arm is generally prohibited.

• Ultrasonic Sensor:

The Ultrasonic Sensor is a device that detects objects and measures the distance between them. It measures distance by emitting ultrasonic waves and receiving waves from objects. Ultrasound vibrates at frequencies above the range of human hearing. Transducers are microphones that receive and transmit ultrasonic waves. Like other ultrasonic sensor modules, the HC-SR04 uses a transducer to send pulses and receive echoes. The sensor determines the distance to the target by measuring the short time between sending and receiving ultrasonic pulses.



Fig 7 Ultrasonic Sensor

➤ Working Methodology:

| Layer Discription Image input layer It inputs 2-D images to a network and normalize data. Convolution layer Convolutional filters are applied to the input. Rectified Performs a threshold operation to each element Values less than zero is set to zero. (ReLU) layer Performs a threshold operation Values less than zero is multiplied by a fixed scalar. Tanh layer Applies the tan hyperbolic activation function Performs down-sampling Input is divided into rectangular pooling regions and average values are computed Max Pooling layer Performs down-sampling Input is divided into rectangular pooling regions and maximum values are computed Fully Multiplies the input by a weight matrix and then adds a bias vector. SoftMax layer Applies a SoftMax function Cassification Computes the cross-entropy loss for multi-class | | TABLE I |
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| | Classification | Computes the cross-entropy loss for multi-class |
| inver classification problems with multually exclusive | layer | classification problems with mutually exclusive |
| classes. | | |

Fig 8 Deep Learning Layers for Image Segmentation and Classification Process

Raspberry pi is used as a microcontroller in this project. All products are related to Raspberry pi. Ultrasonic sensors are connected to robots for object detection. We can capture plants by photographing them using the Pi camera. When a weed is detected, the buzzer will be activated, the detected weed will be displayed on the LCD screen, the robotic arm will be opened to collect weeds by moving up and down, and the robotic arm will turn off after selection. The robot stops every 10 centimeters to control the plants.

CHAPTER 3

DEVELOPMENT OF AN ALGORITHM FOR WEED DETECTION

Convolutional Neural Networks (CNN):

A deep neural network (DNN) can be represented as a graph of neurons interconnected by weights. Each neuron and edge is associated with an activation value and a weight, respectively. CNN basically consists of three parts: convolution layer, maximum flow layer and fully connected layer. General architecture of the CNN model. Layers in CNN include a set of operations such as convolution techniques and joint operations that result in a combination of data called feature maps. The layers in the CNN model include: Layers: A layer is the main layer of CNN; it creates new images called feature maps. The custom menu shows the special features of the original image. Let's take the idea of two-dimensional plant like the Matrix XN1 Wm1, then the Matrix of life Y = X * is the result of X's 2D decision with W and can be mathematically defined as:

$$H = X * W \rightarrow H_{i,j} = \sum_{k=1}^{m} \sum_{l=1}^{m} X_{i+k-1,j+l-1} W_{k,l}$$

• Pooling Layer:

The pooling layer reduces the size of the image as it combines adjacent pixels in a given area of the image into a single representation value. Generally, two types of pooling methods are used, one is maximum pooling and the other is average pooling. In this research, maximum pooling, which can be expressed mathematically as:

$$H_{i,j} = max \{ X_{i+k-1,j+l-1} \forall 1 \le k \le m \text{ and } 1 \le l \le m \}$$

> Block Diagram:

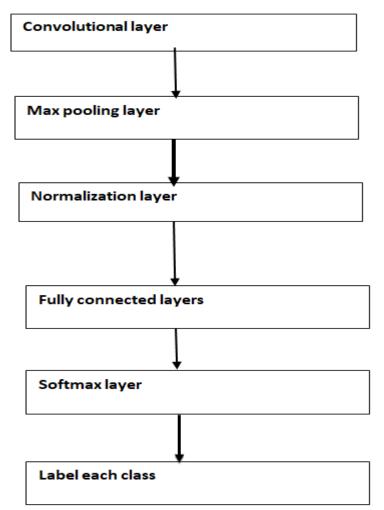


Fig 9 The Proposed Classifier based on CNN described in the Sequence of Image Segmentation in each Layer of the Image Processing

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In the proposed CNN-based architecture, 4 convolutional layers are used first. In the first convolution layer, a 10x10 frequency-period filter is used. Similarly, the 2nd layer 9×9 filter, 3rd layer 5×4 filter and 4th layer 4×3 filter, respectively. Batch normalization and smoothed linear units are used for each convolution layer. A layer of dimension 3 is also used for each layer. The main function of the cell is to remember the importance of the time difference, and all three gates control the flow of information into and out of the cell. In this study, four layers are used in a 32-unit mesh. It also creates a link to communicate between layers to process data output between layers.

➤ Weeds Datasets:



Fig 10 Weeds Datasets

Initially, the data were collected by a research team in Australia. They are collected from various regions in northern Australia. They developed two main objectives to ensure the necessary change and generality of the data. First, collect about 1000 images from different types of crops, it will be useful for depression education if CNN needs a large list. Secondly, they are divided into good and bad for each business. It also helps prevent the design from overfitting with scene-level specifications by allowing objects to be recognized by their local background. Finally, the database required experts to examine each of the 900 photographic records to determine whether they contained a particular plant species. The document contains pictures of nine plant species and their populations.

> Working Explanation:

Each image is randomly scaled by $\pm 20\%$, so the range is [0.8,1.2]. Rotational magnification was applied randomly within $\pm 360^{\circ}$, respectively. The color of each image changes by $\pm 20\%$. Rotation magnification is defined by the Boolean horizontal or vertical rotation parameter for image files. Translation magnification means changing all the pixels of an image in a

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single direction, such as horizontally and vertically; so each image is converted to horizontal and vertical rotation [-0.5, 1]. Image brightening is the random lightening, darkening, or both of an image. In this experiment, each image is randomly cropped from 256×226 to 224×224 .

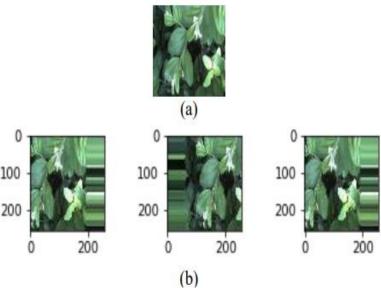


Fig 11 Dataset Training Images (a) Original Training Image, (b) Images which are Generated using Augmentation Scheme

The cost of education plays an important role in education and the focus of deep learning. In these research projects, the researcher's best learning method is used to improve the learning process. If the learning rate is too low, the optimization process needs more time to learn, or if it is too high, the optimizer will outperform or underperform. 5-fold cross validation was used to evaluate the performance of the model. The data were divided into 60%-40% for training and validation, respectively. The model is trained 20 times using each of the five time periods and accuracy is recorded for each training and validation session. Tests were conducted on an HP computer with the following specifications: 16GB of installed memory (RAM), Intel(R) Core[™] i7-4790 CPU @ 3.60GHz processor, and a Windows 64-bit operating system.

Code Explanation for Training (Thonny):

Now that we understand the UI, we have written another small program that uses Thonny. In this section, we'll talk about Thonny features to guide you through our development process.

```
• Write a Code:
```

In the code editor (at the top of the UI), add the following function:

def factorial(num): if num == 1: return 1 else: return num * factorial (num - 1) print(factorial(3))

• Save Code:

Before we go any further, let's save your program. Finally, you will be prompted to do so after pressing the play button. You can do this by clicking the blue diskette icon or by going to the menubar and choosing File > Save. Let's call the program factorial.py.

• Run Code:

Find and click the play icon to run the code.

• Debug Code:

Try these steps to see exactly how this works. Take some big and small steps through the process and see what happens.

Remember, you can do this by clicking the arrow icon:

| factorial.p | y × | | | | Variables | | | |
|---------------------------------|-----------------|--|----------------|--|--------------|--------|--|----------------|
| 1 def | | rial(num): | | | Name | | Value | |
| 2 3 4 5 6 7 8 | r else: r | <pre>m == 1: return 1 return num * fa actorial(3))</pre> | ctor | ial(num – 1) | factorial | | <function factorial<="" th=""><th>at 0x101d117b8</th></function> | at 0x101d117b8 |
| | | | | factorial(3) | | | | |
| | | factorial | | | | | | |
| | | def factorial(if num == return else: <u>return</u> | 1: 1 3 , | <pre>* factorial(2)1</pre> | factorial(2) | | | |
| | _ | | | factorial | | | | |
| Shell | | | | <pre>def factorial(num): if num == 1: return 1 else:</pre> | 1 | | | |
| SyntaxEr | 101. | Local variables | | return num | * factori | al(num | - 1) | |
| ndentatio | on l | Name | Valu | | | | | |
| >>> %Deb | ug f | num | 3 | | | | | |
| 6 | | | _ | | | | | |
| >>> %Deb | ug fac | согдастру | | | | | | |

Fig 12 Demonstration of Saving Code

As we can see, the steps will show you how the computer evaluates each part of the code. Each popup is like a table that the computer uses to describe each part of the code. It would be hard to imagine without this awesome feature - but now we have it!

• Stop Rule:

Until now, there was no need to type the stop symbol for this program, especially since it just popped up right after print(). Try passing a number for 100 to the factorial function:

```
def factorial(num):
```

```
if num == 1:
    return 1
    else:
        return num * factorial(num - 1)
print(factorial(100))
and then descend from the function
```

| factorial.py | x |
|---------------------------------|--|
| 1 def 2 3 4 5 6 7 prim | <pre>factorial(num): if num == 1: return 1 else: return num * factorial(num - 1)</pre> |
| 7 prim | nt(factorial(3)) |
| 8 | |
| | |
| | |
| | |
| | |
| | |
| | |
| Shell AS | |
| Python 3. | 6.6 |
| >>> %cd / >>> %Run | Users/khardson/thonny—article factorial.py |
| 6 | |
| >>> | |
| | |

Fig 13 Stop Rule and Print Function

• Find Syntax Errors in the Code:

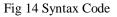
Now that you have a simple program that works, let's break it! By intentionally creating an error in your factorial program, you'll be able to see how Thonny handles these types of issues.

We will be creating what is called a **syntax error**. A <u>syntax error</u> is an error that indicates that your code is syntactically incorrect. In other words, your code does not follow the proper way to write Python. When Python notices the error, it will display a syntax error to complain about your invalid code.

Above the print statement, let's add another print statement that says print ("The factorial of 100 is:"). Now let's go ahead and create syntax errors. In the first print statement, remove the second quotation mark, and in the other remove the second parenthesis.

As you do this, you should see that Thonny will highlight your Syntax Errors. Missing quotations are highlighted in green, and missing parenthesis are in grey:

| 1 | <pre>def factorial(num):</pre> |
|---|---|
| 2 | if num == 1: |
| 3 | return 1 |
| 4 | else: |
| 5 | return num * factorial(num – 1) |
| 6 | |
| 7 | <pre>print("The factorial of 100 is:)</pre> |
| 8 | print(factorial(100) |
| | |



For beginners, this is a great resource that will allow us to help spot any typos while we're writing. Some of the most common and frustrating errors when we start programming are missing quotes and mismatched parentheses.

As we get more comfortable with Thonny, the Assistant can be a useful tool to help us get unstuck!

> Embedded Systems:

An embedded system is a system in which software is embedded in computer hardware, making the system dedicated to various applications or part of an application or product or part of a large system. The Embedded System can be a small standalone system or a large integrated system. It is a micro controller based controller designed to perform specific tasks. Embedded System is a combination of three elements:

• Hardware:

Hardware is physical equipment physically connected to the Embedded System. Microcontroller based connection circuit, power supply, liquid crystal soup, etc.

• Application Software:

Application software allows the user to make various applications that will run on the embedded system by modifying the code in the system.

• *Real Time Operating System (RTOS):*

RTOS monitors how the machine works. It acts as a link between the hardware and software application, monitors the software implementation and keeps the processor running on schedule to control the effect of latency.

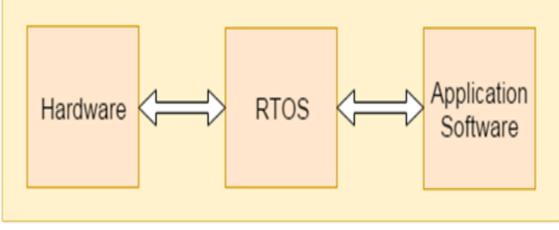


Fig 15 Embedded System Processor

• Designing of an Embedded System:

The basic structure of an embedded system is as shown in below figure.

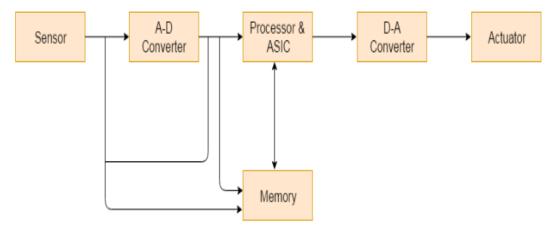


Fig 16 Designing of an Embedded System

✓ Sensor:

Sensor used for sensing the change in environment condition and it generate the electric signal on the basis of change in environment condition. Therefore it is also called as transducers for providing electric input signal on the basis of change in environment condition.

✓ A-D Converter:

An analog-to-digital converter is a device that converts analog electric input signal into its equivalent digital signal for further processing in an embedded system.

✓ Processor & ASICs:

Processor used for processing the signal and data to execute desired set of instructions with high-speed of operation. Application specific integrated circuit (ASIC) is an integrated circuit designed to perform task specific operation inside an embedded system.

✓ D-A Converter:

A digital-to-analog converter is a device that converts digital electric input signal into its equivalent analog signal for further processing in an embedded system.

✓ Actuators:

Actuators is a comparator used for comparing the analog input signal level to desired output signal level for providing the error free output from the system.

• Design Steps for the Development of Embedded System:

Designing steps required for embedded system are different from the design process of another electronic system.

The flow chart represents the design steps required in the development of an embedded system:

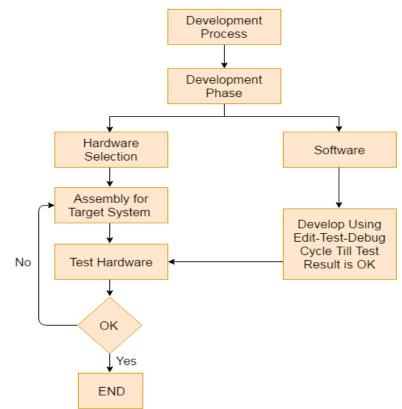


Fig 17 Flow Chart of Development of Embedded System

• Embedded System Processors:

Processors are the major part in embedded systems that take response from sensors in digital form and processing of this response to produce output in real-time processing environment is performed using processors. For an embedded system developer it is essential to have the knowledge of both microprocessors and micro controllers.

✓ Processors Inside a System:

Processors inside a system have two essential units:

• Control Unit:

This unit in processors performed the program flow control operation inside an embedded system. The control unit also acts as a fetching unit for fetching the set of instructions stored inside a memory.

• Execution Unit:

This unit is used for execution the various tasks inside a processors. It mainly comprises of arithmetic and logical unit (ALU) and it also include a circuit that executes the instruction sets used to perform program control operation inside processors.

✓ Types of Processors:

Processors inside an embedded system are of the following categories:

- Application Specific System Processor (ASSP): ASSP is application dependent system processor used for processing signal of embedded system. Therefore for different application performing task a unique set of system processors is required.
- Application Specific Instruction Processor (ASIP): ASIP is application dependent instruction processors. It is used for
 processing the various instruction set inside a combinational circuit of an embedded system.
- General Purpose Processor (GPP): GPP is used for processing signal from input to output by controlling the operation of system bus, address bus and data bus inside an embedded system.

• Embedded System Tools:

✓ Compiler:

Compiler is used for converting the source code from a high-level programming language to a low-level programming language. It converts the code written in high level programming language into assembly or machine code. The main reason for conversion is to develop an executable program.

Let's see the operations performed by compiler are:

- Code Generation
- Code Optimization
- Parsing
- Syntax Direct Translation
- Preprocessing

✓ Decompiler:

A tool used for translating a program from a low-level language to a high-level language is called a decompiler. It is used for conversion of assembly or machine code to high-level programming language.

✓ Assembler:

Assembler is an embedded system tool used for translating a computer instruction written in assembly language into a pattern of bits which is used by the computer processor for performing its basic operations. Assembler creates an object code by translating assembly language instruction into set of mnemonics for representing each low-level machine operation.

✓ Debugging:

Debugging is a tool used for reducing the number of error or bugs inside a computer program or an assembled electronic hardware. Debugging of a compact subsystem is difficult because a small change in one subsystem can create bugs in another system. The debugging used inside embedded system differs in terms of their development time and debugging features.

✓ Simulators:

A simulator is a tool used for simulation of an embedded system. Code tested for microcontroller unit by simulating code on the host computer. Simulator is used for model the behavior of the complete microcontroller in software.

CHAPTER 4 RESULTS AND DISCUSSION

Results:

The plant images used here are degraded by many factors such as low resolution, noise, light changes and many background images. Ultrasonic sensors limit the detection of crops or plants, so they cannot distinguish between obstacles, walls or crops of any type. The robot's wheels can only move forward and backward, which limits the amount of left or right turns that can be made. Remember that crops and herbs are almost identical. Test data was taken as input and fed into training models for plant and crop classification.

Testing Result of 200 images:

Table 1 Distribution of Crops and Weeds used for Training and Result Obtained

| Actual: | 150 crops | 50 weeds |
|-----------|-----------|----------|
| Obtained: | 145 crops | 55 weeds |

The accuracy rate is good enough because the CNN model as a special tool provides better accuracy. Promising Weed Detection Based on Deep Convolutional Neural Networks to Support Automation of Agricultural Processes. This study demonstrates the potential of using the DCNN model to describe vegetation in agricultural areas. In this study, deep learning method was used to detect the plants in the agricultural field. Our models outperform other models in terms of precision, accuracy and recall.

In order to capture rich and quality data, we have developed a computer vision system that can make factory searches independently of other hardware and software and can easily communicate with other hardware devices. A computer vision system consists of a standard camera viewfinder, a camera-compatible lens (provides a field of view of approximately 1m x 1m), and supplied equipment. It can be used for information storage and plant research. The camera lens has been chosen to provide a uniform view of the spray area in the two nozzles. The sight can be installed on vehicles used for weed control by spraying pesticides. For knowledge acquisition, we established this vision of quadricycle.

• Datasets:

The database for crops and plants contains images with a total of 396 images. The plant data includes 99 reference images and 33 test images. Weeds dataset also includes 99 reference images and 33 test images. A third list of was also used, which included unrelated items that were not plants or weeds. This file is still and contains 99 reference images and 33 test images. To improve the accuracy of classification in , all photographs were taken at different times and conditions of the day.

• Illumination Effect:

Illumination affects the segmentation process, which in turn affects feature extraction, which ultimately leads to misclassification. To reduce the effects of illumination, a large number of images were taken under different illumination conditions and various experiments were carried out to set the best segmentation thres hold. Segmentation results of proposed models based on environmental variables.

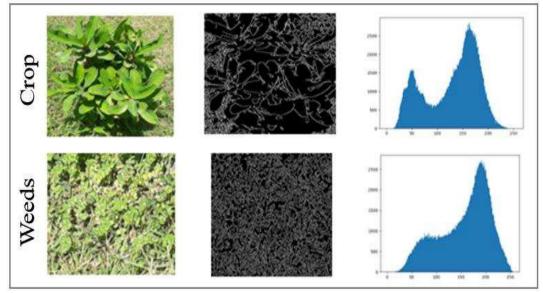


Fig 18 Edge Orientation Feature of Crop and Weed

Due to motion during the capture of the image, the blur in the image affects the segmentation process and the result affects the classification process. Therefore, , it is necessary to know the effect of blurring on the segmentation operation. Different attempts have been made to detect blur by introducing the blanking seen in the picture due to camera movement.

Bad lighting, different scenes, and poor visibility can introduce noise into the image and affect the segmentation process. In this study, the variance of the Gaussian noise is introduced to evaluate the performance of the segmentation process. Show different levels of noise in an image, run different tests and see the performance of segmentation.

• Contouring:

In the last step, we draw the model of the area with the plants we want where we want to spray a certain part of. For this, we use the Contour method to determine the field area of the plant. and divide that area into sprays.

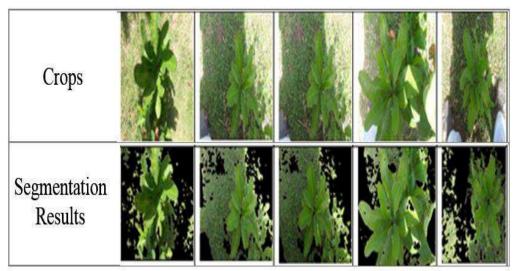


Fig 19 Crop Images and their Segmentation Results

Monitoring machine learning worked well on many computer vision systems. Random Forest Classifier is an efficient method for solving classification and retrieval problems. Execution time shows the probability of real-time computer vision algorithms based on the calculation of values.

| Table 2 Execution Time of different Featu | res |
|---|-----|
|---|-----|

| Processing Module | Execution Time (per Image) | | |
|-------------------|----------------------------|--|--|
| Segmentation | 3.9ms | | |
| EOH | 5.9ms | | |
| Hu Moments | 0.9ms 36.9ms | | |
| Haralick Textures | | | |
| Color Histogram | 1.9ms | | |
| Classification | 7.9ms | | |
| Total Time | 57.4ms (@17.4 FPS) | | |

From the Table, it can be concluded that the proposed algorithm has good time performance. The Haralick feature needs calculations as it needs 38.9 milliseconds. The EOH module runs faster than the Haralick function and takes 5.9 milliseconds. The image analysis module takes 0.9 ms and the color histogram takes 1 second.9 milliseconds. Classification took 7.9 ms and segmentation processes were completed in 3.9 ms. In total, the whole algorithm uses 57. It is done in 4ms and at 17.4 frames per second.

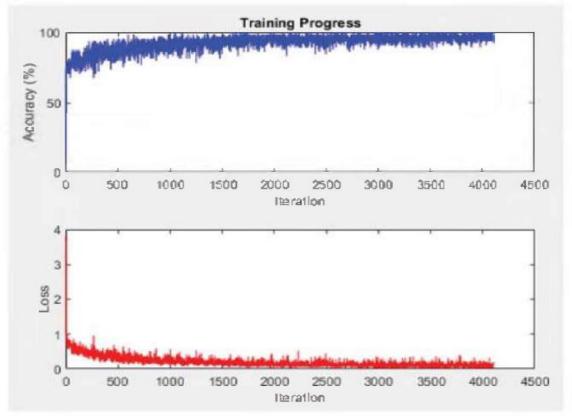


Fig 20 Network Accuracy Measurement in the Training Process

Using the hyperparameter method and comparing the results to CNNs: Batch Spool[^], Base Learning Rate: 0.03, Batch Size: 2, Learning Rate Policy: Exponential Data Gamma: 0.95, Solver Type: Ada delta, 30 By training period: 44 Validation and evaluation of all CNNs, including negative accuracy, are arranged in a binary confusion matrix. The results show that the actual values correctly mapped of the input images to the targets. The truth is not good, the price is great to bring the Haitong crop. The good result is not represented by any of the plant images that are not identified as plants and crops or harmful chemicals.

CHAPTER 5 CONCLUSION

We are trying to create robots that can do things like study plants. Along with the image processing facility, it also provides automatic control of the robotic arm. The main component here is the Raspberry Pi microcontroller, which takes care of the whole process. Initially, the robot reaches all the fields, then the plants are found and cut. For robot control, the robot uses ultrasonic sensors to control the equipment and help the robot navigate the field. It controls these levels using a humidity sensor and informs the farmer. The alarm mechanism is a buzzer module that makes a sound to detect plants. Weed detection has become an important part of agricultural research because plants tend to absorb large amounts of nutrients and water from the crop itself. This has led to a lot of research on plants, from manual to optical. Our edge detection model uses image data to identify plants in crop fields.

Various CNN architectures were explored to obtain the facility. Network performance is judged by three factors: memory usage, latency, and accuracy. The 5-layer CNN architecture was selected from our private network for distribution. This model gave the best results, with the highest accuracy of 97.7% and the lowest latency and memory usage of 1.78 GB and 22 respectively.245 milliseconds respectively. These three network architectures are transmitted to the Raspberry Pi microcontroller to provide the experience. According to this approach, private network with maximum provides powerful metrics of edge equipment, improve facility to see good performance. We are interested in doing some custom engineering on the leaf itself in the future. This will contain various parameters such as shape, color and texture from each segment. A texture provides precise information about the spatial distribution of colors and the level of adjacent pixels in an image. It is caused by the repetitive pattern of local changes in the reference of images. So each explosion can represent its own unique beauty before it gets on the CNN network. An important example of texture representation is GLCM (Gray Level Co-occurrence Matrix, which generates a feature matrix with maximum correlation features (entropy), homogeneity, contrast, etc.). In addition to feature engineering, they will include a quadcopter link and real-time model to render on our Raspberry Pi. Also, add sensors and ensure there is feedback between the microcontroller and the sensors about the health of the crop and water. Research the custom design for the deep learning model is considered the future direction of this research project.

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