Automated Computer Vision based Weed Removal Bot

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Abstract— **Weeds are a dangerous factor for a good yield of crops. The conventional method of removing weeds was either plucking manually or spraying herbicides uniformly all over the field. Spraying herbicides not only contaminates crops but also gives rise to many health-related issues. The purpose of the paper is to develop a mobile model that can detect weeds in real- time with their position coordinates and scrape them off. The model first scans the specific area for leaf detection and classifies it as weed or crop with a prediction accuracy of 99.5%. If the classified leaf is a weed, the coordinates are found and the robotic arm removes them with the help of a high-speed rotating blade, without harming the crops and environment. The left outs can further be utilized as fertilizer and no harmful chemicals have been used.**

***Keywords*—Weed Removal, Image Processing, Smart weeding, Mask RCNN, VGG 16, Smart Agriculture, Delta Robot**

I. Introduction

India's economy is dependent on Agriculture for more than 70%. The source of income for more than half of the population is directly related to the yield obtained in the fields. Farmers working in the field face many challenges in the whole period of crop generation, among which weeds are one of the major threats to the natural environment. They are destroying native habitats and the desired crop which leads to poor production of crops and raised economic challenges. It's a major need for farmers to remove weeds from the crop field to have a better crop production but in a more efficient manner.

As mentioned, one of the major issues in agriculture is the control of weeds growing among the plantation crops. Weed tends to snatch space, nutrients, sunlight, water, and hardly get affected by changing the natural environment. Moreover, the extreme conditions of the environment help them, even more, to sustain as it affects native crops easily. At present, these kinds of plants are being removed manually, wherever possible, or weedicides are being sprayed uniformly all over the field to keep them under check. In conventional weed control systems, herbicides are sprayed uniformly all over the field. This technique is very inefficient as only about 20% of the spray reaches the plant and less than 1% of the chemical contributes to weed control, leading to wastage, contamination of the environment, and health problems in people [1]. To avoid these consequences, an effective weed control system should be employed. These systems must be capable of locating weeds in the field and remove them. The left-outs are eventually decomposed and can serve as fertilizer.

As the major goal of Sustainable Farming is to increase the yield-reducing its reliance on pesticides, herbicides, and to control the growth of the weed. Precision farming techniques are required to address this challenge with many researchers working on this with their vision to create an effective solution. With the development of AgriBot to perform the various agriculture activities are communicated using Wi-Fi technology [2]. Researchers have developed a weed detection and classification method for weed control robots in cornfields with a computer vision algorithm to classify plants like weeds or crops with their properties [3]. An Autonomous Robotic System for Mapping Weeds in Fields [4], is used to identify by aerial image analysis of areas with high bio-mass density, thus indicating areas with weed infestations. It also sparks an idea to identify weeds based on spectral analysis. Visual odometry System is used for weed detection by capturing images with the help of mobile robots [5]. An effective classification system of plants and weeds [6], aims to focus on a vision-based perception system to identify the value and distinguish it from the weed plants. Traditional methods such as Plant identification using leaf images [7] extract features and classify based on geometrical parameters extracted by digital image processing. A self-supervised training method in the context of RGB imaging provides an apt framework for hyperspectral crop/ weed discrimination with prior knowledge of seeding patterns [8]. Besides, much research on autonomous vision systems using features like color, texture, and shape analyzed with different algorithms and techniques such as crop row detection by principal component analysis [9]. Currently, manual weeding is a tedious task to perform mechanical weed control is considered for automation achieved by field robot BoniRob [10] with a very high-speed vision-based weed control and development of a low-cost delta robot [11] for the weed control in organic farms. Advanced robots like Oz weeding robot, which helps during weeding and hoeing chores to increase farm profitability while respecting the environment

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[12], are contributing enormously for better productivity. A lot of models have already been generated in the market as a product, like ecoRobotix which is an autonomous weeding robot for row crops, meadows, and intercropping cultures which detect and selectively spray the weeds with a microdose of herbicide [13]. Consequently, a vast variety of autonomous weed control systems are available and are being developed to address the challenges.

The first step involves image segmentation which separates the plant area from background pixels and classifies the leaf as weed or crop. Spraying herbicide uniformly leads to contamination of crops as well as wastage of costly chemicals. Patch spraying can help in saving chemicals but it's again a disadvantage for the environment. Excessive use of chemicals leads to health problems, affected lungs, skin problems, etc. Instead, removal or uprooting of weed can be a better solution. A mobile system that could make use of the real-time data to find the coordinates of leaf position with computer vision and help in the removal of weeds using the robotic arm would be much more efficient and minimize environmental damage.

II. METHODOLOGY

The proposed system removes the weed in three major steps. Fig. 1 shows the process flow of the system. First, an image is captured employing a Raspberry Pi camera, that is mounted facing downwards, i.e., towards the ground. The image is passed to Raspberry Pi with the assistance of Camera Serial Interface (CSI). With the help of the RGB image obtained from the camera, the leaf is assessed as weed or crop using a set of geometrical parameters. If the identified leaf is a weed, then a delta robotic arm with a high-speed rotating blade as the end-effector reaches the leaf coordinates and cuts the leaf. If the identified leaf is a crop and not a weed, then the robot moves forward and captures another image, such that the antecedent captured space isn't captured once more.

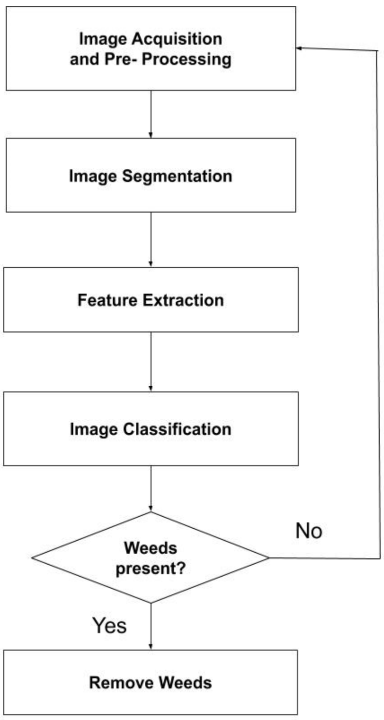

Fig 1 Process Flow

III. WEED IDENTIFICATION

A. Image Acquisition and Pre-processing:

The image captured from the raspberry pi camera is rescaled to the image size on which the algorithm is trained. The image is then filtered using low and medium pass filters to remove noise. Gaussian blur, with a kernel size of 5*5, is applied to the filtered image. All these steps help us get a clear image of the leaf, which results in a more accurate prediction.

B. Image Segmentation:

Image Segmentation is the process of partitioning a digital image into multiple segments. The pre-processed image contains a lot of background details that are not required by the algorithm and has to be removed. To provide better input to the next automated image processing technique we need to extract the leaf pixels from the image and discard others. We extract our region of interest (ROI) using semantic segmentation. Mask Region Convolutional Neural Network (Mask RCNN) [14] has been proven to outperform other semantic segmentation algorithms, and hence Mask RCNN neural network is used to extract the leaf region from the preprocessed image. Fig. 2 explains the architecture of the Mask RCNN neural network. ResNet 101 architecture is used as the backbone model for Mask RCNN and features extracted are passed to a Region Proposal Network. The ROI obtained the network computes Intersection over Union (IoU) to filter weak predictions. And finally, we add a mask branch which returns the region mask for all the detected objects. The segmented image mask is fed for image classification, hence processing one leaf at a time will overcome the problem of multiple leaves in a single frame.

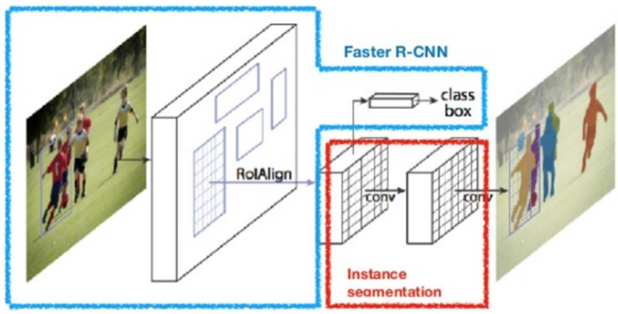

Fig 2 Mask RCNN Architecture

C. Feature Extraction:

Feature extraction is employed to extract relevant features for the recognition of plant leaves. The redundancy is far away from the image and therefore the leaf images are represented by a set of numerical features. They are calculated after the image pre-processing. The subsequent features are derived from the geometric parameters. The subsequent ratios are extracted and computed from the leaf image [15].

1. Rectangularity - It is the ratio of the product of major and minor axis of the ROI to the area of the ROI.

$$\text{Rectangularity} = \frac{Length*Width}{Area}$$

2. Narrow Factor - It is the ratio of the product of twice the radius of the leaf to the major axis.

$$\text{Narrow Factor} = \frac{Diameter}{Length}$$

3. Perimeter to Diameter Ratio - It is the ratio of the perimeter of the ROI to the diameter.

$$\text{Perimeter to Diameter Ratio} = \frac{Perimeter}{Diameter}$$

4. Form Factor - It is the ratio of 4 times the product of PI and area of the ROI to the square of perimeter of the ROI.

$$\text{Form Factor} = \frac{4 * \pi * Area}{Perimeter^2}$$

5. Eccentricity - It is the ratio of the foci of the ellipse to the major axis length of the ROI.

$$\text{Eccentricity} = \frac{Foci}{Length\ of\ Major\ Axis}$$

6. Aspect Ratio - It is the ratio of the major axis to the minor axis of the ROI.

$$\text{Aspect Ratio} = \frac{Length}{Width}$$

7. Perimeter to length and Breadth Ratio - It is the ratio of the perimeter of the ROI to the sum of length and breadth of the ROI.

$$\text{Perimeter to Length and Breadth} = \frac{Perimeter}{Length+Breadth}$$

D. *Image Classification:*

The feature values were calculated and passed to a classification algorithm, to make the prediction. Many algorithms were used to precisely predict the class of the leaf. If the algorithm found a similarity between leaf and the features of images in defined classes of weed, the model classified leaf as weed or else trained model for the detected leaf. The algorithm used includes k Nearest Neigbhors (kNN) with K value as 1, Support Vector Machine (SVM) with radial basis function kernel, Random Forest with 150 trees in the forest, and Decision Tree with a maximum depth of 7. The test set is 20% of the dataset. In the second approach, we use a Convolutional Neural Network (CNN). We use VGG16 architecture, which has 16 layers that have weights and approximately 138 million parameters [16] shown in Fig. 4.

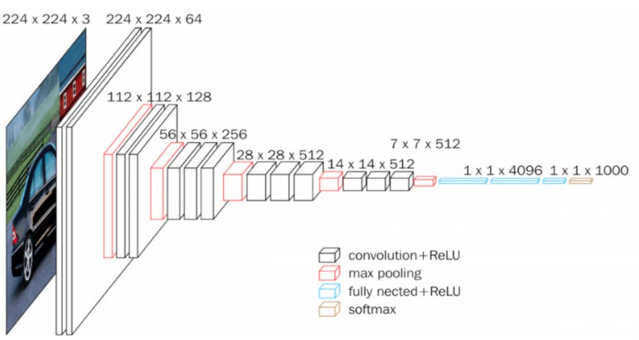

Fig 3 VGG 16 Architecture

We train the model with 100 epochs. initial learning of 0.001 and batch size of 32 images. We directly pass the segmented image to the network for classification. Both approaches were tried on a dataset with 31 different species of leaves, having approximately 60 images per class [17].

IV. HARDWARE

The robot hardware includes a raspberry pi board as the brain, a delta arm that cuts the weed and land moving robot which helps in traversing the field. Both the delta arm and the land robot are controlled by the raspberry pi. Fig. 4 shows the CAED model of the robot.

Fig 4 Top: CAED Model of the robot;
Bottom: Fabricated Model

A. *Delta Arm:*

Delta arm is used to move the blade in the 3D world. The end-effector of the arm has a high-speed brushless motor that powers the blade. The blade rotates at high speed and cuts the weed plants. Fig. 5 shows the delta structure.

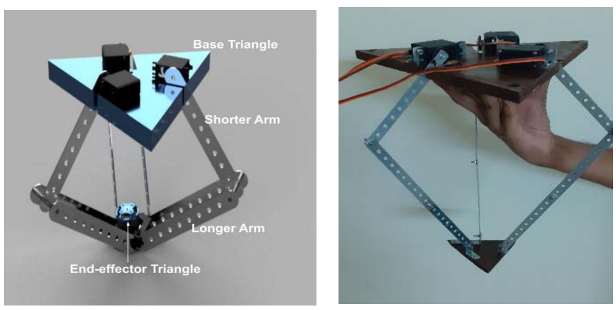

Fig 5 Structure of Delta Arm

Table 1 Dimensions of Delta Arm

Component	Dimension (cm)
Base Equilateral Triangle (s_B)	29
End Effort Equilateral Triangle (s_P)	10
Bicep / Shorter Arm (L)	14
Forearm/ Longer Arm (l)	28

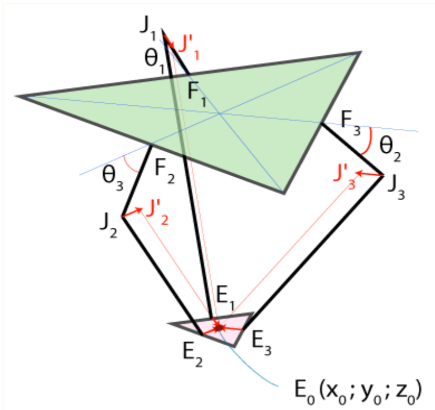

Fig 6 Kinematic Labeling

The angle of joint i to place the end effector at the desired location [18], is given by

$$\theta_i = 2\tan^{-1}(t_i)$$

where, i = 1, 2 & 3

and $t_i = \frac{-F_i \pm \sqrt{{E_i}^2 + {F_i}^2 - {G_i}^2}}{G_i - E_i}$

where,

$E_1 = 2L(y + a)$

$F_1 = 2zL$

$G_1 = x^2 + y^2 + z^2 + a^2 + L^2 + 2ya - l^2$

$E_2 = -L(\sqrt{3}(x + b) + y + c)$

$F_2 = 2zL$

$G_2 = x^2 + y^2 + z^2 + b^2 + c^2 + L^2 + 2(xb + yc) - l^2$

$E_3 = -L(\sqrt{3}(x - b) - y - c)$

$F_3 = 2zL$

$G_3 = x^2 + y^2 + z^2 + b^2 + c^2 + L^2 + 2(-xb + yc) - l^2$

where,

x, y, z are the coordinates of the destination point

and,

$a = w_B - u_P$

$b = \frac{s_P}{2} - \frac{\sqrt{3}}{2}w_B$

$c = w_P - \frac{1}{2}w_B$

where, $w_B = \frac{\sqrt{3}}{6}s_B$

$u_B = \frac{\sqrt{3}}{3}s_B$

$w_P = \frac{\sqrt{3}}{6}s_P$

$u_P = \frac{\sqrt{3}}{3}s_P$

B. Land Moving Robot:

The land moving robot has 3 legs. The middle leg moves between the two target crop rows, and the other 2 legs move on the sides of target rows, hence the robot covers two crop lanes at a time. The robot is powered by a hybrid mechanism in which a 12Ah Sealed Lead Acid Battery, with an output of 12V supplies the required power, and a solar panel of power 50W with 12V output continuously charges the battery. A camera is mounted facing downwards, under the chassis so that the lighting conditions are almost constant.

V. RESULTS

The image was segmented from the background, and the leaf species was classified. If the classified leaf belonged to the weed family it was removed by the robot using a highspeed rotating blade. Fig. 6 shows the output of the pre-processing and segmentation step.

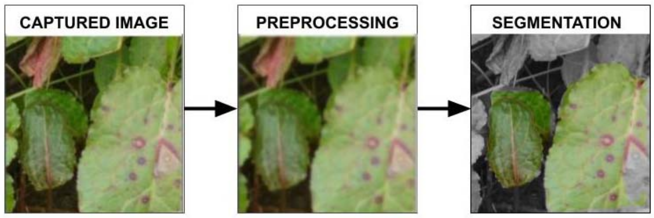

Fig 6 Stages of Weed Identification

In this model, we are using accuracy to measure how close is the data to the true value, precision i.e., how close two or more measurements are to each other and Root Mean Square Error (RMSE)[19] which is a standard way to measure the error of a model in predicting quantitative data. Formally it is defined as follows

$$\text{RMSE} = \sqrt{\sum \frac{(y`_i - y_i)^2}{n}}$$

Where, $y`_1, y`_2 \ldots y`_b$ are predicted values
$y_1, y_2 \ldots y_n$ are observed values
n is the number of observations

Table. 2 shows the classification accuracy using different algorithms.

Table 2 Classification Accuracy

Algorithm	Accuracy	Precision	RMSE
kNN (k = 1)	0.844	0.852	1.390
SVM	0.777	0.710	1.906
Decision Tree	0.788	0.795	1.453
Random Forest	0.900	0.916	1.337
CNN (VGG 16)	0.995	-	-

Clearly, Convolutional Neural Network (VGG16) outperforms other algorithms and predicts with 99.5% accuracy, and hence we use VGG16 architecture to classify leaf species. Fig. 7 shows training and validation loss vs epochs plot for Mask RCNN and training and validation accuracyvs epochs plot for the VGG16 CNN.

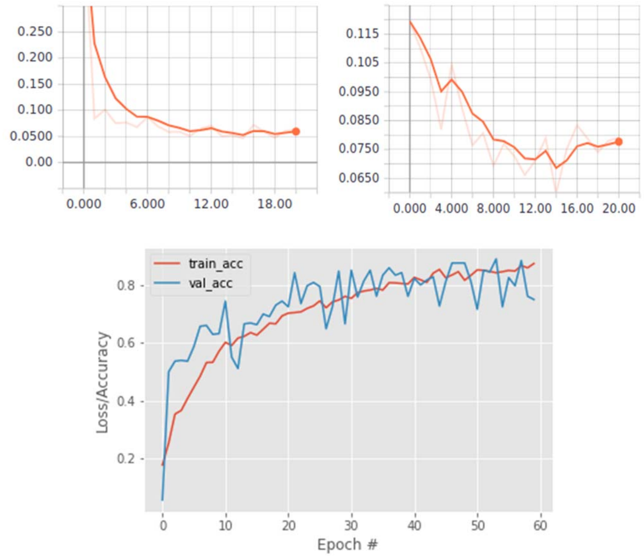

Fig 7 Upper Left: Train Loss Mask RCNN Upper Right: Validation Loss Mask RCNN Bottom: Training and Validation Accuracy VGG16

VI. CONCLUSION

An algorithm for automation of weed removal task was done successfully and the prototype of the model for automatic leaf detection as weed or crop was successfully designed. The method used to identify the correct leaf species resulted in a correct identification rate above 99.5%, which is better than most of the previous works' results. Mask RCNN neural network has significantly improved the segmentation results and directly contributed to better classification accuracy. Our approach uses a high-speed rotating blade to remove the weeds, which eliminates the usage of weedicides and other chemicals, which wasn't ensured in any of the earlier systems. Hence, with low cost and avoiding harmful chemical substances, it is efficient to use a mobile and compact system with a robotic arm cutter with high precision and easy operation.

The system gives good results but has a lot of scope for improvement. A more robust algorithm can be developed for plant identification which can recognize more species of leaves irrespective of their color and shape. The design can be further optimized to suit the needs of farmers and provide maximum area coverage at the same time. The control mechanism for the delta arm can be made more precise and hence improving its precision.

The other aspects of Autonomous robot are:

1. It can be used in the detection of the Drug (Narcotic) leaves among the crops and removal of the same.
2. It can be used in the detection of leaf diseases caused by the plant.
3. It can be used to detect and study rare plants and their variations.
4. It can be used in the soil analysis with required modification in the software and hardware design.
5. The robot can also be used in the plant seeding and plowing with necessary modifications.

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