

A Novel approach for Weed Identification and Classification in Vegetable Plantation

A Venkata Srinivasa Rao¹, M Harshini², V Puneeth³, G Padmasri⁴, K G NagaPriya⁵

¹ Department of ECE, Sasi Institute of Technology & Engineering, Tadepalligudem, W.G. Dist, India.
adabalala@gmail.com

^{2,3,4,5}UG Student, Department of ECE, Sasi Institute of Technology & Engineering, Tadepalligudem, W.G. Dist, India

Abstract - One of the key aspects of agriculture that affects crop productivity is weed. Since traditional weed management methods entail burning, pesticides, manual removal, crop loss, and reduced soil fertility, they also involve the use of trowels. This study suggests a technique to lessen the impact of weeds on agriculture by fusing deep learning with image processing. In order to recognise weeds in agricultural settings, centerNet models and Regional-based Convolutional Neural Networks (RCNN) are used. In contrast to the two-stage RCNN technique, which is utilised for both detection and classification, the Center Net model is a one-stage object detector.

Key Words: Binarization, Complementary of the image, Image documentation, Threshold, local method

1. INTRODUCTION

In India, where basic agricultural activities are the majority of peoples' occupation. More than half of the population of India is involved in Agriculture and related activities. Weeds contribute to our country's declining economy and create severe yield losses in the food producing industry. A plant that grows where it is not wanted is called a weed. A weed is a plant that grows where it is undesirable and another plant ought to grow because it is unattractive, useless, and harmful. A plant that has more potential for damage than for good is also considered a weed. All weeds are undesirable plants, yet not all undesirable plants are necessarily weeds. Due to the uneven spacing of the plants, weed identification in vegetable plantations is more difficult than weed identification in crops. To boost crop productivity and decrease weed-related economic loss every farmer should practise weeding. One of the most crucial practises in many crops is weeding. Weeds compete with main crops for resources like water, sunlight, soil nutrients, and space, so weeding is important. Vegetable yield is decreased by weeds, but their quality is also decreased. So weeds has an impact on the growth of vegetables. In addition to lowering vegetable yield, weeds can lower their quality, which has an impact on their growth. There are many traditional methods of weed control like Herbicides, Transplants, mulching, hand removal, flaming etc but those techniques have many disadvantages. Some of them are listed below:

Disadvantages of Traditional methods of Weeding:

(i) Herbicides

- Herbicides promote to pollution of the air, water, and soil. It may poison the soil, and subsequent pollution of the waterways will result from the chemicals being spread by precipitation to other locations.
- The majority of herbicides are toxic. Because they have a larger quantity of acetic acid, which can seriously harm the eyes and skin, even organic herbicides have hazards.
- Herbicides have a negative impact on people's health, including farmers, gardeners, and even consumers of food cultivated with them.

(ii) Hand removal

- Heavy work and stress on the labour force
- Difficult if the soil surface is not moist and loose
- Expensive (if wages are high)
- Difficult to recognise and eradicate some grassy weeds in their early stages (e.g. weedy rice, Echinochloa spp.). Such weeds must be eliminated from the field when they are in bloom. If pulled and thrown into standing water, weeds might live.

(iii) Transplanting

- High labour costs
- Takes high time for recovery after transplanting,
- plants develop more slowly than when they are grown directly from seed. Harvesting is also delayed.

(iv) Mulching

- Years of heavy mulching may cause soil to accumulate over the crown area of plants.
- One disadvantage of extensive mulching may be the price of some materials.

- Certain mulch types are also hard to get by. When woodchips and sawdust are used as mulch, nitrogen famine can occasionally happen.

(v)Flaming

- Tree trunks and leaves that are dead or brown surrounding target weed might catch fire.
- Your feet could get caught in the crossfire, or if curious kids or beloved pets approach too close, a medical issue could happen.

Xiaojun Jin et al. [1] devised a method to identify weeds in vegetable farms using deep learning and image processing. The representation of the algorithm consisted of two phases. A CenterNet model was trained to recognise vegetables. Thus, the remaining green objects that were visible in the colour image were classified as weeds. To distinguish weeds from the background, a colour index was created and evaluated using genetic algorithms (GAs) in line with Bayesian classification error.

Faisal Ahmed et al.[2] used support vector machine to implement a model for classifying crops and weeds in chilli crops using digital images and evaluated its performance in an automated weed control system. To form the feature vector, the proposed model employs a combination of size and rotation invariant shape, colour, and moment features.

Muhammad Hamza Asad et al.[3] implemented a two-step manual labelling process in data processing and high resolution RGB images of canola fields at two different growth stages of crops using a quad mounted camera, as well as weed detection and mapping in canola fields using Semantic segmentation. A Semantic segmentation consists of two main blocks, one for encoding and the other for decoding. Encoding is a downsampling block that extracts features out of images whereas decoding block is used for sample feature space to image dimensions.

Husrev Mennan et al.[4] developed cover crops in response to weed herbicide resistance and a strong desire for organic vegetable cultivation. Even though there are several alternatives to using herbicides, cover crops are the better choice for weed control. Cover crops such as cereals, legumes, and brassicaceae are widely used in a variety of cropping systems. A cover crop's mechanism of action has been assumed to be competition and allelopathy. A cover crop with a high biomass production rate is more likely to have a good physical effect on weeds, resulting in effective weed suppression. Cover crops' early-season total biomass accumulation reduces the risk of weed emergence.

Kavir Osorio et al. [5] presented three methods for weed estimations . These methods included Mask R-CNN for instance segmentation of each individual, You only look once

(YOLOV3) for object detection, and Support vector machine (SVM) using histograms of Oriented gradients (HOG) as feature descriptors. SVMs are mathematical models whose main goal is to identify the best line that separates two distinct classes. In order to determine the shape of a plant with a well defined geometry, HOG was used to extract the feature in each image object based on the magnitude and orientation of the gradient from a particular set of pixel boxes.

Rohit Vad [6] utilised the ANN model, the CNN model, and a Logistic Regression model on crop and weed photographs to successfully identify and classify weeds in soyabean crops. For classification, a logistic regression model with hyperparameter tuning and an SGD classifier are employed, while ANN, CNN, and tasks involving data processing are used for feature extraction, image recognition, and other tasks.

Srinivasa Rao Madala et al. [7] employed sophisticated feature selection algorithms including the GABOR filter and deep learning techniques like CNN. A trained algorithm was used on the datasets to create the border boxes overlay across the vegetable and weed leaves. Using sophisticated detecting techniques, the remaining area that was outside of the overlay boundary boxes will be recognised as weed. With this strategy, the algorithm focuses just on detecting vegetables, avoiding controlling a variety of weed types. A segmentation technique based on the colour index was used to eliminate weeds from the backdrop.

Pedrao Jarvier Herrera et al.[8] published a method for separating monocot and dicot weeds . A Color-index based segmentation, morphological operations, well-known shape descriptors and classifiers, and a number of fundamental image processing operations surpass the SVM, CFI, SFI, and DES combined decision-making approaches. When the weeds are still in the early stages of development, this strategy works well. A greenness measure was created to distinguish between vegetation and non-vegetation, and adjectives that successfully characterise regions were chosen to discriminate between weed species.

Evan Shelhamer et al. [9] suggested fully convolutional networks as a varied family of models that perform a variety of pixelwise tasks. FCNs for semantic segmentation significantly improve accuracy through the transfer of pre-trained classifier weights, the combining of various layer representations, and end-to-end learning on entire images. End-to-end, pixel-to-pixel action simultaneously makes learning and inference easier and faster.

According to Azam Karami et al. [10], plant location and counting are crucial for both production agriculture and plant breeding experiments. In contrast to location, which offers details on the related diversity within a plot or geographic region of a field, stand count reflects the general

emergence of plants relative to the quantity of seeds that were planted. Recent advances in available hardware enable deep learning approaches to increase accuracy, speed and reliability. A Few-shot learning(FSL) using Center Net model is used for detection of maize plant centre locations and counting.

There are four sections to the paper. The first section provided a brief overview of the introduction, literature review, and problem definition. The second section discussed the algorithm for cleaning the noisy documents. The third section discussed the experimental results. Section four discusses the findings and the scope of future work.

2. METHODOLOGY

We present (Fig-1) a technique for Object detection, is the process of finding and classifying objects in an image. One deep learning approach, regions with convolutional neural networks (R-CNN), combines rectangular region proposals with convolutional neural network features. R-CNN is a two-stage detection algorithm. The first stage identifies a subset of regions in an image that might contain an object. The second stage classifies the object in each region.

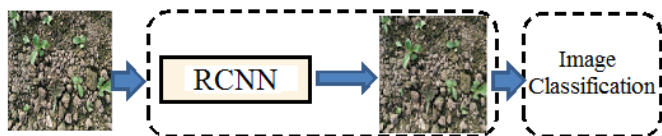


Fig.1 Block diagram of the proposed model

When a RCNN model is applied to dataset to train the model.

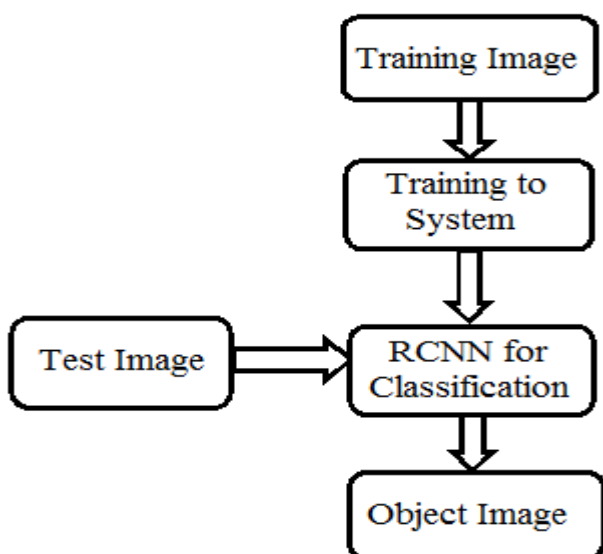


Fig.2 Flowchart of Proposed method

Step-I A System is trained with a set of training images.

Step-II A Testing image is selected from the set of training images.

Step-III An RCNN algorithm is applied to the testing image.

Step-IV An object image occurs as an output after classification.

A result of this action, the noise in the image's background is removed..

3. RESULTS AND DISCUSSIONS

The proposed approach was examined using a variety of samples collected from the NET. We trained our system with a dataset consisting of 300 images. After training the system with the training images a random image is given as an input. The input image is pre-processed using Binarization techniques. The RCNN algorithm we trained classifies whether the given input image is Background /Crop /Weed as follows:

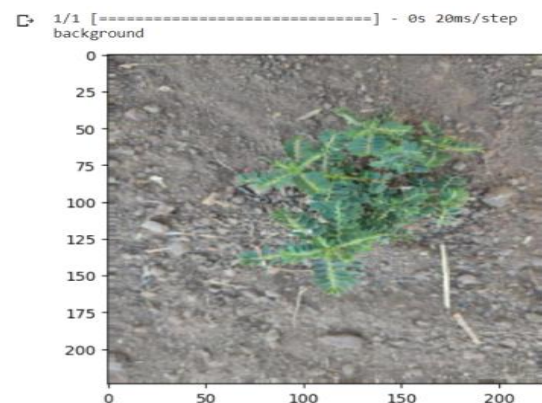


Fig.3 (a) Image identified as back ground after testing

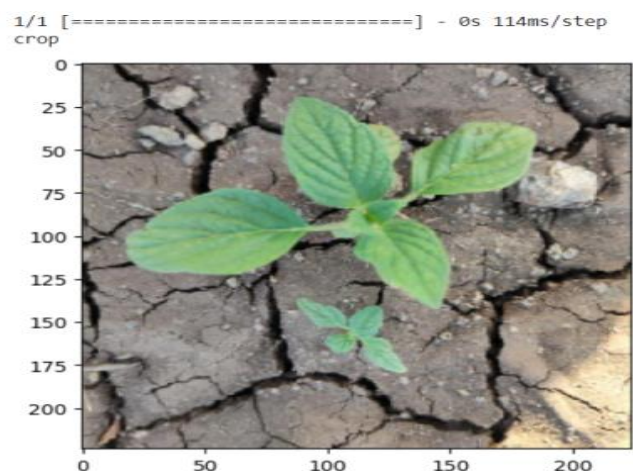


Fig (b) Image identified as Crop after testing

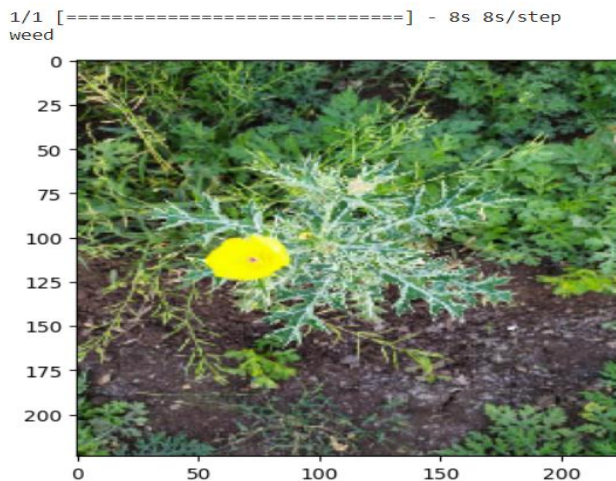


Fig (c) Image identified as Weed after testing

4. CONCLUSIONS

Since Weeding plays a major role in the agriculture, the main Objective of modern Weed identification is to increase the Crop production , Economy of our country and to overcome the loss of crop caused by traditional method of weeding like herbicides, burning, trowels etc.

5. FUTURE SCOPE OF THE WORK

The procedure described above could be extended to noise-free samples that are manually contaminated with various noises at various levels, such as pepper, Gaussian noise, and so on. The noisy documents are then cleaned using a defined algorithm and other methods, and quantitative metrics for identifying information loss during the cleaning process are established.

REFERENCES

[1] Xiaojun Jin , Jun Che and Yong Chen, "Weed Identification Using Deep Learning and Image Processing in Vegetable Plantation", Digital Object Identifier 10.1109/ACCESS.2021.3050296

[2] F. Ahmed, H. A. Al-Mamun, A. S. M. H. Bari, E. Hossain, and P. Kwan, "Classification of crops and weeds from digital images: A support vector machine approach," Crop Protection, vol. 40, pp. 98–104, Oct. 2012.

[3] M. H. Asad and A. Bais, "Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network," Inf. Process. Agricult., vol. 7, no. 4, pp. 535–545, Dec. 2020.

[4] H. Mennan, K. Jabran, B. H. Zandstra, and F. Pala, "Non-chemical weed management in vegetables by using cover crops: A review," Agronomy, vol. 10, no. 2, p. 257, Feb. 2020.

[5] K. Osorio, A. Puerto, C. Pedraza, D. Jamaica, and L. Rodríguez, "A deep learning approach for weed detection in lettuce crops using multispectral images," Agri Engineering, vol. 2, no. 3, pp. 471–488, Aug. 2020.

[6] Rohit Vad, "Weed Detection in Soyabean Crops using Regression Analysis and Deep Learning",

[7] M.SrinivasaRao, "An Advanced Weed Detection Using Deep Learning techniques", Nat. Volatiles & Essent. Oils, Vol.8(6), pp.1273-1280

[8] P. Herrera, J. Dorado, and Á. Ribeiro, "A novel approach for weed type classification based on shape descriptors and a fuzzy decision-making method," Sensors, vol. 14, no. 8, pp. 15304–15324, Aug. 2014.

[9] Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2015, pp. 3431–3440, doi: 10.1109/CVPR. 2015.7298965.

[10] Karami, M. Crawford, and E. J. Delp, "Automatic plant counting and location based on a few-shot learning technique," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 13, pp. 5872–5886, 2020.