WeedOut: An Autonomous Weed Sprayer in Smart Agriculture Framework using Semi-Supervised Non-CNN Annotation

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Abstract. With rising challenges and depleting resources, many automation solutions have been developed in agriculture. Integration of Internet-of-Agro-Things (IoAT) and Artificial Intelligence (AI) helped gain better yields while maximizing utilization of minimal resources. Weed management being a task affecting quality and yield of crop attracted attention of automation. However, due to the diverse nature of agriculture, same crop from various geographical locations in different growth stages exhibit different features. Additionally, unknown weeds might also exist in the farm rendering feature based supervised CNN solutions not suitable for weed classification. The current paper presents a weed management Agriculture Cyber-Physical System (A-CPS) called WeedOut with a novel methodology enabling it to work in feature variant environments. WeedOut uses a Semi-Supervised methodology that classifies crops by their shapes and labels them as primary crop and weed crop with minimal inputs from farmer. An autonomous weed sprayer uses outputted labeled images to spray herbicide at weed locations and save primary crop.

Keywords: Smart Agriculture; Agriculture Cyber-Physical System (A-CPS); Internet-of-Agro-Things (IoAT); Artificial Intelligence; Computer Vision; Semi-Supervised Learning; Weed Pressure; Weed management.

1 Introduction

Agriculture is the primary source of food for all the human beings across the world. Various factors like rapid growth in human population, reduction of farmland, depletion of natural resources and advances in Internet-of-Agro-Things (IoAT) [1] paved path to new paradigm in agriculture named "Smart Agriculture" [2] to automate agriculture routines with help of Artificial Intelligence (AI). Weeds are unwanted plants that grow along with the crop being cultivated and compete with primary crops for resources like sunlight, water, nutrients, space. Weeds can also serve as a habitat for pests and diseases that can infect crops, provide shade which promotes the growth of fungi. These factors present weed management as a significant part of cultivation in agriculture [3]. Manually spraying herbicide to suppress weeds is easier when farm area is small. In cases of large-scale farming where area of farmland ranges from tens of acres to hundreds of acres manual weeding needs lot of physical labor and inappropriate usage of herbicide can have several negative effects on environment [4]. To reduce manpower and use right amount of herbicide there ought to be a system which can scout through farm to identify weeds and spray at locations of weeds so that weed growth is suppressed without affecting primary crop. Such systems where multiple IoAT devices and Al technologies like Computer Vision are deployed in agriculture infrastructure to automate a specific task are referred to as Agriculture Cyber-Physical System (A-CPS). Current article WeedOut is a weed management A-CPS that follows a semi-supervised approach as depicted in Figure 1 to identify weeds and suppress their growth.

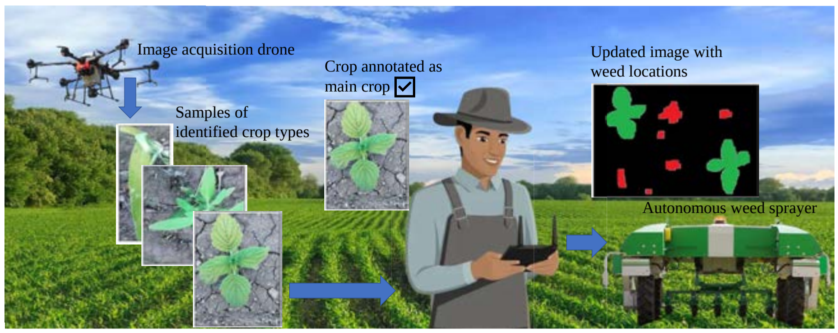

Fig. 1. Overview of proposed WeedOut.

The Rest of the paper is organized as follows: Section 2 presents novel contributions of this article followed by discussion on related works in Section 3. Section 4 demonstrates the working of proposed solution while experimental results are discussed in 5. Section 6 concludes the article.

2 Novel Contributions of the Current Paper

2.1 Problem Statement

There have been many solutions using Convolution Neural Networks (CNN) to detect weeds with high accuracy and efficiency. Any CNN needs ample amount of data (images) to train, and such trained networks will be able to only detect any new images with the help of features learned. But, appearance of same crop varies with growth cycle and geographic locations due to various factors. In addition, there could be new kind of weeds which the model has not learned. So, CNN models will have to be trained with lot of images to encompass all possible cases which would not be available in some cases [5]. In such cases solutions that consider other properties like shape of the crop, area occupied by the crop, patterns in sowing the crop can help us distinguish between primary crop and weed.

2.2 Proposed Solution of the Current Paper

Proposed WeedOut tries to differentiate crops by their shape (profile plots) and clusters similar crops (similar shapes) together. This approach makes proposed method un effected by differences in appearances/features of the crop due to geographical and aging factors. Knowledge of farmer is utilized in identifying the clusters that represent primary crop to classify crops as weeds and primary crop in semi-supervised fashion.

2.3 Novelty and Significance of the Proposed Solution

The following are novel contributions of this article.

1. No prior data or training is required by WeedOut: Proposed methodology does not need any training involving lot of images and manual labeling effort.
2. Provides insights on weeds present and weed pressure: In addition to classifying crops as primary crops and weeds, proposed method also provides the farmer a list of all kind of weed crops in the farm, percentage of their contribution to total vegetation and weed pressure.
3. Simple and computationally low intensive solution: Proposed algorithm pass through image only 2 times to classify and cluster which is quick and simple. Thus, it can run on end devices like mobile or tablet.

3 Related Prior Works

There have been multiple solutions that do not use CNN for identifying weeds in farmland like [6] which detect rows of plantation, row orientation to know crop margins and label crops outside of crop margins and with lower NDVI as weeds. Whereas, in [7] crop rows are detected by help of depth data and crops lying between crop margins are clustered to 2 clusters by their geometric properties and KNN algorithm. Assuming the number of weeds is greater than primary crop, the smaller cluster is marked as primary crop. In [8] authors proposed a method where crop lines are derived and super pixels (obtained by SLIC) that are in contact with crop lines will be classified as crops, super pixels that are not in contact with crop lines are classified by comparing with neighbors.

In contrast to the above solutions that rely on practice of cultivating in rows, some solutions classify crops by the area they occupy. Authors of [9], [10] proposed methods where area covered (number of pixel occupied) by individual crop is computed and the one whose area is below a threshold is classified as weed while the one whose area is above the threshold is classified as primary crop by assuming individual primary crop occupies more area than individual weed crop. But in [11] and [12] the classification is performed the other way assuming individual primary crop occupies less area than individual weed crop. Article [13] proposes use of Active Shape Models (ASM) for classification, which calculates shapes of crops present in the image and compares them to shapes of primary crops in memory (training data) to know if its a primary crop or weed. A brief summary of these works are presented in Table 1.

Unlike the above approaches, current approach makes no assumptions on pattern in cultivation or differences in area occupied by individual crops. Instead, WeedOut utilizes shapes of the crops similar to [13] to cluster similar crops and farmers inputs to classify them.

4 Proposed Method - WeedOut

The solution is an A-CPS comprising of multiple devices/machines like drones, weed sprayers and phone/tablet engaged in weed management as presented in Figure 2. Entire work flow starts with a rover/drone scouting the farm [14] to capture a grid of photos which when stitched together represent the entire farmland.

Table 1. A brief summary of relevant literature.

Work	Year	Assumptions made	Features considered	Remark
Louar-gant et al. [6]	2019	Cultivation of crops is performed in rows.	Spatial and spectral properties of crop.	Specific to crops which vary in vegetation indices.
Ota et al. [7]	2022	Cultivation of crops is performed in rows.	Spatial and geometric features of crop.	Needs more number of weeds for better classification.
Bah et al. [8]	2017	Cultivation of crops is performed in rows.	Position of crop in farmland and orientation of super pixels.	Specific for crops that are cultivated in rows.
Rani et al. [9].	2017	The average area of a primary crop is greater than that of a weed.	Area occupied by individual crop.	Weeds larger in size may be classified as primary crops.
Irías Tejeda et al. [10]	2019	The average area of a primary crop is greater than that of a weed.	Area occupied by individual crop.	Weeds larger in size may be classified as primary crops.
Aravind et al. [11]	2015	The average area of a primary crop is lesser than that of a weed.	Area occupied by individual crop.	Weeds smaller in size may be classified as primary crops.
Siddiqi et al. [12]	2009	The average area of a primary crop is lesser than that of a weed.	Area occupied by individual crop.	Weeds smaller in size may be classified as primary crops.
Maria Persson et al. [13]	2008	NA	Shape of the crop.	Needs to be trained with shapes of primary crop at various orientations.
Weed-Out	**2023**	**NA**	**Shape of the crop.**	**No training needed, works for all types of crops and all patterns of cultivation.**

4.1 Detection and Identification of Individual Crops in Images

Algorithm of crop detection proceeds by processing one image at a time from the set images in the sequence they have been captured.In-order to classify crops, first task is separation of crops from soil by eliminating background. So, image is transformed into HUE color space which represents colors based on hue, saturation and value parameters. Thresholding is performed on image with prior defined limits for green color to detect objects that are in green color (crops) [15]. Image is then resized to 250×250 for ease of computing and converted to binary image as in Figure 3.

In order to classify crops in the image as primary crops and weeds, individual crops in the image have to be identified and labeled uniquely. Two-pass Connected Component Labeling is a Computer Vision algorithm, which essentially identifies and uniquely labels all the objects in a image by just passing over the image twice. When ever a binary image is presented, the algorithm starts to process each pixel of the image column after column in each row. In the first pass, whenever it reads a pixel that is bright it looks for its neighbor pixels that are bright. If there are any neighbors available, highest of their labels would be assigned to the current pixel. If no neighbors are found a unique label is assigned to the pixel and equivalence between

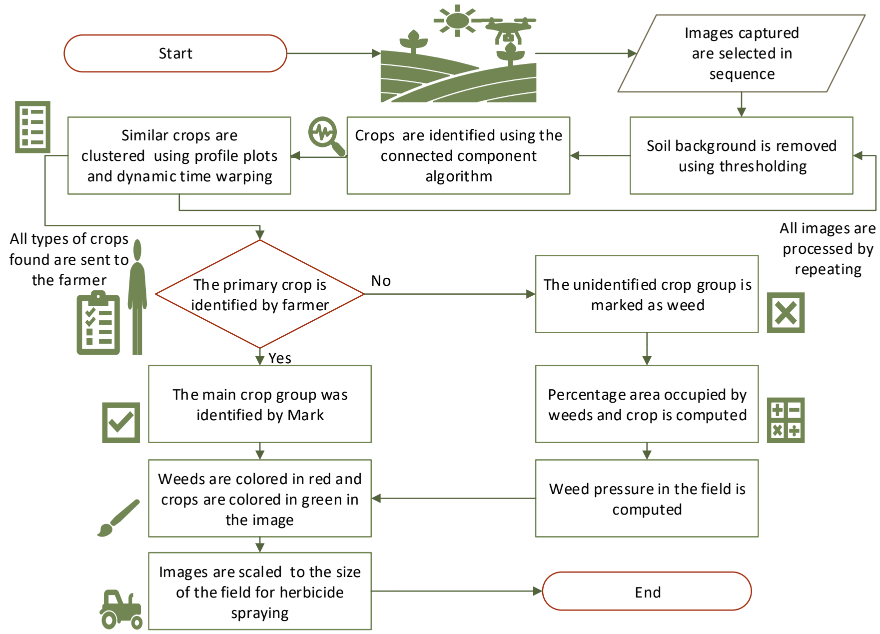

Fig. 2. Working of WeedOut.

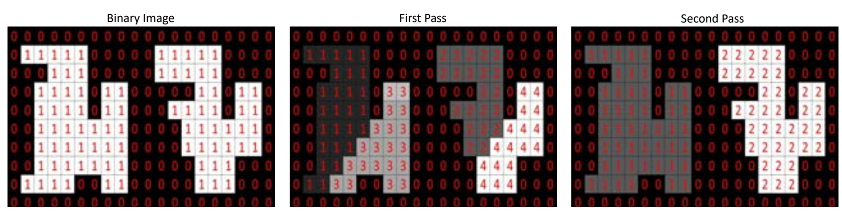

Fig. 3. Demonstration of 2 Pass Connected Component algorithm.

neighboring labels is saved. This process of labeling continues till all the pixels in current image are assigned a label. Second pass identifies various labels assigned to a single object and replaces them with label that is unique to every object as represented in Figure 3.

4.2 Grouping Identical Crops into Clusters

Every crop essentially differs with others in properties like length of leaves, width of leaves, number of leaves, orientation of leaves. All these features effect how the whole crop looks and how width of crop changes with its length from tip to tip. A plot describing variation in width of a plant with length is termed as Profile Plot, Figure 4 shows profile plots of two crops demonstrating how profile plots can help differentiating crops.

After computing profile plots for all crops identified in the image, they are extrapolated to length of 250 for ease of visualization. All these profile plots are compared with one another by Dynamic Time Warping (DTW). Dynamic Time Warping of two signals is finding best

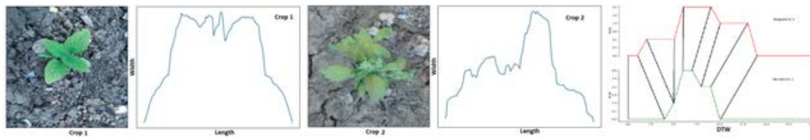

Fig. 4. Visualization of profile plots and Dynamic Time Warping.

alignment between them by stretching and compressing one of them along time axis while distance between corresponding points is being minimized as in Figure 4. DTW distance is the minimum distance required to align the signals. In simple terms, signals those are highly similar would have low DTW distance and thus, can be used as similarity measure. This helps in finding pairs of crops that are similar and all pairs that have a common element are merged to form clusters in iteration till no clusters have a common element. DTW is performed between identified crops for couple images at the initial stage to detect all kinds of crops present. Later on instead of performing DTW between crops identified in a image, DTW is performed between each identified crop and identified crop types to group with similar ones.

4.3 Classification and Targeted Herbicide Application

Once all possible clusters are identified, contribution of each cluster to the entire vegetation is computed by dividing area occupied by each cluster with area occupied by all clusters. Results are presented to farmer with image of one instance from each cluster. From the list of images presented to him, he classifies/labels the image that is similar to his primary crop as primary crop. The label is propagated throughout the cluster to classify crops in that cluster as primary crops. Rest all crops from other clusters are considered as weeds. Thus labeling is performed in semi-supervised fashion with minimal manual intervention. After classifying clusters as primary crops an weeds, area occupied by primary crops and weeds are calculated to determine the percentage of contribution by weeds to the total vegetation known as weed pressure.

All the crops in the image classified as primary crop are marked green and the ones classified as weeds are marked red. Results are now presented to user/farmer and updated images are sent to autonomous weed sprayer. Autonomous weed sprayer is a rover that can travel across the field with provision to carry herbicide. The weed sprayer starts processing each pixel of the image scaled to actual size of farm with a spray nozzle moving correspondingly. When the processor finds a red color pixel belonging identified weed, nozzle sprays herbicide at the location.

5 Experimental Results

Proposed solution was implemented with python and a Computer Vision library OpenCV on a data set from kaggle [16]. To create an image of a farmland multiple images were combined and results of one of such image are discussed below. Thresholding and Connected Component Algorithm are performed on inputted image to identify individual crops, profile plots are plotted for 8 individual crops identified shown in different shade of gray in Figure 5. DTW is then performed to detect and group similar crops to 3 clusters in Figure 6.

A sample from each cluster is now presented with percentage of contribution of that cluster to the total vegetation to farmer as in Figure 7. In this experiment farmer selected cluster 1 as his primary crop. All other clusters except cluster 1 are marked weeds and colored red while primary

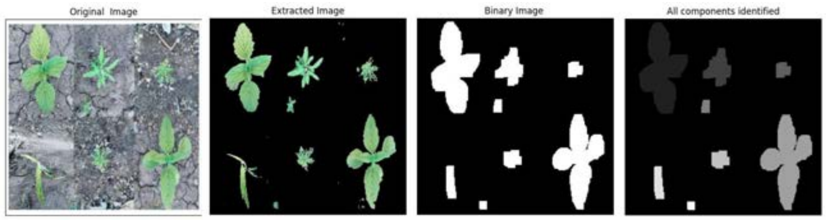

Fig. 5. Different stages in crop identification.

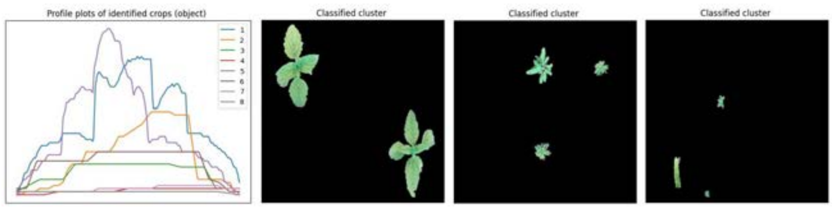

Fig. 6. Clustering of similar crops.

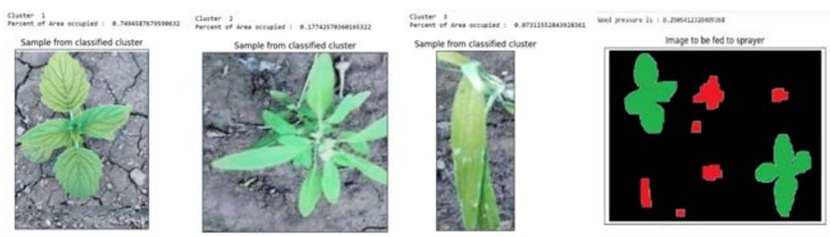

Fig. 7. Results of WeedOut presented to farmer.

crops are colored green. Final results are presented in Figure 7 along with computed weed pressure. and can be used as an input to autonomous weed sprayer to spray herbicide at weed location.

The same algorithm is fed with 20 of such images to simulate a small sized farmland and calculate its performance metrics. The proposed clustering method showed an accuracy of 93% while F1 score for primary crops and weeds were 0.80, 0.95 respectively indicating that the proposed method was particularly effective at identifying weeds.

6 Conclusion

Current article proposed a novel methodology for an A-CPS delegated with weed management utilizing shape of crops and domain knowledge of farmer to detect weeds in the farmland instead of CNN methods which depend on visual features of crops. WeedOut identifies various crops in the image using Connected Component Labeling Algorithm which checks if any pixel has a directed connection or connected path to other pixel of a object to decide if it belongs to same object or not. This assumption leads to two crops with some overlap be considered as single crop. which means this solution only works for non-overlapping crops in farmland. Proposed method classifies crops by their shape which poses chances of misclassification if two crops have similar profile. Methods to distinguish crops even in cases of overlap with help of edge detection and considering some additional geometrical features that help in more accurate identification can be explored as future works for the proposed solution.

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