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A Comprehensive Survey for Weed Classification and Detection in Agriculture Lands

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Abstract

In modern agriculture, there are many technologies that improve the performance of farming and production of the main plant. Few such important technologies are the machine learning and deep learning for the automatic weed classification and detection. It is very useful to control or remove the weeds in the agriculture lands by automated weed control systems. This paper gives the overall survey of the existing research of the weed classification and detection using various techniques present in the digital image processing, machine learning and deep learning field. It also covers the merits, demerits and challenges of the existing methods and the future scope of the research.

Keywords: Weed Classification, Machine Learning, Deep Learning, Object Detection

1. Introduction

In agriculture farms, weeds are the major concern that affects the production of the main plant. It takes the nutrients, vitamins, water, sunlight, space from the main plant. It leads to the loss of the performance of the crop. According to the results [1] in the United States, the yield losses increased from 37% to 61% in grain sorghum due to their weed interference. According to the field study results [2] in Canada and United States, the average loss of yield increased from 31% to 94% in dry bean and 61% to 83% in sugar beet farms due to their weeds. So the weeds must be removed or treated in earlier seasons. In worldwide there is a loss of 30% of crop yield due to the weeds and it is reported that there is a potential economic loss of $25 million annually for corn and soybean crops in North America. The traditional approach is plucking the weeds by the humans or applying the pesticides to the weeds

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directly. It requires large man power and time consuming. So, it requires a fast, cost effective and accurate weed identification and detection of weed locations to remove and control them.

Computer Vision is very first method for object classification and detection task. In these systems includes the digital image processing techniques to process the weed images and extracting the features from them. The extracted features from the weed images are used for the object recognition task by using various machine learning algorithms like Naïve Bayes, K-Nearest Neighbors, Decision Tree, Support Vector Machines, etc. The drawback of the machine learning algorithms are it takes lots of time for extracting the features and accuracy of the model will be low.

Then the deep learning creates the better model compared to the machine learning models. Especially, Convolution Neural Networks (CNN) gives the better results for the image classification task compared to the other machine learning models. One advantage of the CNN is the automatic feature extraction from the RGB images. But it also has some drawbacks like requires more number of images, large memory (mostly GPU) and manual hyper parameter tuning.

Now days, Transfer learning is a emerging technique for the image classification tasks due to transferring the functionalities of pre-trained CNN models whose are all well performed for one particular task (i.e. imagenet challenge). There are several advantages of the transfer learning techniques. Few of them are requires small amount of dataset, lower training time and comparatively limited number of hyper parameter tuning and improves the performance of model.

Once the object has identified, then it must be removed by the automated weed control system. In order to achieve this, the accurate location of the weed must be identified. For this localization task, the system uses the object detection algorithms like RCNN, Faster RCNN, YOLO, etc. One important point to be noted is object detection algorithms requires the images, labels with bounding box co-ordinates.

This survey focused on the earlier approaches used for the weed classification and localization task and their advantages, pitfalls and challenges faced by the researchers and the final idea to solve all the stated problems. The paper organized as follows. Section 2 describes the literature survey of the weed classification and detection process. Section 3 gives the comparative analysis of the existing methods. Finally, section 4 concludes this survey and gives the proposed idea to implement in future.

2. Literature Survey

In this section, the previous researches of the weed classification and detection has been presented and analyzed which are done by earlier researchers. It includes what type of main plant considered, what are the weeds growing around that particular main plant, which methodology has been used for the classification and detection and performance of each methodology.

Faisal Ahmed,et al., [3] proposed the machine learning classifier for the classification of 5 types of weeds present in the chilli (Capsicum frutescens L.) fields. They captured the weed images by using camera with resolution of 1200 x 768 pixels. From the captured images, they extract the features by computing color features (Red, Green and Blue), Size independent shape features (form factor, elongatedness, convexity and solidity) and Moment invariant features. For the better classification the optimal features has been selected by forward-selection and backward-selection method. Then the extracted features and corresponding labels are given as input to the Support Vector Machines (SVM) classifier with RBF kernel (Radial Basis Function). The proposed method gives 97% accuracy on 224 test samples.

Borja Espejo-Garcia,et al., [4] presented the multiple classifiers for the classification of the weeds presented in the cotton and tomato fields at the early growth stage. The weed images captured by digital cameras and augmented by random rotation, blurring and shifting. The augmented images are fed into the pre-trained CNN models like DenseNet, VGG16 and VGG19 for extracting the feature vectors only. The extracted feature vectors fed into the SVM, Logistic Regression and Random Forest algorithms for the classification task. The performance of the proposed method has been measured by F1 score. From the obtained results, the DenseNet + SVM is the best classifier with the 99.29% F1 score.

Junfeng Gao, et al., [5] suggested the model for prediction of weeds in the maize crops that are captured by novel hyper spectral snapshot mosaic camera. There are 185 spectral features like reflectance and vegetation index features has been constructed. Also, the principal component analysis has been used for reduce the dimension of the dataset. After feature extraction, the data given as input to the random forest classifier. This method gives 94% precision and 100% recall value.

Christoph Kunz,et al., [6] proposed the camera guided mechanical weed removing system in the sugar beet,maize and soybean fields by using the Intra-row weeder (Fingerweeder , Torsion weeder , Rotary harrow and Ridging blades) and Inter-row weeder (Camera-steering with ducks-foot blades, Band sprayer over row with inter-row hoe). The data collected from camera are analyzed using linear model (in R language). The significance has been tested by Tukey-HSD test. The proposed method has completely removes the weeds in sugar beet and reduces the herbicide usage by 65%.

Corey Lammie, et al., [7] presented the Deep learning enabled FPGA engine for the weed classification. They used the DeepWeedsX dataset with resolution of 256 x 256 pixels. In first phase, the original images are down-sampled and augmentation techniques like rotation, changing brightness, contrast and saturation are applied. Then the XNOR kernel has been implemented on FPGA for the implementation of Neural Networks. Then the pre-trained CNN models like VGG-16, DenseNet are used for the classification purpose.

The authors Pan Li, et al., [8] proposed the method for classifying the weeds of corn fields using soft sets. The weed images are captured by camera with resolution of 1920 x 1040 pixels. Then the captured images will be segmented from the soil by the image fusion by NIR-Red method followed by watershed segmentation algorithm based on distance transform. From the segmented images, the shape features (Rectangularity, Elangation, etc.,) texture features (GLCM) and the fractal dimensions will be extracted. From the obtained results, Soft sets for the dataset have been created by the classification algorithm. Soft sets gives the better results compared to other machine learning algorithms like SVM, Naïve Bayes.

Alex Olsen, et al., [9] created and contributed a multiclass weed species dataset for various weed species present in the Australian lands. They are collected the images and contributed as a publicly available dataset. It consists of nearly 17,509 images. First they created the own CNN architecture. Then several popular deep learning architectures like Inception-V3 and ResNet-50 used for evaluating the performance of the dataset. From the obtained results, the dataset performed average classification accuracy of 95%.

Lyndon N. Smith, et al., [10] proposed the CNN architectures like ResNet26 and MobileNet architectures for the classification of weeds present in the grasslands. They used 2 different types of datasets, one was a two class dataset (rumex and grass) and another one was a three class dataset (rumex, grass and clover). All of the images will be augmented by random rotation, scaling, zooming, etc. Then download the pre-trained ResNet26 CNN 2model and MobileNet model. They performed normal complete training for ResNet26 architecture and transfer learning applied to the MobileNet. From the obtained results, ResNet26 performed well compared to MobileNet.

Kavir Osorio,et al., [11] performed the localization of weeds present in the lattice crops by using several methods of object detection. All images are preprocessed by alignment and fisheye correction, the preprocessed images will give as an input to the following 3 models.

(i) HOG-SVM : Histogram of Gradients (HOG) is used for extracting the features from the image by using the gradients. It was mainly used for generating the mask by NDVI and OTSU method. Then the pre-trained Support Vector Machines (SVM) is used for the classification of lattice and weed and it creates the mask to generate the weed potion. The generated mask will be multiplied by the original image and it leads to the weeds location.

(ii)YOLO-v3 (You Look Only Once) and

(iii) Mask R-CNN

From the obtained results, Mask R-CNN gives the better results compared to others.

Shaun M. Sharpe, et al., [12] proposed the goosegrass detection in strawberry and tomato fields. For the object detection task, they used the Tiny-YOLO-v3 detection algorithm and performance of the model will be evaluated by F-score. The proposed method was achieved 0.75 and 0.56 for strawberry and tomato fields respectively.

Shaun M. Sharpe, et al., [13] proposed the object detection model for detecting the weeds present in Florida vegetable crops. They used both in-discriminate i.e. one class and discriminate i.e. three classes of vegetation for this research which are generally grows in Florida vegetable. The proposed methodology using the YOLO-v3 object detection model. The results show that the model performs well for the detection of vegetation.

Yeyin Shi, et al., [14] proposed the various object detection models for detection of the weeds present in the soybean farms. The images are collected by UAV and manually annotated for ground truth boxes. Images and annotations given as an input to the Patch Based CNN, Faster R-CNN and SSD (Single Shot Detector) algorithms. From the obtained results the SSD performs well compared to other methods.

The authors Aanis Ahmad , et al., [1] used the various pre-trained models for the weed classification and detection in the corn and soybean plant. They used the DeepWeeds open source dataset for this research. They used the pre-trained CNN models such as VGG16, ResNet50 and InceptionV3 for the classification task. Then YOLO-v3 algorithm used for object detection task. The results shown that, the VGG16 model performs well compared to other models and YOLO algorithm gives the 54% of mAP. One of the important key note in this research, they trained the models using both Keras library and PyTorch library.

3. Comparative Analysis

The Table 1 summarizes the previous work on weed classification and detection by using various techniques. It also includes the advantages and pitfalls of the existing work.

Table 1. Comparative Analysis

Ref. No	Year	Observations	
		Methods Used	**Findings**
[3]	2012	Support vector machines used for the classification of weeds present in the chilli fields.	Manual feature extraction is very time consuming and training of the SVM classifier requires large time.
[5]	2018	PCA used for dimensionality reduction and Random Forest used for the classification of weeds growing in the maize crops	Random forest classifier justifies the reduced training time compared than SVM, but still the manual feature extraction requires large time.
[9]	2019	Convolutional Neural Networks are used for the classification multi class weeds.	Automatic feature extraction is the one advantage of CNN and also improves the classification accuracy. But one of the major problem is hyper parameter tuning.
[4]	2020	Pre-trained CNN models like VGG16,ResNet,etc., has been used for the classification of the weeds present in the cotton and tomato fields.	Improves the accuracy and performance of the classification and Feature extraction has been done by freezed layers. So it requires lower training time compared than other classifiers.
[11]	2020	Lattice weeds localization done by Mask HOG-SVM, Mask R-CNN and YOLO-v3 object detectors.	HOG-SVM requires large time to reach better inference for the coordinates of the bounding boxes. Mask R-CNN gives better results but requires multiple stages. YOLO-v3 achieves the faster detection results.

[12]	2020	Tiny YOLO-v3 detector used for the localization of the goosegrass in the strawberry and tomato fields.	Tiny-Yolo-v3 has lower training time, but it gives the lower F-score of prediction of bounding boxes.
[14]	2020	Patch based CNN, Faster R-CNN and SSD used for the object detection algorithms.	SSD algorithm achieved better results compared than others and predicts the bounding box with a single shot.

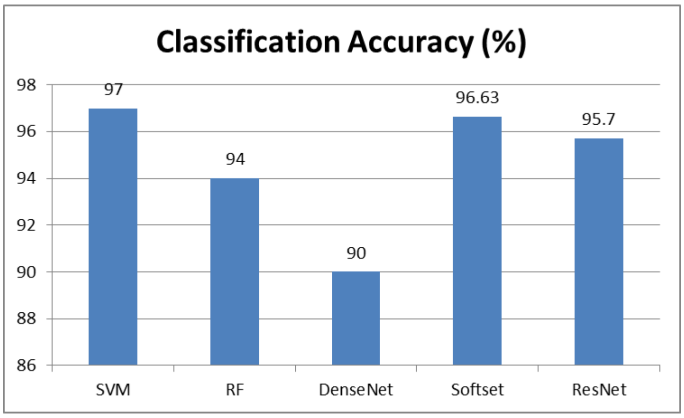

Figure 1. Performance of various classifiers

Figure 1 shows the accuracy of the various classifiers for the weed classification task. From this figure, it is identified that SVM, Softsets and ResNet give the better results. But compared than others, ResNet (Transfer Learning techniques) achieves better performance.

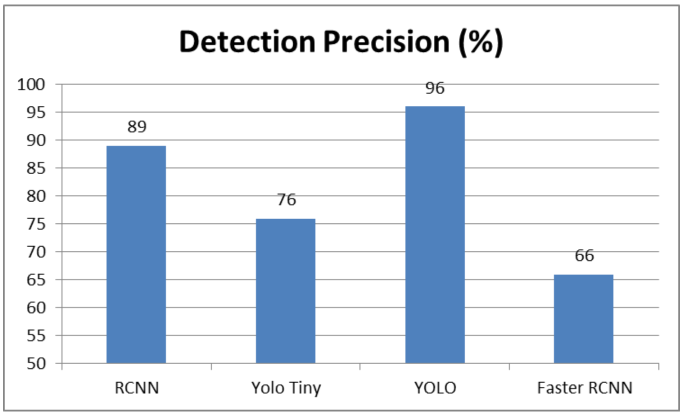

Figure 2. Performance of various object detectors

Figure 2 shows the precision value of the various object detection algorithms for the weed detection task. From this figure, it is identified that YOLO gives the better bounding box precision.

4. Conclusion

In this paper, a thorough review on the existing methods and algorithms that are already in the classification and detection of weeds in agriculture lands and farms by using various machine learning, deep learning classification algorithms and object detection algorithms. From this study, it is observed that transfer learning outperforms better results for the classification tasks and SSD, Yolo-v3 algorithms are best for the object detection task. In future work, segmentation may be applied along with this methods for weed classification and detection task for better efficiency.

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