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Deep Learning based Weed Detection

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Abstract: *Weeds are one of the most harmful agricultural pests that have a significant impact on crops. Weeds are responsible for higher production costs due to crop waste and have a significant impact on the global agricultural economy. The importance of this problem has promoted the research community in exploring the use of technology to support farmers in the early detection of weeds. Artificial intelligence (AI) driven image analysis for weed detection and, in particular, machine learning (ML) and deep learning (DL) using images from crop fields have been widely used in the literature for detecting various types of weeds that grow alongside crops. This paper proposes a new method for weed detection. Firstly, a trained CenterNet model was used to detect vegetables and draw bounding boxes around them. Afterward, the remaining green objects falling out of bounding boxes were considered as weeds. In this way, the model focuses on identifying only the vegetables and thus avoids handling various weed species. Furthermore, this strategy can largely reduce the size of the training image dataset as well as the complexity of weed detection, thereby enhancing weed identification performance and accuracy.*

Keywords: weed dataset, deep learning, weed identification.

I. INTRODUCTION

Weeds are undesired plants that compete against productive crops for space, light, water, and soil nutrients and propagate themselves either through seeding or rhizomes. They are generally poisonous, produce thorns and burrs, and hamper crop management by contaminating crop harvests. Smaller weed seedlings with a slow growth rate are more difficult to detect and manage than larger ones which grow vigorously. Weed management is complicated because the competitive nature of weeds can vary in different conditions and seasons. For instance, the tall and fast-growing fat hen weed is considered dangerous to adjacent crops, but fat hen seedlings that appear in late summer are considerably smaller in size and not potentially dangerous [1]. Similarly, chickweed is smaller and less dangerous during the summer season, but in winter, it can have a high growth rate and can swamp crops such as onions and spring greens [2]. Moreover, weeds can co-exist 'peacefully' with the crops earlier on in their growth period but start competing for more natural resources later on. Another difficulty in managing weeds is determining the exact time when a weed actually starts to affect the harvest. Moreover, several weeds, such as couch grass and creeping buttercup, can survive in drought and severe winter weather as they store food in long underground stems. Weeds are also potential hosts for pests and diseases which can easily spread to cultivated crops. For instance, the charlock and shepherd's purse weeds may carry clubroot and eelworm diseases, while chickweed can host the cucumber mosaic virus [3]. Finally, different weeds have different seeding frequencies, further complicating weed management; for instance, groundsel can produce 1000 seeds per season, while scentless mayweed might produce 30,000 seeds per plant. These seeds might stay in the soil for decades until exposed to light; for instance, the poppy seed can survive even up to 80 years.

For several decades weeds have been managed, detected, and controlled manually [4]. The most common method of weed detection is manual surveillance by hiring crop scouts or by tasking crop farmers to do the same, which is expensive, difficult to manage, and infeasible to execute in unfavorable weather conditions Scouts only work on a sample of the field and have to follow a pre-determined randomized pattern (e.g., zigzag). Such a setting does not always ensure that all weeds will be detected and removed. Scouts also carry specialized equipment (e.g., hand-held computers with GPS and geo-tagging), which adds to the expense. They need to repeat the process regularly and fill up a report. All these limitations make crop scouting difficult to manage, and hence, weeds continue to affect crop harvest each year globally. Motivation and Contribution In this paper, we focus on smart farming techniques that can detect

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weeds in crop images through machine learning methods, particularly DL. This can potentially eliminate the need for crop scouts while scanning the entire field for weeds with no management overload. However, ever since the introduction of Graphical Processing Units (GPUs), DL has demonstrated an unparalleled pace of research and superior performance across a wide variety of complicated applications involving images, text, video, and speech datasets [5]. DL was considered nascent till 2010 due to a lack of hardware technology to process its complex architectures. One of the initial researches on weed detection found in 1991 [7], which highlighted the limitations of using tractor-mounted weed detectors, and proposed the use of digital image processing (IP) techniques [7] to detect weeds from both aerial and previous manually-snapped photographs by crop scouts. Research efforts using pure IP and CV techniques for automated weed detection remained very limited for the next two odd decades [8]. This paper demonstrates that such applications are still in their infancy with respect to applications in ML and DL.

II. LITERATURE REVIEW

In [4], the authors review seven research papers based on deep learning and discuss three previously-used techniques for the classification of weeds such as color-based, threshold-based, and learning-based techniques. The authors review the papers over different parameters such as the type of deep learning used, targeted crops, training setup, the training time of the algorithm, dataset acquisition, dataset strength, and accuracy of the algorithm. Research gaps are also identified, and one of the gaps was the lack of a big dataset which could be a major contribution in this field. Moreover, in [5], the challenges faced by vision-based plant and weed detection and their solutions have been discussed.

Two main challenges of weed detection are the light problems, i.e., the algorithm may work differently due to the presence of light, and discrimination between crop and weed, i.e., sometimes both may look similar. Shading or artificial lighting can be used to control the variation of natural light, or image processing techniques like segmentation of background (and then converting the image into Grayscale).

In [6], the authors analyze different techniques for weed detection using IoT technology. The authors discuss several DL algorithms employed in the context of IoT and perform their comparative analysis, for example, CNN, SegNet (with a synthetic dataset for achieving higher accuracy), and summarised training set technique with CNet, which is a deep CNN based on image segmentation. The authors also propose an IoT-based architecture where different devices and sensors are connected to one central data server, and users can communicate with the server through the Internet. This model can be controlled by a desktop computer or mobile device.

In [7], the authors focus on the methods and technologies used in weed detection with particular focus on the requirements of weed detection, its applications, and the system needed for weed detection, such as satellite-based positioning, crop-row following, and multi-spectral images. They have also drawn attention to the limitation of previously constructed detection systems, such as the lack of within-row plant-detection facilities.

In [8], the authors discuss DL techniques and architecture. In the former, they discuss Artificial Neural Networks (ANN), CNN, and Graph Convolutional Networks (GCN), and in the latter, they discuss image classification, object detection, semantic segmentation, and instance segmentation. They also mention the significance of public datasets, specifically carrot-weed, CWF-788, CWF-ID, DeepWeeds, GrassClover, Plant Seedlings, Sugar Beets 2016, Sugar Beet/Weed Dataset, and WeedCorn/Lettuce/Radish, to demonstrate how images were acquired, size of the dataset, pixel-wise annotation and modality. They also discuss data augmentation by mentioning limitations in the size of public datasets to work in varied conditions. They discuss fine-grained learning that overcomes the problem of general deep architectures, which ignores the challenges of similarities between crops and weeds, along with low-rank factorization, quantization, and transferred convolutional filters to solve the resource-consumption problems in analyzing real-time data for weed detection through DL.

For the manual collection of datasets for weed, identification could be expensive, so weakly supervised and unsupervised methods can be necessary. For weakly supervised, object detection or segmentation can be used on image-level annotation, and for unsupervised learning, domain adaptation and deep clustering can be used. The existing methods for deep learning cannot deal with new species once a model is trained; to overcome this problem, incremental learning is proposed that is used to extend the existing trained model without retraining it.

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2.1 Weed Types

Weeds can be generally classified as annual, biennial, and perennial. Annual weeds germinate, bloom, and die within one year, while biennial weeds have a life cycle of two years, with germination and blooming happening in the first year and dying out in the second year. Perennial includes all weeds which last longer than two years in that they can germinate, bloom, and seed for several years. Some sample weeds are illustrated in Figures 1–3.

Fig. 1. Pigweed, Blackgrass, Bluegrass, Dockleaf, Canadian Thistle

Fig. 2. Mayweed, Meadow grass, Nutsedge, Paragrass, Shepherd's purse

Fig. 3. Benghal dayflower, black nightshade, hedge bindweed, Indian jointvetch, snakeweed

We extracted more detailed information about all these weeds from the Invasive Species Compendium section of the Cab Institute's website and Wikipedia entries along with websites of Garden Organic, Crop Protect, Gardening Know How, LawnWeeds, Farms, and the USA Department of Agriculture. Moreover, several weeds are categorized as both annual and perennial, for example, chickweed, but we have considered them as annual weeds for classification purposes.

2.2 Deep Learning (DL) Algorithms

Deep Neural Networks (DNNs) are extensions of Artificial Neural Networks (ANNs) in terms of complexity, number of connections, and hidden layers. A CNN is a DNN that assigns learnable weights and biases to various aspects and objects of input images to distinguish and classify objects such as weeds. CNNs do not require manual feature selection; rather, the network learns important features automatically from training data to reveal useful information hidden. CNNs are robust at classifying various objects with different scales, orientations, and levels of occlusion. CNNs capture the spatial and temporal dependencies of the input image through relevant filters autonomously and hence

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provide better and more efficient image processing with a considerably lesser number of estimable parameters and processing time.

Max pooling is generally preferred as it discards the noise (data values unreliable for machine learning) in the data and performs the de-noising operation. Due to the possibility of saturation in sigmoid and tanh activation functions, CNNs employ the rectified linear activation unit (ReLU) as the activation function g(z), which outputs the aggregated value z if it is greater than 0, and 0 otherwise.

One application of convolution and max pooling with ReLU forms one layer of the CNN pipeline. Typically multiple such layers can be employed. In each layer, we can have parallel processing based on different color channels or feature maps, for example, RGB. The output from the last pooling layer is flattened as a 1-D vector and fed to the fully connected layer (i.e., conventional Multilayer Perceptrons (MLP)) for image classification, e.g., detecting weeds within a given image.

III. PROPOSED WEED DETECTION METHODOLOGY

3.1 Image Acquisition

In practice, the weeds should be controlled at the growth stage between three and six leaves so that the crops could occupy the dominance in further growth competition. Conventional algorithms for weed identification use image processing technology to extract the image features of weeds, crops, and backgrounds.

Vegetable images were acquired using a digital camera. The original dimensions of the images were 3024 x 4032 pixels. Some images were taken under various conditions, such as varied illumination conditions.

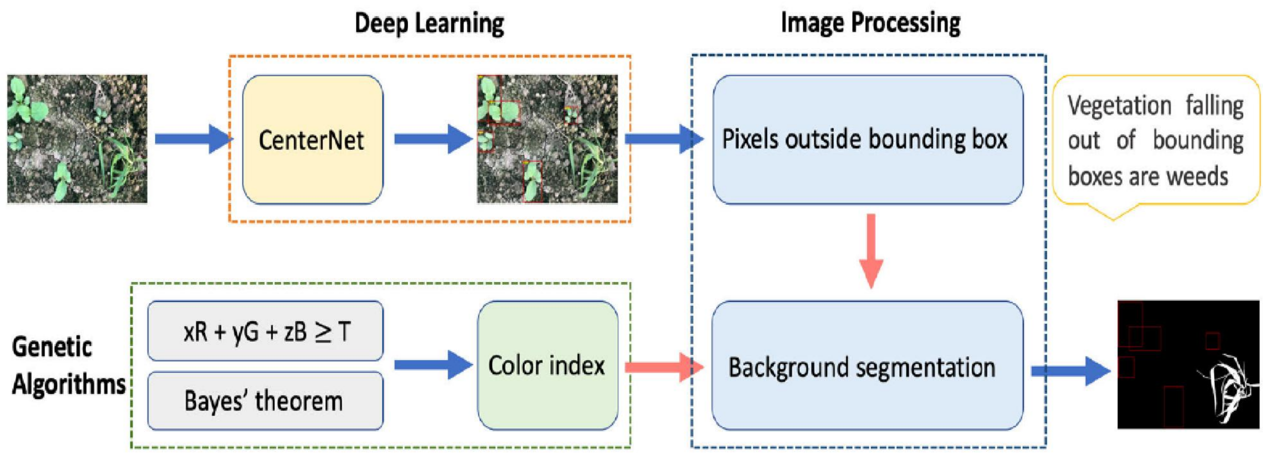

Fig. 4. Weed detection

3.2 Classification of Dataset Structures

Vegetable images were acquired using a digital camera. The original dimensions of the images were 3024 x 4032 pixels. Some images were taken under various conditions, such as varied illumination conditions. The Weed25 dataset contained 14,023 images in 25 categories, which was more diverse than the existing dataset, with most of the weed images collected from the field. The collected weed dataset was divided into training, validation, and test datasets with a ratio of 6:2:2. Specifically, all images of Weed25 were divided into 8,409 training images, 2,807

To show the advantages of the weed database Weed25 in terms of species diversity and species average (species diversity: the number of all weed species in the dataset, abbreviated as diversity, that was characterized in this paper by the number of species; species average: the mean of the image number of each weed, abbreviated as diversity average, that was used in this paper to characterize the average number of weeds),Weed25 was compared with several existing datasets related to weed identification, as shown in the fig. 5. The dataset includes 25 weed species from 14 families.

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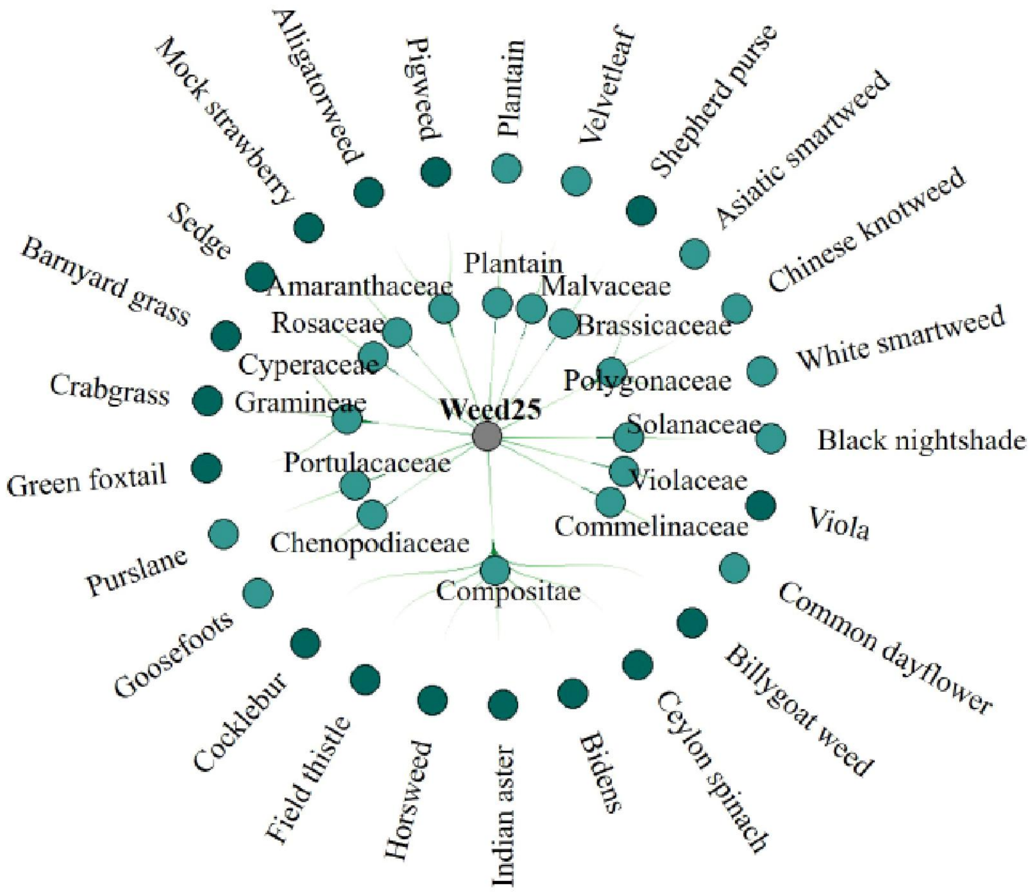

Fig. 5 Classification structure hierarchy of Weed25 dataset.

3.3 Training and Testing

In CenterNet, objects are represented as a single point, and a heatmap is used to predict the centers of objects. Heatmap is created using a Gaussian kernel and an FCN, estimated centers are derived from the peak values in the heatmap [2]. CenterNet is a single-stage detection model, and it does not require the non-maximum suppression (NMS) as the post-processing step, thus it provides much faster detection. For the feature extraction, Hourglass was selected as backbone architecture in this study. To train the network, each ground truth key point is transformed to the lower size of key-point heatmap using a Gaussian kernel, with focal loss.

All images in the training set are resampled to a fixed size. While detecting the object, it predicts bounding boxes as well as their confidence scores. During the detection process, objects are represented as a single point - the center point of its bounding box, which is then obtained from key-point estimation. This anchor-free strategy used by CenterNet to only detect the object from the center point and regress the object size enables it to work more accurately and efficiently, and thereby making it outperforms most of the detection methods.

IV. TEST RESULTS

The training results are listed in Table 4. It presented that the YOLO model training indicators using Weed 25 were generally acceptable. The difference of mAP between YOLOv5 and YOLOv3 was very small as the values were 92.4% and 91.8%, respectively. The precision was 88.0% and 89.0%, respectively. Moreover, the recall for both reached 99.0%. It showed that Weed25 was available for the YOLO models. For the sake of excluding the advantages of the YOLO model on the training results, Faster R-CNN was employed for the training as well. The results showed that the mAP of Faster R-CNN network was 92.15%, which was lower than the mAP of the YOLOv5 networks. It indicated that Weed25 would be capable for precision weed identification model training in future studies.

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Figure 6 presents the training results of YOLO networks. It could be seen that the box_loss, obj_loss means, and cls_loss means of the training and validation datasets during the training of the model were constantly decreasing. The average precision under mAP_0.5 was constantly increasing. The mAP_0.5 of both YOLOv3 and YOLOv5 was close to 0.9. It indicated that the training effect was good with the dataset Weed25.

TABLE 1 Weed identification model training results

Networks	Precision (%)	Recall (%)	F1 score	Mean average precision (%)
YOLOv3	89.0	99.0	0.88	91.80
YOLOv5	88.0	99.0	0.89	92.40
Faster R-CNN	65.9	98.0	0.78	92.15

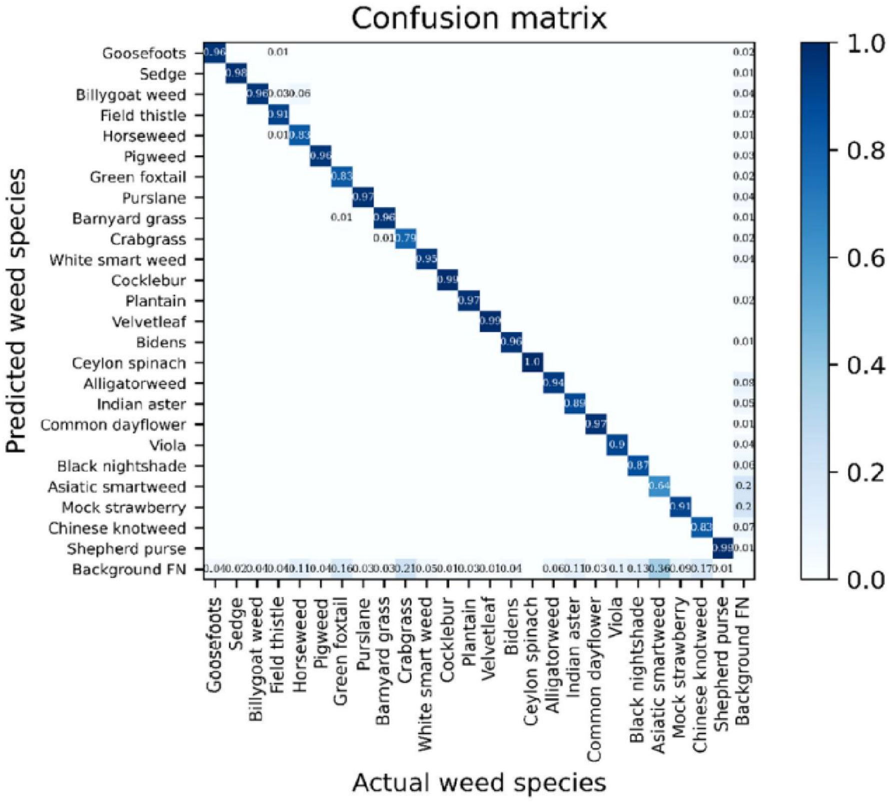

Figure 7: Confusion matrix of You Only Look Once models.

V. CONCLUSION

In this paper, A CenterNet model was trained to detect weeds. The Weed25 database is used here. The images of the dataset were mainly collected from farmlands and lawns. A total of 14,035 images including 25 different weed species were included. Compared with the existing weed dataset, Weed25 contains the weeds that are prevalent in fields. It has the advantages in diversity and average. In addition, YOLOv3, YOLOv5, and Faster R-CNN were employed to train weed identification models using the Weed25 dataset. The average precision was 91.8%, 92.4%, and 92.15% respectively, which indicated that the proposed dataset has the capability for further development of precise weed identification models, which would contribute to the application of intelligent weed control technology in practice.

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