SpotWeeds: A multiclass UASs acquired weed image dataset to facilitate site-specific aerial spraying application using Deep Learning

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Abstract.

Unmanned aerial systems (UASs)-based spot spraying application is considered an emerging field of research in Precision Agriculture (PA) domain. Because of spot spraying, the amount of herbicide usage has reduced significantly resulting in less water contamination or crop plant injury. In the last demi-decade, Deep Learning (DL) has displayed tremendous potential to accomplish the task of identifying weeds for spot spraying application. Also, most of the ground-based weed management technologies have relied on DL techniques to classify weeds from crop plants. However, aerial spraying via UASs is also emerging and is in the nascent stage of development. Therefore, to add to the development of aerial spraying application, we are releasing a multiclass UASs acquired weed image dataset called, SpotWeeds. In the past, a lot of weed image dataset has made its way on the public domain, but most of them have been acquired either using handheld camera or different ground-based sensors. UASs acquired weed dataset is lagging behind that could be used to facilitate aerial spraying application. Primarily, by releasing this dataset we are contributing towards big data for DL to leverage aerial spraying applications. This image dataset comprises of 6 different types of weed classes, namely, greenfoxtail *(Setaria viridis)*, horseweed *(Conyza canadensis)*, kochia *(Bassia scoparia)*, common ragweed *(Ambrosia artemisiifolia)*, redroot pigweed *(Amaranthus retroflexus)*, and waterhemp *(Amaranthus tuberculatus)*. To create this dataset, we have captured a total of 11,100 aerial and greenhouse RGB images using a Phantom 4 Pro V2.0 and a hand-held Canon 90D, respectively. To organize SpotWeeds dataset, individual images of each weed class were clipped and saved inside a test, train, and validation folder. Additionally, to add variations to the clipped dataset, we have performed augmentation technique by rotating, shifting, flipping, zooming, and normalizing each image within single class of weeds. After augmenting, a total of 30,815 images have been generated pertaining to a split of testing (10%), validation (20%), and training (70%) subsets. On top of this, we have included high-resolution videos of our test plots by flying UASs at ~ 10 ft (3 m) height. These videos can be further used to deploy trained DL architectures to simulate near real-time weed detection. We invite researchers, industrialists, DL experts, and weed scientists to use this dataset for building a powerful DL model that can be used to automate weed detection for aerial spraying applications.

Keywords. Aerial spraying, big data, deep learning, UASs, weed detection

Introduction

The advantages of unmanned aerial systems (UASs) have been proved to be an effective solution to address site-specific weed management (SSWM) (Esposito et al. 2021). Benefits of employing UASs-borne sensors over ground-based sensors are that UASs can cover larger areas in less time and can reach steep terrains to monitor weeds and crop plants. In the last decade, a surge in the application of UASs-based weed classification has been reported in the literatures (Islam et al. 2021; de Camargo et al. 2021; Huang et al. 2020) . A common approach to classify or map weeds in an aerial imagery involves integrating machine learning (ML) (Kawamura et al. 2021; De Castro et al. 2018) or deep learning (DL) approach (Beeharry and Bassoo 2020; de Camargo et al. 2021).

Machine learning approach requires training a classifier on soil and weed pixels. Subsequently, the trained classifier is validated or tested on an unseen part of the orthomosaic. This approach is commonly adopted to create weed prescription maps which are then uploaded in a conventional sprayer to spray weeding areas. Although this approach has been widely adopted by researchers to map or classify weeds from crop plants, however it fails to solve the distinctiveness (information on the type of weed specie) associated with classifying multiple weeds (Louargant et al. 2018; Peña et al. 2013). Additionally, creating weed prescription maps are accomplished offline, therefore, it is time consuming that may result in a different weed physiology when spraying in an agronomic field. To overcome these barriers, a number of research effort on sensor-based real-time approaches are being done and is in the nascent stage of development (Khan et al. 2021; Qin et al. 2021).

Object-based detection technique (Lin et al. 2014), a type of DL approach, is integrated with the UASs-borne sensors to perform weed monitoring in real-time conditions. A lot of ground-based technologies such as, John Deere's See and Spray, Carbon Robotics, Agrointelli, etc. have already adopted object-based detection approach to classify weeds from crop plants. However recently, aerial-based weed detection has also been recognized as the emerging research field that promises to deliver good results for SSWM (Khan et al. 2021). In addition, to make advancements in aerial-based weed detection, big data will play a big role that would fuel the success of adoption rate of this technology. Therefore, to add to the area of big data for aerial-based weed detection, we are releasing UASs acquired open-source dataset that can assist in recognizing or identifying weeds amongst crop plants using UASs. Since DL is data hungry (Najafabadi et al. 2015), therefore, contributing to the image dataset would be more beneficial in the years to come.

In this paper, we present SpotWeeds*,* a multiclass UASs acquired weed image dataset to train DL models. To create this dataset, 11,100 aerial images of 6 different weed species were captured in 2021 across three different locations in the state of North Dakota. To create an ImageNet dataset type, 30, 815 images were cropped out from these aerial images. Additionally, we have recorded 1080p videos of our test plots that could be used to simulate near real-time weed recognition at 10ft (~ 3m) altitude. SpotWeeds dataset consist of, greenfoxtail *(Setaria viridis)*, horseweed *(Conyza canadensis)*, kochia *(Bassia scoparia)*, common ragweed *(Ambrosia artemisifolia)*, redroot pigweed *(Amaranthus retroflexus)*, and waterhemp *(Amaranthus tuberculatus)*. We have specifically relied on capturing aerial dataset because of three specific reasons, (1) acquiring aerial dataset will boost DL's generalization capability to recognize weeds at 10ft altitude, (2) despite the accomplishments of DL-based weed detection in ground-based technology, the performance of DL has yet to be evaluated/tested in aerial-based weed detection, and (3) by releasing this dataset, we are exploring the potential of research in real-time aerial-based weed detection using UASs. We anticipate that after the release of this dataset, research questions pertaining to aerial-based weed detection will be addressed. These questions may include:

1. What was a major setback in integrating DL for aerial-based weed detection?
2. What parameters of DL algorithm should be altered for obtain better accuracy for weed detection?
3. How can we optimize DL algorithms to detect weeds accurately with low latency?
4. What will be an optimal height and speed to fly and recognize weeds using an UASs?
5. Based on the trained architectures, can we scale this to multiple agronomic fields as well?

We invite researchers, industrialists, DL experts, and weed scientists to explore more effective yet simple ways to accomplish aerial-based weed detection.

Literature review on open-source weed image dataset

Computer vision-based applications have taken deep roots in the agricultural industry (Jiang et al. 2020) . Numerous human dependent tasks such as, plant disease detection (Liu and Wang 2021), crop monitoring, etc. have now been automatized by leveraging the potential of robots through computer vision. But what drives computer vision-based tasks? The answer is, big data. Coble et al., (2016) explains the term "big data" as the data sets acquired via sensors, instruments, satellites, and any other digital sources that could be used to draw insights by visualization or could be used as a decision support system when integrated with a technology.

There are numerous contributions of open-source image dataset for weed detection. For example, Haug et al., (2015) released an open-source crop/weed classification dataset for benchmarking purpose. Similarly, Lameski et al. (2017) also published carrot-weed dataset for weed detection tasks. Although these published datasets fueled the application of DL over time, however they are not labeled (names attributed to a specific weed specie, Table 1). On the contrary, Olsen et al. (2019) published DeepWeeds dataset that consisted of 8 different weed species grown across northern Australia. These datasets have been named distinctively and captured under variable environmental conditions across several locations within Australian rangeland. Sudars et al. (2020) also took the similar approach by releasing online weed dataset that consists of 8 weed species. Jiang et al. (2020) collected the corn and lettuce weed datasets on variable soil background with moisture levels and wheat straw residue coupled with multiple illumination conditions. Giselsson et al. (2017) published a plant seedlings dataset that aimed specifically on ground-based weed detection.

As seen in Table 1, there are 12 public crop-weed image dataset published in the last 7 years but only dos Santos Ferreira et al. (2017) published a dataset that was captured using a UASs. This shows that there are not a lot of UASs acquired public dataset that could be used to leverage DL or ML methods for aerial-based weed detection.

Table 1. Summary of publicly available crop-weed image dataset.

Reference	Dataset Name	Weed Species	Source	Image Acquisition Tool
Haug et al., (2015)	Crop/Weed Field Image Dataset	N/A	https://github.com/cwfid/dataset/tree/master/images	JAI AD-130GE
Giselsson et al., (2017)	Plant Seedlings Dataset	Scentless mayweed, Common chickweed, Shepherd's purse, Cleavers, Redshank, Charlock, Fat Hen, Small-flowered Cranesbill, Field Pansy, Black-grass, Loose silky-bent	https://vision.eng.au.dk/?download=/data/WeedData/Fullimages.zip	Canon lens
Chebrolu et al., (2017)	N/A	N/A	http://www.ipb.uni-bonn.de/data/sugarbeets2016/	JAI AD-130GE
Lameski et al., (2017)	Carrot-Weed	N/A	https://github.com/lameski/rgbweeddetection	Phone camera (10 MP)
dos Santos Ferreira et al., (2017)	N/A	Broadleaf and grass weeds	https://data.mendeley.com/datasets/3fmjm7ncc6/2	***DJI Phantom 3 Pro***
Bosilj et al., (2019)	Carrots Dataset	N/A	https://lcas.lincoln.ac.uk/owncloud/index.php/s/RYni5xngnEZEFkR	Teledyne GALSA Genie Nano
Bosilj et al., (2019)	Onions Dataset	N/A	https://lcas.lincoln.ac.uk/owncloud/index.php/s/e8uiyrogObAPtcN	Teledyne GALSA Genie Nano
Yu et al., (2019)	N/A	Spotted spurge, Ground Ivy, Dandelion	Available on request	Sony Cyber-Shot, Canon EOS Rebel T6
Jiang et al., (2020)	N/A	Bluegrass, Chenopodium Album, Cirsium Setosum, Sedge	https://github.com/zhangchuanyin/weed-datasets	Canon PowerShot SX600 HS
	Open Plant Phenotyping Database		https://vision.eng.au.dk/open-plant-phenotyping-database/	
Sudars et al., (2020)	N/A	Goosefoot, Catchweed, Field pennycress, Shepherd's pursue, Field chamomile, Wild buckwheat, Field pansy, Quickweed	https://data.mendeley.com/datasets/nj4vtk4tt6/1	Canon 800D, Sony W800, Intel RealSense D435
Espejo-Garcia et al., (2020)	Early-crop-weed dataset	Black nightshade and Velvetleaf	https://github.com/AUAgroup/early-crop-weed	Nikon D700

Alam et al., (2022)	TobSet	N/A	https://github.com/mshahabalam/TobSet	CMOS-image sensor (IMX258 Exmor - Sony)

Dataset description and partitioning

SpotWeeds dataset consists of images of weeds at different growth stages collected across three different locations in the state of North Dakota (Table 2). These three locations were, greenhouse (controlled environment) at North Dakota State University – Main Campus (46°53'42.5" N 96°48'19.8 "W), Casselton (46°54'1.8" N, 97°12'40.896" W), and Carrington (47° 22' 25.7556" N, 99° 12' 8.5032" W) (outdoor environment). The time frame chosen for data collection ranged from early May to early September. The weeds were planted in the grenhouse in late April so that the data collection could be facilitated for capturing images of weeds at early growth stages. The time frame chosen to collect and build SpotWeeds dataset resulted in a very comprehensive set of images pertaining to dynamic environmental conditions and different growth stages of weeds at multiple locations. Image acquisition was accomplished using a hand-held camera (Canon 90D) and a UASs (DJI Phantom 4 Pro v2) inside the greenhouse and experimental plots, respectively. A total of 11,100 aerial images of the experimental plots were acquired out which 30,815 images of weeds have been clipped and saved inside the specific folders (Table 3 & Figure 1). Further, the images were split into 70%, 20%, 10% for training, testing, and validation respectively.

Table 2. Dataset collection information.

Location	Time frame	Image acquisition	Controlled environment
Greenhouse (NDSU – Main Campus)		Canon 90D	Yes
Casselton		DJI Phantom 4 Pro v2	No
Carrington		DJI Phantom 4 Pro v2	No

Table 3. Dataset partitioning.

Weed species	No. of images		
	testing	training	validation
Greenfoxtail	172	1,547	421
Common ragweed	550	4,956	1,376
Kochia	500	4,533	1,258
Redroot pigweed	500	4,542	1,261
Waterhemp	360	3,241	900
Horseweed	376	3,384	938
Total	**2,458**	**22,203**	**6,154**

Images in this dataset has not been conformed to be clipped at any specific dimension. Resizing has been avoided so that the images are in its original form and can be trained based on the way it was captured. Generally, training a lot of images with similar context in terms of background and lighting conditions might affect the generalization capability of the trained model (Serre, 2019). Therefore, no image pre-processing steps such as, segmentation (Jeon, Tian, and Zhu 2011), whitening (Tang et al. 2017), etc have been implemented so as to preserve the originality of the dataset. Although, the SpotWeeds dataset has been captured across multiple field locations and different environments, we have applied various data augmentation technique to increase the dataset size and quality of the dataset (Shorten and Khoshgoftaar 2019).

Dataset format and organization

The SpotWeeds dataset is organized according to the ImageNet dataset (Deng et al. 2009). We chose ImageNet dataset because of its popularity amongst many DL-based benchmarking architectures (Krizhevsky, Sutskever, and Hinton 2012; Shen and Savvides 2020). Therefore, releasing the dataset in this format will assist to boost development of new algorithms for weed recognition. As per now, we have relied on creating this dataset for weed recognition only. In weed recognition, the term *recognition* is defined as the ability transferred by humans to computers via algorithms to recognize only one weed specie amongst crop plants. This simply means that the algorithm is only smart enough to recognize a single class of weed in an image by eliminating the need to necessarily localize it. Within the dataset (Figure 1), the SpotWeeds folder consists of 3 separate folders, test, train, and val (validation). The images of all the weeds species are jumbled and kept inside the test folder. This is to ensure that random and unseen images are tested using the developed algorithm. On the contrary, images of each weed species (in *.jpg format) are kept inside the associated folder names pertaining to each weed species. Also, a filename called, labels.txt contains the name of all the weed species. SpotWeeds dataset also consists of aerial videos of the experimental plots. According to Kamilaris et al., (2017), one of the characteristics of big data is data variety. It means that big data should be multi-source with different formats addressing particular problems within any domain. Therefore, we have included *.mp4 format videos of our test plots by flying the DJI Phantom 4 Pro v2 over the 5 different weed species. We anticipate that in the future the developed computer-vision algorithm will be efficient enough to recognize weed species in (nearly) real-time environments with high accuracy.

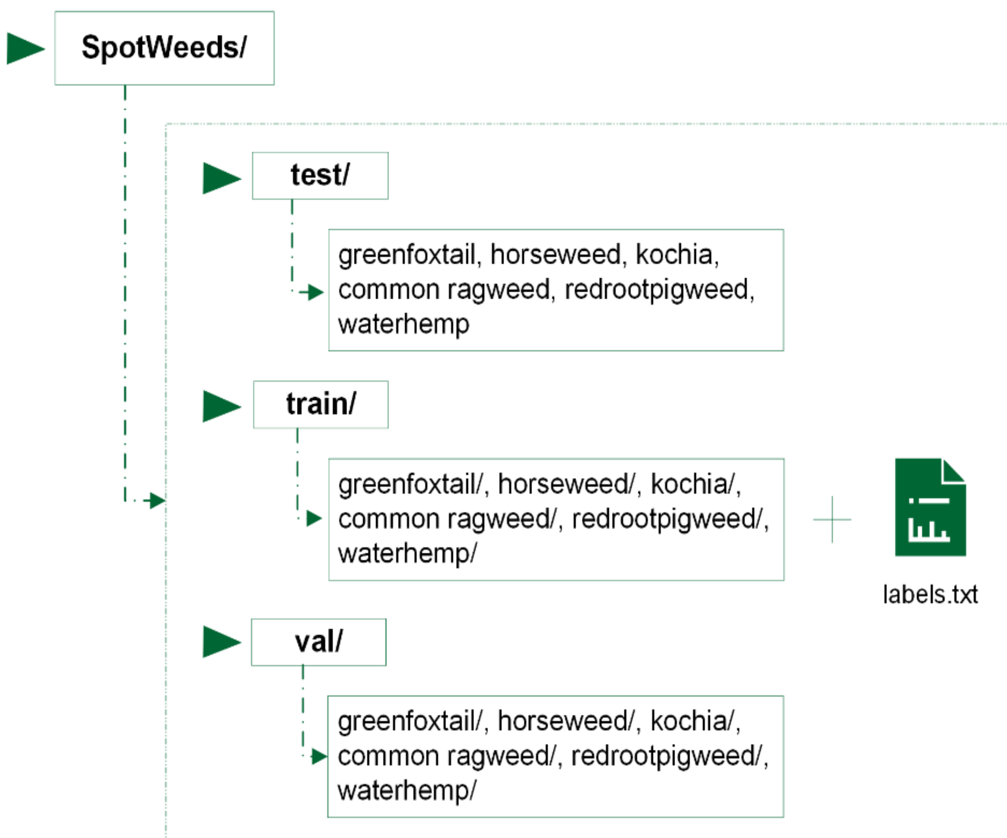

Figure 1. SpotWeeds dataset

Facets of SpotWeeds Dataset

A detailed description of big data has been characterized based on 5 dimensions, volume, velocity, variety, veracity, and valorization (Kamilaris et al., 2017). In the same work, the author has performed a thorough analysis of the use of big data in agriculture thereby concluding that a lowest variety of weed dataset appears in the remote sensing domain. Therefore, the developed SpotWeeds dataset has been created with aforementioned dimensions in mind. Table 4 presents the description of SpotWeeds datasets with respect to meeting all the dimensions.

Table 4. SpotWeeds dataset description.

Dataset name	Categories	Definition	Description of dataset
SpotWeeds	Volume	Size of the dataset collected	Consists of 30,815 images of 23 GB (approx.) in size
	Velocity	Time frame of the collected dataset to achieve reasonable task	Collected over 4 months across 3 different locations
	Variety	Multi-source and different formats of the collected dataset	Collected in 2 different formats, RGB (still images) and *.mp4 (videos of the test plots)
	Veracity	Quality, accuracy, and the potential of the dataset	
	Valorization	The value of the dataset in terms of innovation	

To meet the velocity and veracity of the dataset, we have relied on capturing dataset in variable environmental and lightining conditions. To create a diverse dataset, we employed ideas that would involve not just the presence of weeds in the image but also other weeds along with crop plants with different soil and weather conditions. Figure 2 shows image samples of weeds collected across three locations in 2021. For example, greenfoxtail (Figure 1b) was captured inside the greenhouse in the presence of other weeds along with greenfoxtail. In a similar manner, common ragweed, horseweed, and kochia (Figures 2b, 3b, 5a) were captured in field conditions along with the presence of other crop plants and weeds. These images can be used to test the models accuracy and generalization capability. Figure 3a has an image of kochia with some occlusion and shadow. Also, Figure 2a is ragweed captured on a cloudy day with minimal lighting conditions. Similarly, Figure 4c was captured by increasing the ISO of a hand-held camera. This resulted in a very bright lighting conditions. On the contrary, the image of waterhemp (Figure 6c) was captured in low lighting condition.

1

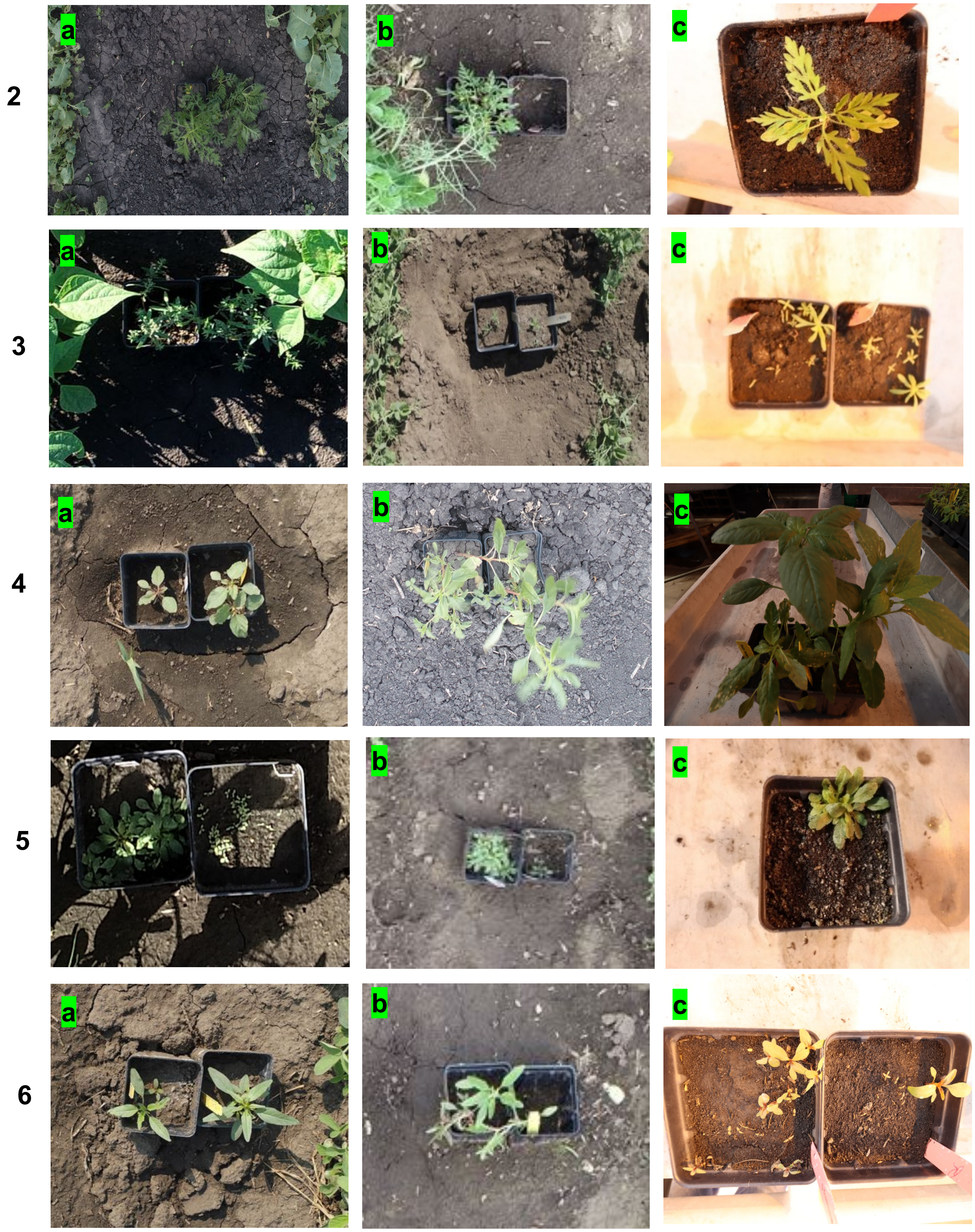

Figure 2. SpotWeeds Dataset. (a) Greenfoxtail; (b) Ragweed; (c) Kochia; (d) Redrootpigweed; (e) Horseweed; (f) Waterhemp

Initial results on weed recognition

Recognition of weeds amongst crop plants is an important step towards ensuring that a proper algorithm has been established for spot spraying application. Here, we have performed initial experiments on the SpotWeeds dataset using the ResNet-18 convolutional neural network (CNN) architecture commonly used for image recognition tasks. We have tested some of the images that were captured in a very diverse setting. As per our experimental results are concerned, ResNet-18 architecture was successful in recognizing some of the weeds in in-field setting. For example, in Figure 3b, the algorithm detected the occlusion of corn crop on horseweed as redroot pigweed with 33.17% accuracy. Rest of the images (Figure 3 a, c & d), ResNet-18 architecture successfully recognized ragweed, horseweed and redroot pigweed with 90.37%, 72.83%, and 99.95%, respectively.

Figure 3. Weed recognition. (a) Horseweed; (b) Horseweed with occlusion; (c) Redoot pigweed; (d) Ragweed

Downloading the SpotWeeds Dataset

To maintain the wholeness of this dataset, we choose not to upload it on GitHub or any other open source websites. Rather, we will be happy to mail the link those who wants to develop novel algorithms for aerial-based weed recognition. Please email to the corresponding author at: xin.sun@ndsu.edu.

Conclusions

In this paper we presented the SpotWeeds dataset for weed recognition using DL-based algorithms. The dataset contains 30,815 images of 6 weed species collected across 3 different location in the state of ND. To create variations in the dataset, we have captured images under different lighting conditions coupled with the occlusions of other weeds, crop plants, unknown objects, and the presence of shadows. This dataset is a good starting point for the development of DL-based algorithm trageted towards aerial-based weed reocgnition for spot spraying application. We anticipate that interested researchers in the field of DL or related engineering fields would be willing to contribute to the advancements in aerial-based weed recognition for spot spraying application.

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