Detection of Senecio jacobaea in drone images, using a machine-learning approach

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Abstract

Senecio jacobaea (S.j.) often grow on extensive grassland and pose a threat to farm animals due to toxic substances. For an effective weed control, site-specific counter measures targeting the toxic plants are sought. This, however, requires precise knowledge of the locations of the S.j. In the present work, we adapt an approach that has been successfully applied to *Colchicum autumnale*: When the flowers were blooming, the fields were mapped using a consumer-grade camera mounted on a drone. The resulting images can then be stitched together to obtain an orthomosaic of the whole field. The S.j. flowers were located in the images using a convolutional neural network with a U-Net architecture. The relatively low number of labelled ground truth images was compensated by applying image augmentation techniques during the training of the neural network. On the test dataset, 95% of the predicted S.j. flower locations were correct (precision), and 70% of the true locations were found by the detector (recall).

Keywords: Senecio jacobaea; convolutional neural network; drone image; object detection

Introduction

Senecio jacobaea (S.j., also known as *Jacobaea vulgaris*, or ragwort) is a flowering plant with very distinctive 15-20 mm yellow flowers clustered in inflorescences of about 20-60 flowers (Söchting 2010). Because of its toxicity, it poses a threat to grazing animals. On pastures, animals usually avoid the plant. However, the poisonous substance is conserved in hay and silage where the animals cannot distinguish it anymore. S.j. can be found on extensive grassland sites or jaggy pastures and is often spread out from fallow land to agricultural land. Grassland with a high density of S.j. must be ploughed and resowed with new grass. If only a few plants occur, they must removed manually. Both measures are not satisfactory, because they mean additional costs for machines and labour time. Therefore, an automated and selective weed control system is required. For this, it is necessary to have precise information about the locations of the S.j. For this reason, the aim of the present paper is to investigate a method that locates S.j. flowers in images taken by a drone flying over the grassland site. The resulting output could then be fed into an automated treatment tool, which allows to efficiently controlling the weed. In Petrich *et al.* (2020) the considered detector (which we call flower detector in the following) is presented for locating *Colchicum autumnale* (C.a.) flowers in drone images. The approach is based on a convolutional neural network and was originally applied to S.j. in Forster (2020), on which the present paper is based. In contrast to other attempts in the literature (Zacharias 2017), the flower detector does not rely on manual feature engineering, but rather learns the features of the flowers through the training. This makes it applicable to different kinds of plants (given suitable training data).

Materials and methods

The necessary image data was obtained on two grassland sites near Bad Überkingen/Burren and Konstanz, Baden-Württemberg, Germany. During the acquisition time between July 22nd

and August 21st, 2019, the S.j. were approximately 50-60cm of height. On the site near Burren, the surrounding vegetation was about 25-30cm tall and almost the same hight as the S.j. on the site near Konstanz. The camera (Sony alpha 7 RII with a Sony lens FE 12-24mm 4G and a resolution of 7952x5304 pixels) was mounted on a drone (Octocopter MK ARF Okto XL 4S12) flying roughly 10m above ground.
In order to keep the workload feasible, 13 disjoint drone images were chosen for manual labelling. For this, each inflorescence (or separate flower) was circumscribed by a polygon (instead of a coarser bounding box as in Petrich *et al.* (2020)), and all polygons belonging to the same drone image were drawn to a binary image ('ground truth segmentation maps') of the same size as the drone image. The result was a dataset of 13 colour drone images and corresponding ground truth segmentation maps, the latter of which described the locations and rough shapes of the S.j. flowers and were thus the desired outputs of the trained detector. This ground truth dataset was split into a training dataset (comprised of 7 drone images and segmentation maps), a validation dataset (3 images), and a test dataset (3 images) at random. For details regarding the flower detector and its calibration to data, we refer to Petrich *et al.* (2020) and concentrate only on the differences in the following. The segmentation maps of the training dataset were further refined by removing all non-green pixels from the labelled polygons and were used to train different models of the flower detector (each having different hyperparameters) under the application of image augmentation. For the post-processing parameters, bounding boxes of the S.j. flowers were required, which were obtained by computing the bounding boxes of each connected component of the refined segmentation maps. Based on the validation dataset, the best model of the flower detector was selected. In total 48 models were evaluated corresponding to all combinations of the considered hyperparameters (four values for the base number of convolutional layers, three values for the initial learning rate, whether to use batch normalization, and which loss function to use, see Petrich *et al.* (2020)). The test dataset was used to judge how the (selected) flower detector model performs on previously unseen image data.

Results and discussion

The best model resulted from the flowing hyperparameters: It employed the (weighted) cross-entropy loss function and batch normalization, had a base number of convolutional filters of 8, and a initial learning rate of 0.00014211.

Table 1: Cluster-based evaluation results for the validation and the test datasets of the best flower detector model

	Validation				Test			
	Summary	Image 1	Image 2	Image 3	Summary	Image 1	Image 2	Image 3
#TP	298	103	194	1	225	206	13	6
#FP	63	25	22	16	11	2	8	1
#FN	49	26	21	2	96	96	0	0
#TN	0	0	0	0	0	0	0	0
precision	0.826	0.805	0.898	0.059	0.953	0.990	0.619	0.857
recall	0.859	0.798	0.902	0.333	0.701	0.682	1.00	1.00
F2 score	0.852	0.800	0.902	0.172	0.740	0.727	0.890	0.968

In Table 1 the results of the cluster-based evaluation are shown. That is, each labelled polygon of a drone image was considered and counted as a true positive (TP) if there existed a foreground cluster in the predicted output of the (selected) flower detector model that intersected this polygon. If there was no corresponding prediction, it was a false negative (FN). All foreground clusters which did not intersect a polygon were considered false

positives (FP). From these values the precision ('probability that a predicted foreground cluster is actually a S.j. flower'), the recall ('probability that a S.j. flower was detected'), and the F2 score (an aggregated value of precision and recall that puts more weight on the latter) were computed, see Goodfellow *et al.* (2017).
Table 1 shows a good precision (0.826) and recall (0.859) for the validation dataset. More important are the results for the test dataset, where a very high precision of 0.953 could be achieved and a reasonable recall of 0.701. A more in-depth analysis showed that many of the false positives were yellowish leaves, but there were also cases where it was not clear from the image whether a yellow flower actually should have been labelled as S.j. flower. False negatives, on the other hand, tended to be smaller isolated flowers. The fact that all false negatives in the test dataset and most of the true positives were from a single drone image indicates that the ground truth dataset might have been too small for a definitive judgement on the flower detector's performance to locate S.j., and further interventions are necessary. Compared to the results presented in Petrich *et al.* (2020), the recall is decreased (0.701 for S.j. vs. 0.986 for C.a.). Even though the yellow flowers of the S.j. might be considered as not as distinct as the purple flowers of the C.a., the number of false positives and therefore the precision is better (0.953 for S.j. vs. 0.571 for C.a.). It is important to note that the ground truth dataset is with 13 drone images compared to 56 drone images (of the same resolution) much smaller in the present paper. Moreover, the interfering objects, which were one of the main sources of misclassification in Petrich *et al.* (2020), did not occur in the S.j. ground truth dataset and the resilience of the model regarding those could thus not be evaluated.

Conclusion

It was shown that the flower detector originally develop for C.a. in Petrich *et al.* (2020) can be used to locate S.j. in drone images with a recall of 0.70 and a precision of 0.95 on the test dataset. These initial results are very promising, but further research is needed in order to evaluate the detector's performance on larger and more diverse (different site locations, surrounding vegetation, ...) datasets.

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