Development of a UAV image Dataset for Cauliflowers Ripeness Classification with Deep Learning

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Accurate, early estimation of cauliflower ripeness level provide crucial information for harvesting. Currently, many crop production systems still fully depend on human labour with respect to manual harvesting. So, knowing the right moment to pick a cauliflower allows growers to use their harvest crew more efficient decreasing production costs. Despite the advance in technology such as artificial intelligence (AI) which can provide more consistent predictions on plant state or quality compared to humans [2], there have been few efforts in developing useful tools for determining degree of maturity of cauliflower fruits. Thus, for instance, Bender et al. [1] used an autonomous field robot to collect field data of cauliflower plants trough out the growth. A deep learning (DL) model (Faster R-CNN) with detection performances, expressed in average precision (AP), of 94.79 and 92.48 percent for IoU (Intersection over Union) thresholds of 0.5 and 0.75, respectively, were achieved. As a cauliflower grows bigger, the visible white head emerges, but the leaves of neighbouring plants start to overlap, so plant detection becomes more difficult. Grenzdörffer [3] acquired cauliflower field data with an unmanned aerial vehicle (UAV). Using color segmentation techniques, 966 out of 1468 cauliflower heads could be recognized automatically ($\approx$ 65%). Both studies did not specifically include ripening of the cauliflowers, which in practice is an important factor for growers. The aim of this study was developing and testing a dataset which serves to determine the ripeness of cauliflower using DL. The study took place in an organic farm located in Zeewolde (The Netherlands). The aerial survey was conducted on October 22 2019 between 13:00 and 15:00, during the harvest. It was a cloudy day with a medium wind speed. The UAV system employed was a DJI Mavic PRO 2 with a Sequoia camera. The images were collected with an average flying height of 10 m above ground level at nadir. A total of 3000 images were acquired. The model Mask R-CNN [4] with Detectron2 were implemented. A total of 120 RGB images were used to create annotations with LabelMe [5]. For training and validation, 2500 and 650 annotations were used respectively. The per-class AP for multiple IoU thresholds is given in Table 1.

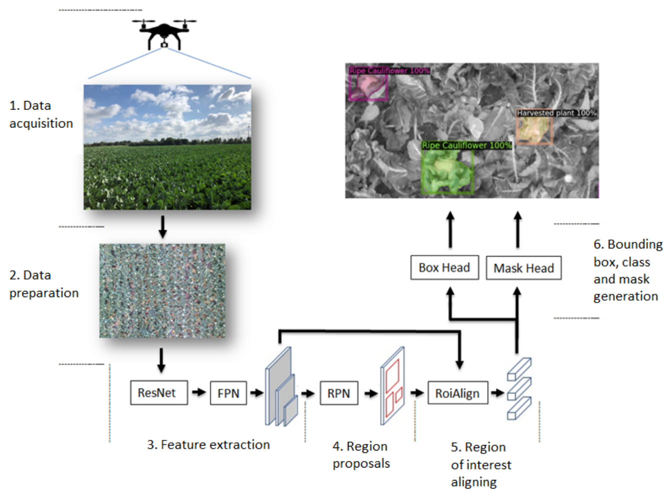

Fig. 1. Workflow of the approach proposed.

Table 1. Per class average precision of the model for different IoU thresholds

Class	IoU 0.5	IoU 0.75
Ripe cauliflower plants	70 %	40 %
Harvested plants	50 %	20 %

Although the classification performance must be increased, the UAV-based image classification is promising showing an AP up to 70% for ripe cauliflowers. The final goal of this research will be developing an intelligent decision support systems (DSS) which provides information, such as number of ripe cauliflower heads, that can be used by a grower to optimize his harvesting strategy. In this way, with a cheap setup and easy-to-use DSS the harvest costs can be reduced and crop quality and yield can be increased.

References

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