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Sugar beet disease detection based on remote sensing data and artificial intelligence

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Abstract

Plant disease detection for precision chemicals application is a field of interest to reduce the use of chemicals in the field. Detection of diseases with an RGB sensor camera simulating real acquisition on a sprayer was performed. For dataset preparation, about 986 images were collected from a sugar beet field in North France under varying conditions. The accuracy assessment was performed using statistical indicators which are Precision, Recall, F1-score, and Average Precision. The Mask RCNN model detects sugar beet disease with an average precision of 92.73 % for the three disease types. Artificial intelligence has a strong potential to reduce the use of chemicals thus costs optimization and environmental risks minimization over agricultural fields.

Keywords: Sugar beet, disease, remote sensing, deep learning, artificial intelligence.

Introduction

European policies encourage farmers to reduce the use of phytochemicals (European Commission 2022). Precision agriculture (PA) can be a major key towards decreasing phytochemicals use in the fields. High progress has already been achieved on detection of weeds with UAVs (Nikolic *et al.*, 2021), with sensors directly embedded on sprayers or with mechanical weeders (Esposito *et al.*, 2021), in order to reduce the herbicides application. The second major use of phytochemicals is on diseases treatment, but the research made on PA to reduce the use is still scarce. Several steps have still to be performed to have an on-hand solution for farmers. The first thing to be done has been to discriminate the disease from others in several physiological status of the plant, research have been conducted and results are encouraging on individual leaves (Mahlein *et al.*, 2014), but few of them work at field level to detect diseases on crop canopy (Guo *et al.*, 2021). Later it will be necessary to localize the disease and determine the infection severity to modulate the fungicide use without yield impact. This modulation could be based on the type of disease, its capacity of dispersion and the impact on the yield or based on the potential yield of the plant (biomass already accumulated) or based on the level of infection.

Many sensor types have been used in literature for plant disease detection (Fahey *et al.* 2020). However, the use of sensors for spot application of fungicide was reported in limited studies (Esau *et al.* 2018; Hussain *et al.* 2020). The novelty of this study consists

in the development of a machine learning-based approach for Cercospora Leaf Spot (CLS) and Beet Yellow Virus (BYV) diseases identification in sugar beet fields. Compared to previous research, this study explores the use of RGB spectral information captured from camera to simulate a variable rate application of chemicals, based both on disease identification and biomass estimation. In the following sections, the study explores the methodology for CLS and BYV diseases identification in sugar beet fields.

Materials and methods

On field measurements and instrumentation

Analyses were done a month before harvest on a field of sugar beet variety Libelulle sown on March 23rd 2022 and harvested on November 14th cultivated in the North of France. Photos were taken at a height of 1.5m with a camera tilted to 45° to simulate the same position of sensors placed on a sprayer boom. Around each sample, photos were captured from 4 different directions and with different light conditions to simulate all the possibilities which will be encountered by the sensors during real data collection on sprayer boom. The camera used was a SONY DSC-RX0M2 collecting spectral information in three wavelengths: red, green and blue. A level of disease was scored from saine plants (0) to complete diseased plants (10). The sugar beet diseases considered in this study were the Cercospora Leaf Spot (CLS) and the Beet Yellow Virus (BYV). These two diseases affect the sugar beet leaves and cause important reductions of yields. Each sample was harvested, the leaves area was calculated thanks to a planimeter LI-3100C (LI-COR Germany). Roots were cleaned, dried and weighted fresh. Then leaves and roots, separately, were dried at 80°C till constant weight, to get the dry matter weight. In the following steps, spectral information from photo will be considered for implementation in the Mask RCNN model.

Image pre-processing

After field data collection, several pre-processing steps were conducted to make data ready for implementation in the machine learning algorithm. The methodology presented here is based on the use of photos from the RGB Sony sensor (Figure 1).

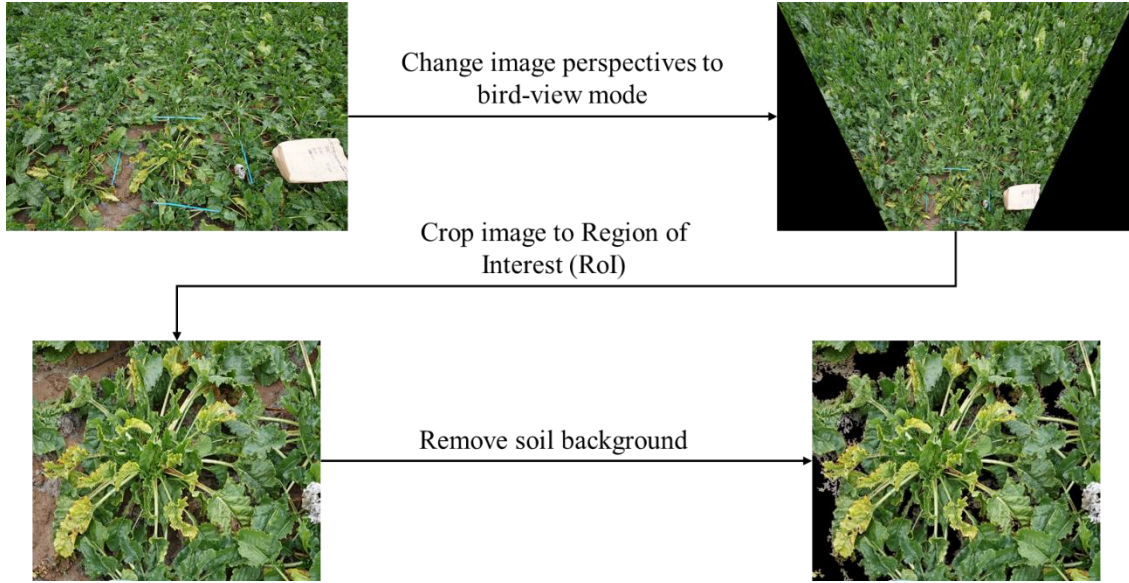


Figure 1. Preprocessing of sugar beet images for Mask RCNN model implementation

Data from the camera were pre-processed using OpenCV and NumPy libraries in python environment to change image perspectives to bird-view mode, reduce size, and remove soil background. The pre-processing step consists of three major operations.

Firstly, warping perspectives of the photos was performed using the openCV library of python. All the collected images were transformed based on definition of warping points and camera sensor properties. The obtained images were at nadir view and each pixel on the image represented 1mm in reality. These transformations were done to further perform correlations between data measured on field samples, especially leaves area and biomass.

The following step consists of data cropping to Regions of Interest (RoIs). The RoIs were defined in the field using bleu stakes. Image cropping was done manually to be sure each individual plant was inside the stake borders and comprised within the photo.

The final pre-processing step was the soil background removal of cropped images. For this purpose, the Colour Index of Vegetation Extraction (CIVE) vegetation index was used (Equation 1).

$$CIVE = 0.441 \cdot R - 0.811 \cdot G + 0.385 \cdot B + 18.787 \quad (1)$$

Where R, G and B represent spectral bands in red, green, and blue, respectively.

Afterwards, data were split into training and testing datasets. Data annotation was performed using the VGG annotator tool developed by Oxford university (Dutta and Zisserman, 2019). Three classes were defined during annotations: CLS, Healthy, and BYV, for cercospora leaf spot, healthy leaves, and beet yellow virus, respectively (Figure 2). Data annotations were stored in a Json file format.



Figure 2. Example of manual annotations of Sony camera images after pre-processing.

Mask RCNN implementation

The Mask RCNN algorithm was deployed to perform sugar beet disease detection based on annotated images as an input dataset. It was employed to automatically segment and classify the diseased areas. The Mask RCNN is based on two stages which are object detection and segmentation. First, it generates region proposals where there is a predicted object based on dataset in input. Second, the model predicts the class of each object, improves the bounding boxes (bboxes) and creates masks based on region proposals of the first stage. The Mask RCNN architecture consists mainly of three parts which are: the backbone, the Region Proposal Network (RPN) and the feature branches (Su et al. 2020). A Residual Neural Network (ResNet) model with 101 layers (ResNet-101) was employed. Model training was carried out using a limited number of annotated images (Figure 3).

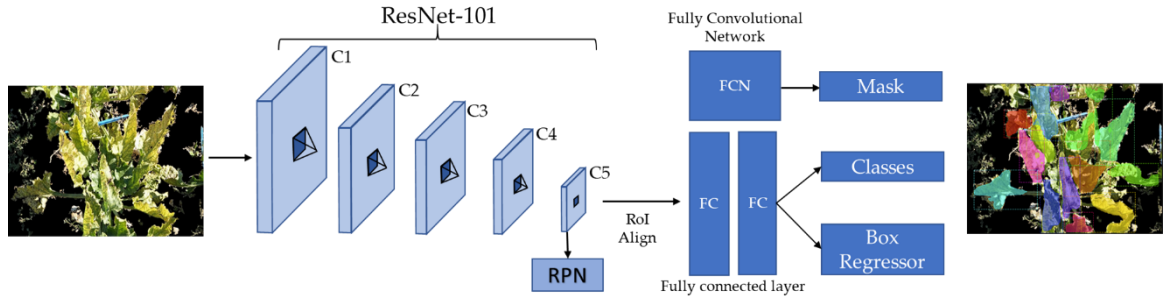


Figure 3. Overview of the mask RCNN model architecture

The performance of the mask RCNN model was evaluated using different statistical estimators: F1-score, Precision, Recall, and mean average precision (mAP) were computed. The statistical estimators are expressed by the following equations:

$$precision = \frac{TP}{TP+FP} \quad (2)$$

$$recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - score = \frac{2 \cdot P \cdot R}{P+R} \quad (4)$$

$$mAP = \frac{1}{n} \sum_{i=1}^n AP_i \quad (5)$$

Where, TP, FP, FN, P, R, n, and AP are the true positive, false positive, false negative, precision, recall, number of classes, and average precision respectively.

Results

Figure 4 presents an example of successfully predicted diseased leaves of sugar beet using the Mask RCNN model. The predictions were performed on validation dataset. The model output is composed of bounding boxes, class scores and masks. The confidence values of class scores of detected objects varied between 0.91 and 0.98.

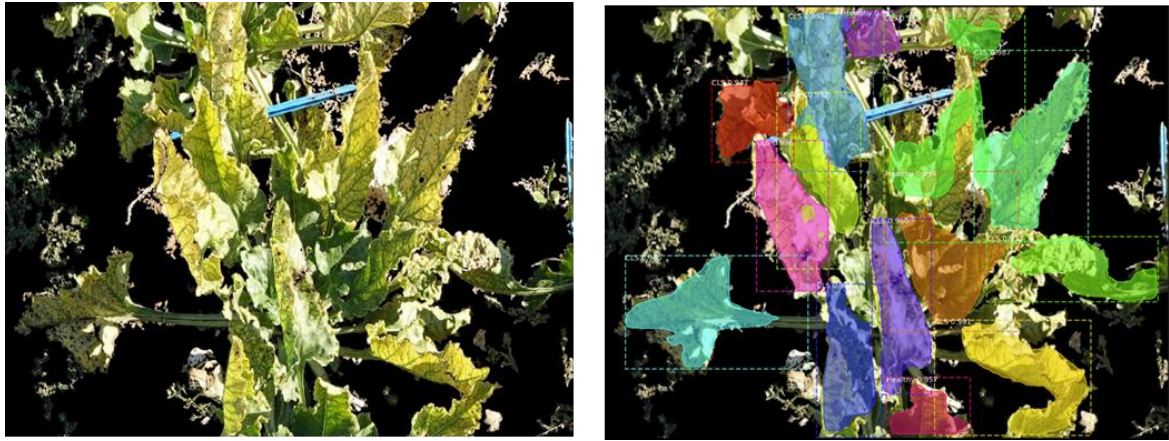


Figure 4. Diseased sugar beet plant with Cercospora Leaf Spot & Beet Yellow Virus (left); detection results using the mask RCNN model (right).

The reported average precisions of the Mask RCNN model (mAP) was about 92.17%. This value was calculated as the mean of all the average precisions (AP) issued by the model.

Table 1. Results of the Mask RCNN model for sugar beet diseases detection. CLS: Cercospora Leaf Spot; BYV: Beet Yellow Virus

Disease classes	Precision (%)	Recall (%)	F1-score (%)
CLS	93.05	89.21	91.69
Healthy	94.43	95.84	93.12
BYV	90.71	90.15	91.74

The Mask RCNN model results based on test images showed that the precision reached 93.05% as the higher value for CLS class and 90.71% as lower one for BYV class. In order to further assess the accuracy of the Mask RCNN model, F1-score was calculated for each class. The algorithm presented an acceptable performance for sugar beet disease detection with a higher value of F1-score around 93.12%. These results show and proves that the developed model was effective for the identification of sugar beet disease at field level.

Discussion

This research proposed an approach for sugar beet disease detection based on Mask RCNN model. The reported metrics from the accuracy assessment of the model provide a wide view about the potential of this deep learning algorithm towards decision in precision agriculture field. The adopted methodology was able to identify diseased

leaves of sugar beet plants at the field scale. However, the prediction of disease is not performed in the edges of the images.

For sugar beet leaves not detected, the issue could be related to pixel distortion in the image edges and to blurred pixels presents in the image. These false detections could be related to other factors such as the limited number of annotated images. In order to enhance the results of the Mask RCNN model more images should be annotated with precise and good knowledge about sugar beet disease identification. Wrong annotations lead to model mismatching between predicted and observed data (Su et al. 2020).

As presented above, this study aims to develop a variable rate application of chemicals over sugar beet fields. However, using results from the Mask RCNN model only, could be not sufficient for making decisions on a variable rate application. The study looks for developing a decision support tool including disease detection from sensor photos and data from covariate variables (e.g., rainfall, temperature, disease level...) to modulate the use of chemicals. At this stage the Mask RCNN model will be used for variable rate application of chemicals especially for CLS disease, since treatment after occurrence of BYV disease will not be considered but may conduct to a modulation of the doses as the yield is already compromised in the contaminated plants.

Conclusion

A Mask RCNN model for plant disease prediction was developed. The methodology consists of data collection, pre-processing, annotations, and model calibration/validation. Many suggestions of enhancement could be considered for achieving more robustness with the developed model such as using near infrared sensors (NIR), assess other deep learning models, and increase the number of annotated images. The results obtained show the importance and the strong capacity of this kind of application in decision-making and the enhancement of agricultural management practices.

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