PERFORMANCE OF REMOTE SENSING DATA AND MACHINE LERNING FOR WHEAT DISEASE DETECTION
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ABSTRACT

The evolution of remote sensing applications in precision agriculture may lead to a reduction in phytochemical use. The development of data processing techniques allows speeding up the treatment of the information then making it possible to apply the right amount of chemical at the right place and time. In this study, the use of spectral information from remote sensing data using camera sensors coupled with artificial intelligence techniques at the field scale to detect wheat diseases is evaluated. In this study a Region based Convolutional Neural Network (R-CNN) model was evaluated for wheat disease detection. Besides, the methodology considered environmental variability during data collection to simulate real conditions during data acquisition in the field. The preliminary results of the model show a mean average precision of 0.45 and a precision between 0.2 to 0.6 for each image. Considering limitations in terms of data annotations for training the model, these results look promising on the way to consider further improvement of the model to reach higher accuracies and precisions. Furthermore, the study aims to develop a methodology for treatments reduction based on the enhanced version of the R-CNN model. Therefore, wheat disease detection and localized treatment in the field have a strong potential to reduce the use of chemicals. The developed methodology will optimize the costs and the use of chemicals over agricultural fields.

INTRODUCTION

French agriculture has reached high yield levels in many field crops. However, to reach them, it has required an intensive use of plant protection products (PPP) during the last decades. This intensive use of PPP situates France as one of the first users within the European countries (Eurostat, 2022). Since 2008 European and national policies have been trying to reduce the use of PPP to develop a more sustainable agriculture (European Parliament 2009). The development of precision agriculture may have an important impact on the reduction of PPP application, especially with the spot application technique (e.g., only when and where it is necessary), which reduces the use of PPP. Major progress has been made in weed detection and herbicides localized application (Nikolić et al, 2021) with the development of sprayers or weeders carrying cameras to detect weeds. On the contrary, the reduction of fungicides used to control diseases in plants has been the object of less studies, because of cumulated difficulties encountered in the implementation process. The first step has been to discriminate leaves with symptoms of diseases from healthy leaves (Sujatha et al. 2021), here the main difficulty was the diversity of symptoms within the diseases and along the development of the disease on the leaves. The second step has been to discriminate different plant diseases (Martinelli et al. 2015), to treat with more efficient treatment. Next difficulty will be to find diseased leaves on a field crop at different growing stages of the crop. The last step will be to be able to modulate the fungicides doses in function of the disease pressure or to make localized applications that may be able to stop or slow down the progression of the disease. For these reasons, this study will discuss the possibilities of wheat disease detection based on camera sensors and machine learning algorithms to identify diseased areas and variable rate application of treatment.

MATERIALS AND METHODS

In France there are decision support systems for farmers to alert the risk of diseases on the crops based on rainfall events, presences of spores, soil type, rotation, and the level of resistance of the variety to each disease. This study discusses the possibility, once there is a disease risk in a field, to implement a modulation of the dose of fungicides to be applied based on direct identification of the presence of the disease (Colbach et al 1997).

The wheat diseases considered in this study are the Septoria leaf blotch (*Mycosphaerella graminicola*) and the yellow rust (*Puccinia striiformis f.sp. tritici*). These two diseases affect the wheat leaves and cause important reductions in yields.

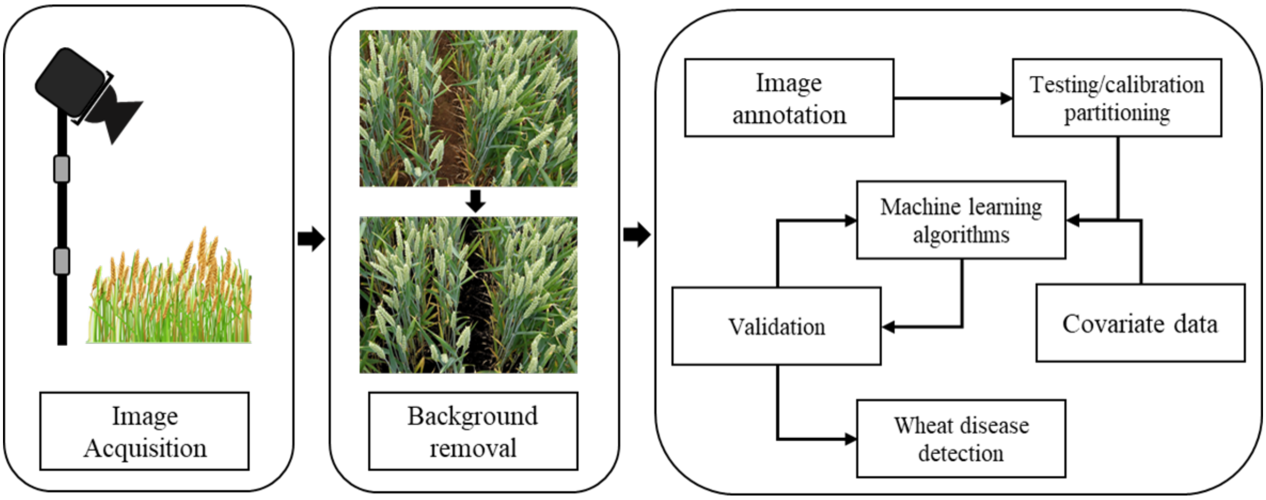

Fig. 1. General methodology for wheat disease detection. a) data collection using field camera with a 45° tilt, b) methodology of background removal based on the Colour Index of Vegetation Extraction (CIVE) vegetation index, c) general machine learning steps to perform wheat disease detection.

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 methodology discussed here is based on the use of an RGB sensor from a Sony camera which will be mounted on a support and tilted to 45° degrees to simulate the position of sensors on the sprayer boom (Fig. 1).

After field data collection, the pre-processing steps will be conducted to make data ready for implementing in the machine learning algorithm. The first pre-processing step consists of soil background removal using the CIVE index. The formula used for CIVE computing is indicated below:

$$CIVE = 0.441 * R - 0.811 * G + 0.385 * B + 18.787 \qquad \text{(Eq 1)}$$

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

Mask-RCNN model was employed in this study to automatically segment and classify the diseased areas of wheat fields. The Mask-RCNN is based on two stages which are object detection and segmentation. It consists of three parts mainly a backbone, Region Proposal Network RPN, and feature branches (Su et al. 2020). A Residual Neural Network (ResNet) model with 101 layers (ResNet-101) was employed in this study. Model training was carried out using a limited number of annotated images.

RESULTS AND DISCUSSION

Fig. 2 presents the result of wheat diseases detection using Mask-RCNN model. The predictions were performed on validation dataset. The confidence values of detected objects vary between 0.3 and 0.65. The average precisions of the model for each image were relatively low and were between 0.2 to 0.6. In addition, the mean average precision (mAP) is about 0.43.

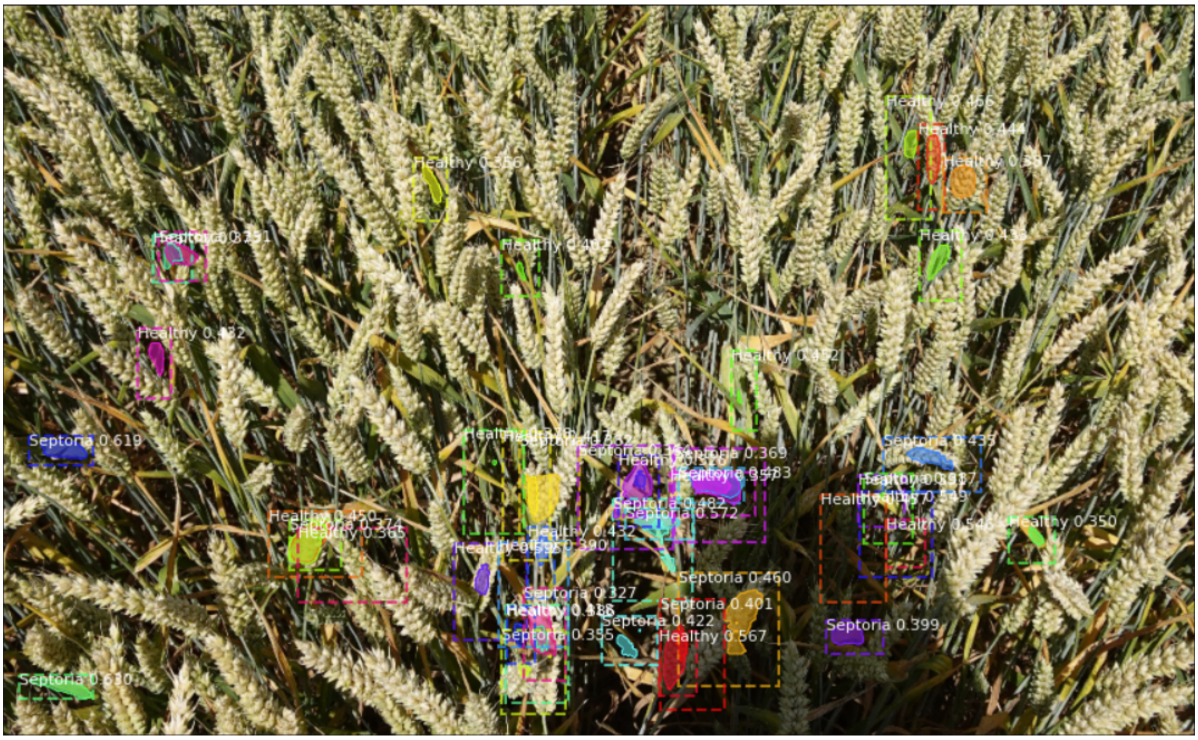

Fig. 2. Result of wheat disease detection using the validation dataset with the Mask-RCNN model.

Regarding the results obtained and precisions of the model, we can conclude that the model did not perform well for detecting diseased leaves. These raised errors could be originated from many issues that should be reviewed for the next application of the model. The intense presence of wheat heads in the images is the main source of errors during segmentation and identification of objects, as during the labelling step wheat heads were not labelled as a separate class to avoid mismatching with other classes. Moreover, related to some scheduling constraints the field data collection was performed during a late stage of phenological development where most leaves reach the senescence phase which makes the identification of leaves more difficult.

Different data acquisition platforms for plant disease detection were reported in previous studies, by using satellites, UAVs, land robots or handheld sensors (Mahlein, 2016) which allowed unequal diseases detection and time required for data acquisition and treatment. In this study, a handled sensor was chosen to provide accurate acquisition of images and simulate the configuration of sensors on the engine boom. Some studies have used UAV images to detect disease on wheat crops (Bohnenkamp et al. 2019; Deng et al. 2022). However, the use of drones is usually related to technical limitations, such as flight planification for data acquisition, limitations related to weather conditions and the time needed from data acquisition to action release at the field.

Machine learning algorithms for identification of wheat disease using images from sensors, especially deep learning, have provided significant advances to accurately identify and monitor diseased plants. Recently, Convolutional Neural Networks (CNNs), a subset of machine learning techniques, have gained popularity as a flexible tool for operating on large and diverse amounts of data and producing accurate predictions of difficult and complex problems (Su et al. 2020). Besides, many datasets have contributed to the training of algorithms to enhance predictions, such as Plant Village (PV) (Martinelli et al. 2015), Global Wheat Head Detection dataset (GWHD) (David et al. 2021), and IPM and Bing datasets (Ahmad, et al. 2022).

These preliminary results obtained during this study and made with a limited number of images are promising to use machine learning to detect disease and spray localized chemicals on the high yield compromised section of the field.

CONCLUSION

The use of machine learning techniques and data from sensors for plant disease detection combine the expertise and knowledge of agronomists and data scientists for better decision making and the understanding of the plant's behaviour during phenological cycle. These kinds of applications are encouraged especially for transitioning towards a rational use of chemicals and adapting new strategies for yield enhancement and preserving soil and human health in a climate changing situation.

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