Deep learning for interpreting images of crops acquired under field conditions

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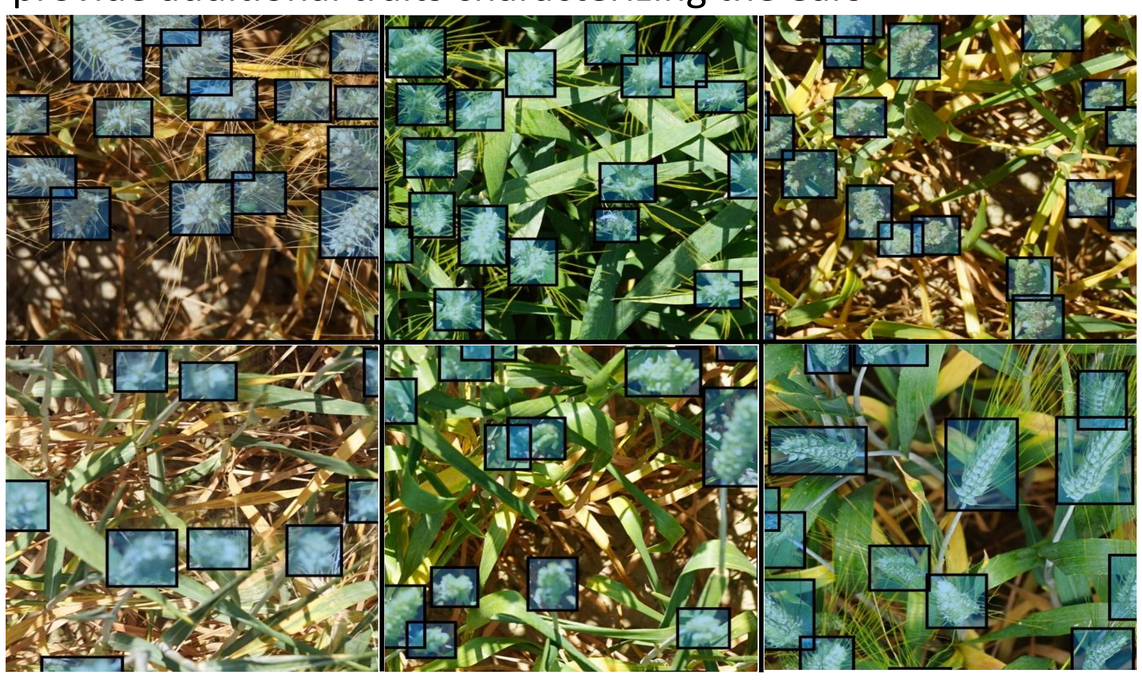
BACKGROUND

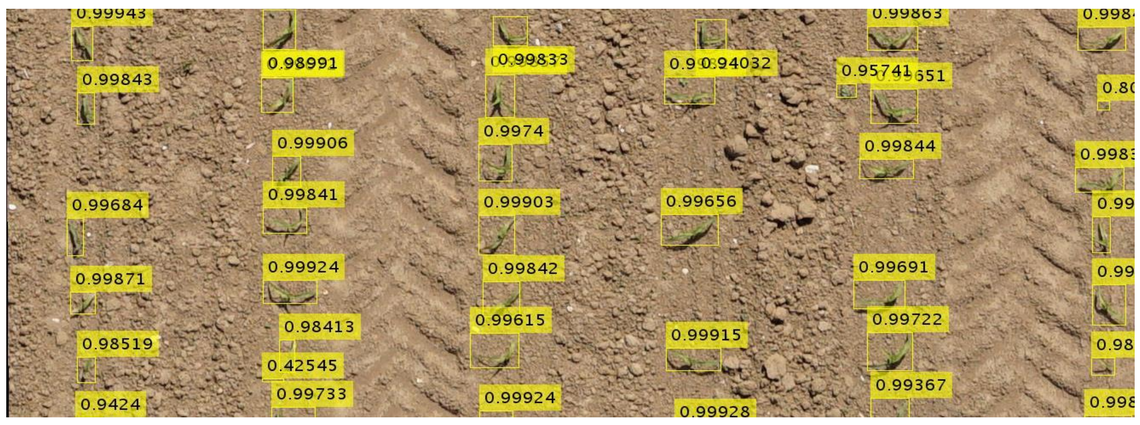
Genetic progress is one of the major leverage used to increase food production. Increasing the yearly genetic gain is therefore mandatory to feed the increasing human population under global change issues. Selecting or creating the optimal cultivar for a given location is very challenging considering the very large spatial and temporal variability of environmental conditions. Over time, public and private sectors have developed breeding programs based on comprehensive observations of the crops to better describe its functioning and the associated genetic control. The combination of proximal sensing with the IoT technologies, rover robots and unmanned aerial vehicles (UAVs) allows gathering a large amount of images of the crops. Multiple attributes of the crops could then be retrieved using deep learning approaches. These attributes describe important physiological traits associated to biotic (diseases) and abiotic (climate, soil) stress. We illustrate here the use of Convolutional neural networks (CNN) to estimate those various traits from images taken in the fields.

Some applications of deep learning in field crops

Nadir high resolution RGB images were acquired under various conditions for different wheat genotypes using robots and UAVs. A two-stage object detection algorithms (Faster-RCNN) [1,2] is then used to identify ears and thereby get the ear density. Likewise, using this deep learning approach will provide additional traits characterizing the ears



Approaches based on CNNs provide a solution to increase the throughput as well as the spatial representativeness which was found to be critical in a context of field phenotyping platform and human limited resources.



Imagery from UAV at low altitude allows identification of plant at emergence and plant density estimates. A centimetric localization of the plants also allows precise monitoring.

Semantic segmentation identifies the presence of pathogens. The cover fraction is also estimated. High spatial resolution is therefore required (IOT images) to get optimal performances.

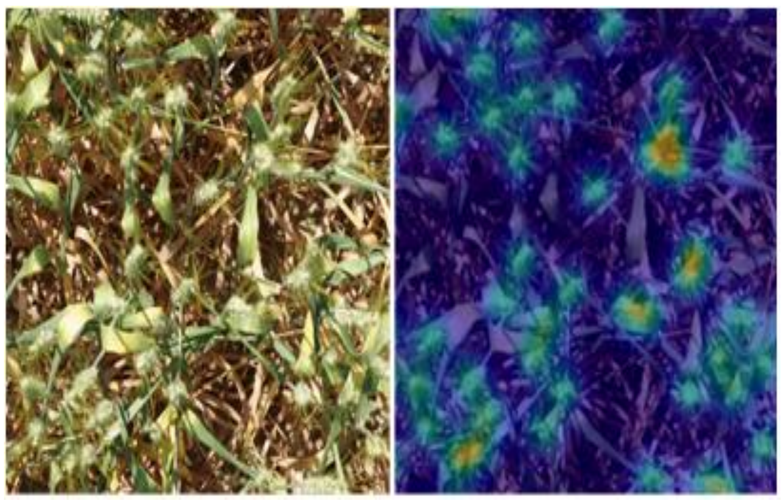
Main results and limitation

CNNs models trained with transfer learning from large scale object dataset (COCO,OpenImage) were found to be more robust when applied to images taken under changes in illumination conditions and camera configuration.

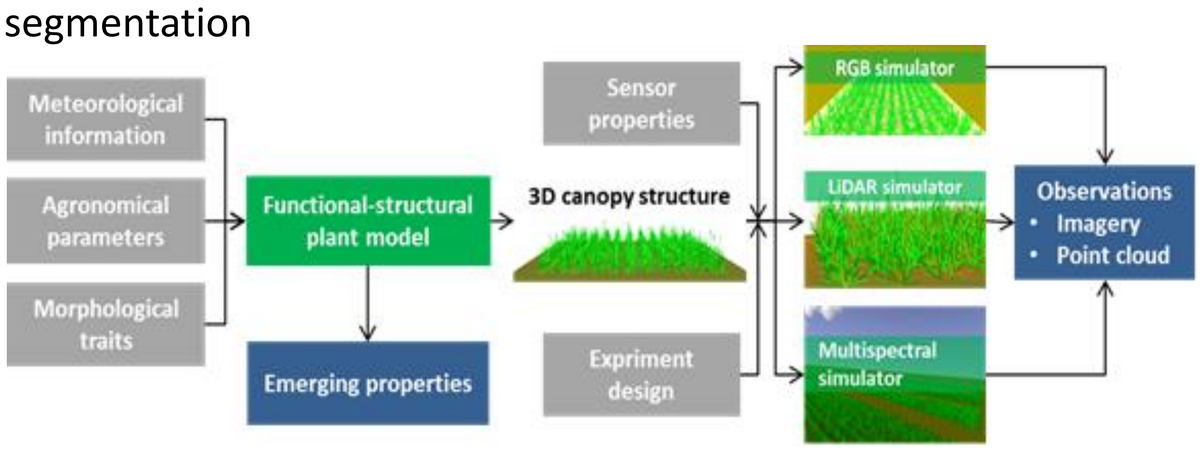
Deep models often required spatial resolution of a fraction of millimiter. This is a trade-off between spatial representativeness and throughput. Some work on photogrammetric solutions (videos, multi-focal features …) and vectors (UAV, robots) also have to be conducted.

Future challenges and prospective

CNNs with regression output can be used to estimate various traits. Multispectral images [3] and depth measurement from LiDAR and photogrammetry may also add significant information



Digital Plant Phenotyping Platform (D3P) that simulates the images taken over crops under field conditions [4] may complete the need far large scale labeled images required for semantic segmentation



Computing resources is often critical.

Data augmentation and domain adaptation are suppose to improve the robustess of the models. Open source algorithms and dataset have to encouraged in the agriculture fields

References

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