CIDAI Centre of Innovation for Data tech and Artificial Intelligence

AI4Agriculture – Grape quality and yield estimation

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1. Abstract

This work has been developed in the framework of AI4EU. The aim of the AI4EU project is to build a comprehensive European on-demand AI platform to reduce barriers to innovation, drive technology transfer and catalyze the growth of start-ups and SMEs. In this context, the AI4Agriculture pilot aims to show how AI4EU can stimulate scientific discovery and technological innovation in the field of agriculture.
The aim of AI4Agriculture is threefold: 1) to evaluate the quality of grape production 2) to count the number of fruits (grapes) and 3) to predict the yield. It will be done using computer vision and other AI techniques, and showing the AI4EU platform in the context of agriculture.

1.1. Objectives

Artificial Intelligence has positioned itself in recent years as a disruptive technology that offers great benefits to various sectors, but the availability of these resources is key to ensuring European leadership and creating opportunities for companies. The European project AI4EU aims to build the first European platform and ecosystem "on demand" of Artificial Intelligence (AI), which will facilitate the collaboration between different actors in the creation of products and services, or experiment with AI tools for the creation of prototypes and applications.
AI4EU has been developed under the umbrella of Horizon2020, the European Commission's research and innovation framework program, and started in January 2019.
The platform offers and displays services, experience, algorithms,

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software frameworks, development tools, components, modules, data, IT resources, prototyping features, and access to finance. Eight industry-driven AI pilots will demonstrate the value of the platform as an innovation tool thus enabling real applications, promoting adoption, solving the technical challenges posed by advanced industrial applications, and stimulating partnership between research and industry. As part of this project, the IDEAI@UPC is participating in the AI-focused pilot for agriculture (AI4Agriculture) [1].

This pilot aims to apply Artificial Intelligence to Agriculture with the aim of helping farmers reduce production costs and obtain the highest possible product quality. The AI4Agriculture pilot implements advanced analysis of data from satellite, drone and mobile phone images, for the automatic counting of fruit in a plant and the evaluation of the maturity and the quality of the harvest in the vineyards located in the region of the Ribera del Duero. These features will allow growers to make decisions, for example, to select the optimal time of harvest, identify the water stress of the plants or provide data to predict which areas of the vineyards have adequate production to create different types of wines.

1.2. Summary of the problem

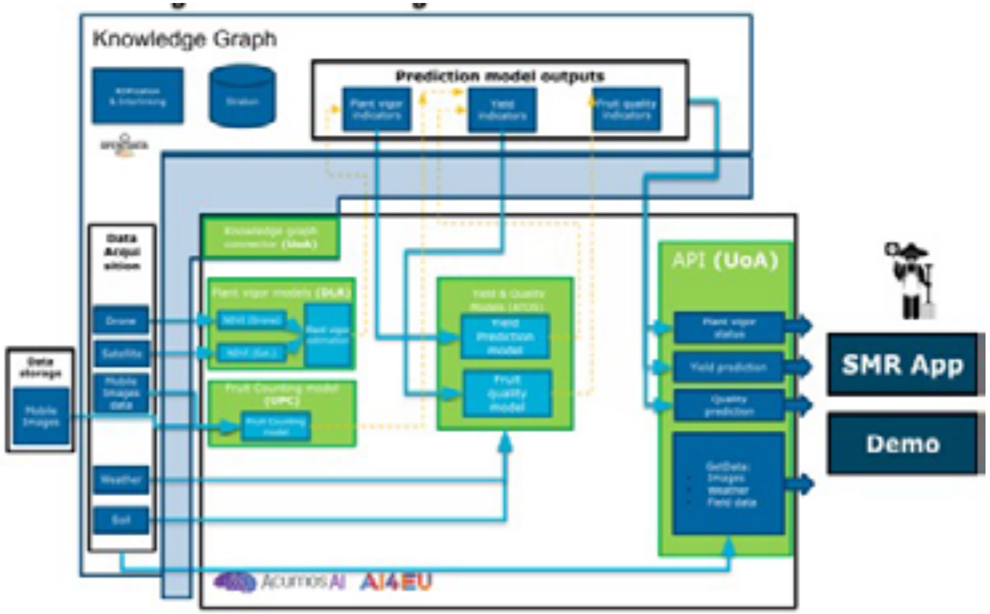
In a nutshell, the AI4Agriculture pilot addresses the following problems:

- Vineyards need to know in advance (predictions) the estimated yield production and its potential quality.
- Farmers need Help on the decision-making process based on data (i.e. prune the vines to respect the production quota or to decide the parcels assigned to produce wines of different quality).
- A knowledge base is needed to provide mapping services to be integrated into third-party apps

2. Solution

The architecture of the model can be seen in Figure 1. The process can be summarized in three main blocks: data collection, prediction models and knowledge graph. The data is collected from various sources: ground, drone and satellite images, soil, plant variety, laboratory and wine analyses, weather conditions history, etc. and stored in the Knowledge Graph, a relational database along with an ontology that models the results. The prediction models use this data to predict the production and quality of the crops.

Figure 2.1. Block diagram of the solution



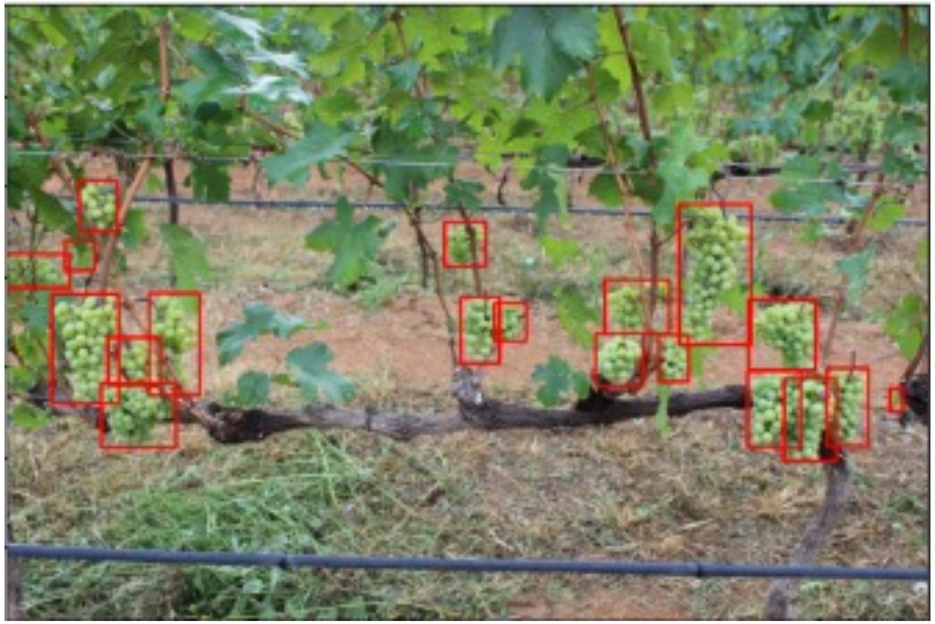
Several partners were involved in this scheme, as shown in Figure 2.1: ATOS Spain, SmartRural (SMR), DLR, Universitat Politécnica de Catalunya (UPC) and the National and Kapodistrian University of Athens (UOA).

3. Implementation of the solution

3.1. Datasets

To implement and demonstrate the pilot, two different datasets were created: the grape dataset and the drone dataset.
The Ai4Agriculture grape dataset [2] is a collection of 250 images taken in a vineyard in Ribera de Duero. The grapefruits in the images are annotated using bounding boxes. The goal of this dataset is to provide images and the associated annotations to train and validate object detection models. These models can be used in viticulture applications, such as yield estimation, fruit counting, and field robotics.
The images were captured by SmartRural and annotated by ATOS, Universitat Politecnica de Catalunya, Deutsches Zentrum für Luft- und Raumfahrt, and National and Kapodistrian University of Athens. The images are annotated using bounding boxes. Figure 3.1 shows an exemple of the annotations.
The images were taken in twelve different parcels. Six areas were defined in each parcel. Each area contains several lines of plants (grapevines). For each line of plants, 4 picture samples have been taken (two on each side). The samples are from non-contiguous grapevines, so the pictures never overlap. The grapefruits are from the Tempranillo variety.

Figure 3.1. Example of annotated image



The pictures were taken by a Xiaomi Redmi 8 (with resolution 4032x3024), Xiaomi Mi A3 (with resolution 3000x4000) and a Xiaomi Redmi 9 (with resolution 3264x2448). To avoid showing grapes from other rows, the pictures were taken at approximately half the height of the vine-tree rows.
For each image, a .xml file was generated, with the Pascal VOC format, containing all the labeled items (with bounding boxes) in that image. Annotations in YOLO format were also provided (*.txt)
Some images have issues: i) reflections caused by the sun ii) group of grapes partially hidden by leaves or iii) hidden by other objects (e.g. irrigation pipes), iv) color and direction similar to a tree trunk v) dead grapes in the floor or vi) grapes from the plant behind the plant analyzed.

The Drone dataset [3] contains multi-spectral drone imagery from 3 Ribera de Duero vineyards This dataset comprises imagery from three vineyards in Ribera de Duero region, obtained with a multi-spectral sensor attached to a drone. The images in this dataset are composed of 4 bands: NIR, Red, Red-Edge, Green bands. For each image, the NDVI Index is also available.

3.2. Counting model

The Counting Model is a computer vision model to automatically detect grape bunches in vineyard pictures. The bunches are detected by using bounding boxes.

The proposed solution is based on a Cascade-RCNN [4] convolutional neural network. This model, pretrained on the COCO 2017 dataset [5] has been fine-tuned using the Ai4Agriculture dataset.

The Cascade-RCNN is a multi-stage variant of the Faster-RCNN model [6]. The stages are trained sequentially using increasing Intersection over Union (IoU) thresholds. This strategy provides more selectivity against close false positives. At inference time, the same cascaded architecture is used.

The MMDetection [7] implementation of the Cascade RCNN has been used. This implementation uses a ResNet50 [8] backbone. MMDetection is an open source object detection toolbox based on PyTorch.

As the counting model is used to determine the yield, the output of this model is the area covered by grapes in each image, as this quantity is more related to the final weight than the number of clusters. Figure 3.2 shows the obtained results. Note that the final mask F1-score is comparable the F1 score between human annotators.

Figure 3.2: Counting model results

Validation Set Metrics

Mask Precision	Mask Recall	Mask F-Score	Mask AP
0.7957	0.8594	0.8186	0.7293

Test Set Metrics

Mask Precision	Mask Recall	Mask F-Score	Mask AP
0.7968	0.8330	0.8022	0.7134

3.3. Knowledge graph

The knowledge graph is a dataset from Earth Observation, Machine Learning models and vineyard data. This data set contains all the data used and produced by the pilot. It has been designed using an OWL ontology to model the resources and then interlinked the different data both in the temporal and spatial dimensions.

The dataset contains in the form of a Knowledge Graph information coming from Earth Observation, Machine Learning models and vineyard data, that were used in the AI4Agriculture pilot. The dataset is distributed in RDF N-Triples format. The OWL ontology that was used to model the data is also provided.

The Knowledge Graph (KG) contains information from various sources regarding different attributes of grapes in specific parcels of the sample vineyards. Based on the geospatial information of each sample area, it links information coming from Earth Observation, Machine Learning models and vineyard data.

The KG contains the following data for the years 2020 and 2021, that were used in the pilot:

- Vineyards data (parcels, sample areas, petiol analysis, production, soil metadata, grape maturity)
- NDVI (corrected NDVI values based on Satellite images)
- Drone Images (geolocated plant images from the sampling areas)
- Number of Clusters (clusters of grapes detected in the plants of the sample areas, based on a counting model and drone images)
- Yield and Quality (data for each sampling area calculated by a model that uses the above sources along with meteorological data)

The classes and properties that were created to model and link the data are available in the OWL ontology that is provided along with the KG (RDF N-Triples format).

3.4. Yield and quality indicators prediction

This component deploys a server that performs the yield and product quality predictions carried out in the AI4EU agriculture pilot. The component queries the different pilot data sources (i.e. soil, plant variety, laboratory and wine analyses, weather conditions history, etc.) stored in the Knowledge Graph, and generates a training set to generate prediction models to address the different queries sent as input.

The quality and yield prediction model is a machine learning model that can predict yield, and several quality indicators (i.e. pH, total acidity, etc.). The predictions can be shown over a map, such as the one shown in Figure 3.3. No quantitative results are provided for these models. The model parameters need to be adjusted for each vineyard to obtain valid results.

Figure 3.3: Strabon-generated map of the sampling areas, showing pilot results

3.5. Integration in the AI4EU platform

The pilot modules are integrated in the AI4EU platform [1], that is based on ACUMOS. The ACUMOS AI Platform is a complete open-source environment for the full lifecycle of AI and ML application development. It makes easy to build, share, and deploy AI apps. ACUMOS standardizes the infrastructure stack and components required to run an out-of-the-box general AI environment.

[1] https://aiexp.ai4europe.eu/#/marketPlace#marketplaceTemplate

4. Potential impact

Precision agriculture is a technology with a very high potential impact. Nowadays, most of the planning for future crops and the allocation of resources to deal with them are performed by experts, in an ad-hoc fashion that sometimes makes it difficult to consider all the variables involved in the outcome. By providing methods to estimate the quality and yield, the developed models allow making more informed decisions that may result in a better efficiency. One of the partners in this project, Smart Rural, is interested on exploiting this type of solutions in their applications, as they are dealing with customers in the smart farming ecosystem.

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6. Bibliography

[1] AI4EU Deliverable D6.2 Pilots Evaluation Results (PER) - 2021

[2] Josep Ramon Morros, Tomas Pariente Lobo, Sergio Salmeron-Majadas, Javier Villazan, Diego Merino, Ana Antunes, Mihai Datcu, Chandrabali Karmakar, Edmundo Guerra, Despina-Athanasia Pantazi, & George Stamoulis. (2021). AI4Agriculture Grape Dataset (1.0.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5660081

[3] Ana Isabel Duarte Antunes. (2021). Image Dataset-Drone-AI4Agriculture [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5733926

[4] Zhaowei Cai, Nuno Vasconcelos, Cascade R-CNN: Delving Into High Quality Object Detection, IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2018

[5] Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., Perona, P., Ramanan, D., Zitnick, C. L. & Dollár, P.. Microsoft COCO: Common Objects in Context. ECCV 2014

[6] Ren, Shaoqing, He, Kaiming, Girshick, Ross B. and Sun, Jian. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks” Paper presented at the meeting of the NIPS, 2015.

[7] Kai Chen et al. MMDetection: Open MMLab Detection Toolbox and Benchmark.   arXiv:1906.07155, 2019

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren,Jian Sun. Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

7. Referencias

[1] M. Weber et al., "Anti-Money Laundering in Bitcoin: Experimenting with Graph Convolutional Networks for Financial Forensics," arXiv preprint arXiv: 1908.02591, 2019.

[2] Hodler, A., 2019. How Graphs Enhance Artificial Intelligence. [Blog] Neo4j Blog, Available: https://neo4j.com/blog/how-graphs-enhance-artificial-intelligence/ [Accessed 22 September 2021].

[3] T. N. Kipf and M. Welling, "Semi-Supervised Classification with Graph Convolutional Networks," arXiv preprint arXiv: 1609.02907, 2017.

[4] M. Fey and J. E. Lenssen, "Fast Graph Representation Learning with PyTorch Geometric," arXiv preprint arXiv:1903.02428, 2019.

[5] M. Wang et al., "Deep Graph Library: A Graph-Centric, Highly-Performant Package for Graph Neural Networks," arXiv preprint arXiv:1909.01315, 2019.

[6] C. Data61, StellarGraph Machine Learning Library. GitHub, 2018. [Online]. Available: https://github.com/stellargraph/stellargraph

[7] D. Grattarola, Spektral Graph Deep Learning Library. GitHub, 2018. [Online]. Available: https://github.com/danielegrattarola/spektral

[8] A. Paszke et al., "PyTorch: An Imperative Style, High-Performance Deep Learning Library," in Advances in Neural Information Processing Systems 32, H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché Buc, E. Fox, and R. Garnett, Eds. Curran Associates, Inc., 2019, pp. 8024–8035. [Online]. Available: http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf

[9] NVIDIA, P. Vingelmann, and F. H. P. Fitzek, CUDA, release: 10.2.89. 2020. [Online]. Available: https://developer.nvidia.com/cuda-toolkit

[10] M. Abadi et al., TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. 2015. [Online]. Available: https://www.tensorflow.org/

[11] T. Chen et al., MXNet: A Flexible and Efficient Machine Learning Library for Heterogeneous Distributed Systems. 2015.

[12] AWS, Amazon Neptune ML - Easy, fast, and accurate predictions for graphs. [Online]. Available: https://aws.amazon.com/cn/neptune/machine-learning/

[13] J. Leskovec, Class Lecture, Topic: "Lecture 6.3 – Deep Learning for Graphs." CS224W: Machine Learning with Graphs, Stanford Online, 2021.

[14] J. Leskovec, Class Lecture, Topic: "Lecture 7.2 – A Single Layer of a GNN." CS224W: Machine Learning with Graphs, Stanford Online, 2021.

[15] W. L. Hamilton, R. Ying, and J. Leskovec, "Inductive Representation Learning on Large Graphs," arXiv preprint arXiv: 1706.02216, 2018.

[16] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio, "Graph Attention Networks," arXiv preprint arXiv: 1710.10903, 2018.

[17] J. Bruna, W. Zaremba, A. Szlam, and Y. LeCun, "Spectral Networks and Locally Connected Networks on Graphs," arXiv preprint arXiv: 1312.6203, 2014.

[18] M. Defferrard, X. Bresson, and P. Vandergheynst, Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering. 2017.

[19] A. Vaswani et al., "Attention Is All You Need," arXiv preprint arXiv: 1706.03762, 2017.

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