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AI-Driven Yield Estimation Using an Autonomous Robot for Data Acquisition

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Abstract

The quality of the harvest depends significantly on the quality of the grapes. Therefore, winemakers need to make the right decisions to obtain high-quality grapes. One of the first problems is estimating the yield of the crops. It allows winemakers to respect the specific norms of their appellation (yield quota, alcohol levels, etc.). It is also necessary to organise the logistics of the harvest (start date, human resources required, transportations, etc.).

Traditionally, the yield estimation is performed by collecting grapes and berries over small, randomised samples, a destructive and laborious task. This work explores how automatic data acquisition combined with artificial intelligence can drive an automated and non-destructive yield estimation, adapted to the characteristics of each vine parcel.

Keywords: yield estimation, precision viticulture, image segmentation, fruit counting, deep learning, LiDAR sensor, vine balance.

4.2.1 Introduction

Winemakers use yield estimation to get decisive information for the organisation of the harvest and the business's economy. Therefore, it is necessary to estimate the yield for the organisation of the harvest, whether in the field or at the wine press.

Today, most winemakers estimate their yield using Equation (4.2.1) on a given land parcel. Traditionally, the counting is visually performed by an operator, leading to uncertainties on the precision and repeatability; in addition, the weight of the grapes requires them to be harvested. Estimations using historical data are also used; however, important variations can skew the predictions. The number of grapes and their weight varies from year to year. Despite the method, a variation of 30% can be found between the estimations and the reality [2].

$$\text{Yield (in kg per hectare)} = \frac{\text{nb of vine plants} \times \text{nb of grapes} \times \text{average grape weight}}{\text{parcel's area}} \tag{4.2.1}$$

Artificial Intelligence (AI) allows a clear improvement of work conducted in businesses using decision aids. AI can be better than humans in repetitive, time consuming, and tedious tasks. For example, automating the counting of grapes and fruits, in general, is one of the central problems in precision agriculture.

Many methods have been proposed these past years. Some methods are based on a classic image analysis approach, which consists of developing algorithms for segmentation, shape recognition, and problem-specific feature extraction. This method has been applied for the detection of oranges [8] and peppers [12]. Another approach is based on deep learning and convolutional neural networks. This type of neural network can solve multiple tasks like classification, segmentation, or object detection by automatically learning the correct representations needed for the job. This approach requires a large quantity of raw data rather than subjective criteria and specialised algorithms developed by humans. Deep learning has been used a lot since 2012 [6] and is now state of the art for classifying and detecting objects and fruits [7].

This paper aims to summarise the different methods of fruit detection and counting applied to viticulture for yield estimation.

4.2.2 Artificial Intelligence for Grape Detection

Grape counting is one of the yield estimation methods used by winemakers today. Grapes are harvested among a random sample allowing an estimation of the number of grapes by vine, the number of berries per grape, and the weight of the berries. These three components make up for 60%, 30%, and 10% of the variability in the yield, respectively [1]. However, this method is destructive, hence limiting the number of samples. An alternative consists of using images to estimate the components to allow for the automation of the tasks and limiting the biases due to the perception of the human eye.

The detection algorithm must take an image containing grapes as input and output an image that includes the location of the grapes and their number. This task is potentially difficult for several reasons: (*i*) there are many sources of variations in images taken in natural conditions (lighting, distance, background), (*ii*) the leaves can hide some of the grapes, and (*iii*) the leaves are green and share a similar colour to the grapes before they ripen.

Several classic methods or using deep learning can be used for the detection of grapes. A first naive approach is to use a threshold. One or several thresholds are chosen and applied on each pixel to separate the areas of fruit from the rest of the image [4]. These algorithms are fast, but they have several limitations that render them difficult to use in the field unless the lighting is controlled. In rare cases, this technique can be employed in natural conditions, however, only in simple cases where the berries are ripe, of a black variety, and the vine has been trimmed [3].

A second approach uses a segmentation method with active contours. It has been used for the detection of white grapes for automatic harvesting [14]. However, it remains limited to being used at night with a controlled light source, which can erase the image background (sky, ground, and the vine rows).

A third approach uses classic machine learning to develop methods for grape detection that are more robust to the variations in natural lighting conditions. They perform a segmentation pixel by pixel using a pixel's neighbourhood, or block, as an input to the classification model. The model produces a binary output (grape or not grape) which is then applied to the central pixel or the entire block. These methods do not work with the raw image; the extraction of features is a necessary step before analysing each block. The average of the RGB channels of a block is an example of simple features. This method suffers from several limitations, including sensitivity to colour (grape variety) and a high execution time (potentially long).

Deep learning has been recently applied to help solve the problem of detecting and counting grapes. A naive approach consists of a block-by-block (or pixel by pixel) classification with a convolutional neural network. The usage of CNNs allows for simplifying the detection algorithm because the model will learn the appropriate features from the data. Several popular object detection models, Faster R-CNN, R-FCN, and SSD, have been applied to the problem of detecting grapes and counting them using videos [5]. In addition, the model Mask R-CNN, which allows for simultaneous object detection and object segmentation, has also been used [10].

4.2.3 Towards an Automated Protocol for Yield Estimation

The detection of grapes is the first step for automated yield estimation. It requires converting the counting into an assessment in kilograms per vine or kilograms per hectare. The benefits of image analysis are that it can rapidly process large quantities of data to avoid random selection and destructive methods in the field. However, most automated methods have drawbacks linked to detecting hidden grapes and the estimation of the number of berries using 2D images.

Since 2019, we have performed image collection campaigns on parcels of the Vranken-Pommery domain in Reims for the project H2020 AI4DI[15], using different cameras and methods, for example, with a GoPro fixed on a picket or embarked on a tractor (Figure 4.2.1a). Approximately 400 pictures have been taken in the 2019 campaign, from which 322 photos have been labelled to train the segmentation models. The model is a UNet encoder-decoder with a ResNet-34 backbone. At the end of the training process, the generated model has an IoU (Intersection over Union) score of 0.69 and an F1 score of 0.8. The IoU is limited due to the lack of precision in the labelling. However, the model allows detecting nearly 100% with a false positive rate near 0% (Figure 4.2.4). The main problem is that grapes on the background can also be counted, reducing the counting precision. Several filtering methods, including the suppression of areas that are too small or morphological openness, have been studied to control this problem. The model was then applied to 200 images taken in 2020, allowing for the total count of the number of grapes (hidden and visible) and the precise location of each visible grape.

In addition, [9] carried out a systematic tracking of several rows in the vineyard, allowing calibrate our deep learning algorithms for automated yield estimation. This tracking, performed over four rows (200 vines) at

Figure 4.2.1 (a) Camera attached to the vehicle, (b) defoliated vine.

different phenological stages, has included the counting of classic organs (vine, flowers/grapes) thanks to other strategies (random counting or by the sampling of the parcels) as well as sampling the berries to estimate their volume and ripeness.

The counting of the grapes has also been done by unveiling hidden grapes by defoliation. Hence, the operator first counts the visible grapes in the plant and, after defoliation, takes a second picture (Figure 4.2.1b). Around 30 images were taken in this way and were then labelled and used to help identify partially hidden grapes. An example of the comparison between automated and manual counting where hidden grapes have been exposed is illustrated in Figure 4.2.4.

Thanks to the manual and automated counting data, a linear regression model has been generated for each row then a cross-examination of each model is done using the three other rows. Although the error rate varies from 0% to 31%, depending on the model and the row, we obtain an average error rate of 14%. This is better than current error rates with the traditional approach but remains perfectible. Hence, the improvement of this analysis is based on a better distinction between grapes in the foreground and grapes in the background as well as using non-linear regression models and other variables such as the porosity of the canopy.

Another improvement relates to the average weight of the grapes. Indeed, the measurements performed by [9] show a high dependency on the pluviometry before the readings. Also, the vitality of the vines varies each year, leading to a high variability when comparing with historical averages. The following section details one approach that may help our algorithms to compensate for this variability.

Figure 4.2.2 Example of grape segmentation. On the left: the original image. On the right: the segmented image.

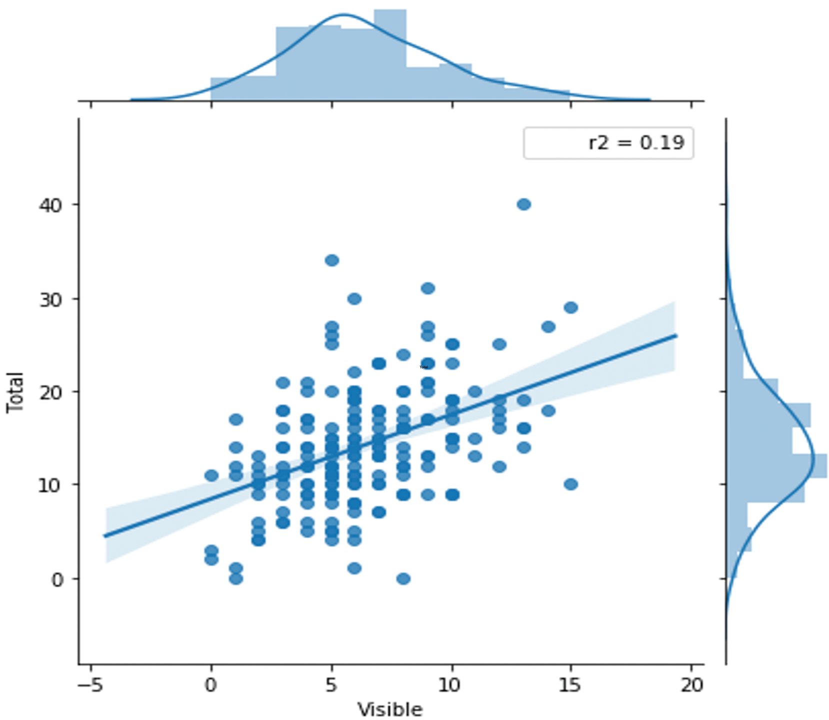

Figure 4.2.3 Correlation between visible grapes and the total number of grapes.

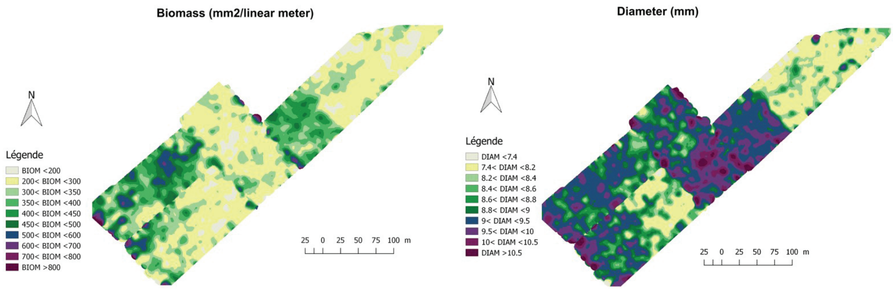

Figure 4.2.4 Biomass estimation and vine cane diameters obtained from Physiocap©.

4.2.4 Assessing the Vine Vitality Using an Embarked LiDAR

The yield estimation depends not only on the grape count but also on the relative weight of the grapes and berries. As a result, estimation divergences may appear between different vineyard parcels. Indeed, vineyard management practices and terroir characteristics may influence the fruit quality and quantity. Also, the vine balance can affect grape content as sugar, acids, and flavours concentrations [11]. Therefore, vine vigour evaluation is an important tool to estimate the vine balance, which is directly linked to the number of branches per linear meter and the diameter of these branches.

The traditional measurement technique is based on counting and weighing the winter dormant canes manually. This method is time-consuming, and the accuracy can be compromised by manual sampling, which does not consider all vineyard densities. An alternative for the traditional approach is the mapping of the dormant canes using a 2D laser scanner LiDAR sensor before pruning to assess variability in vine vigour within vineyards. This scanner allows to create charts representing the vineyard parcels, as seen in Figure 4.2.4. Previous works suggest that laser scanners offer great promise to characterise field variability in vine performance [13].

In addition, the LiDAR sensor can be installed on a vineyard robot, allowing a fully autonomous measurement of all the vineyard areas with few human interventions (Figure 4.2.5). Using a robot is a safe, more ecological, and less time-consuming support than a straddle vine tractor. Coupled with the image acquisition cameras used for grape detection, the robot becomes a fully automated tool to improve the yield forecasting for the winemakers.

Figure 4.2.5 (a) Vineyard robot Bakus©, (b) Physiocap© LIDAR installed on the robot.

4.2.5 Conclusions

The work that has been developed since 2019 shows an interest in deep learning for the detection and counting of grapes in natural conditions. These approaches have greater flexibility with respect to classic methods based only on image analysis. Indeed, deep learning has achieved better results for fruit and flower detection by avoiding the subjective selection of the algorithms and features.

These good performances have only been evaluated for grape count estimation. Yet, yield estimation requires an extra modelling step to determine the hidden part of the fruits: number of grapes hidden by the leaves, number of berries per grape, etc. Therefore, better performances are expected with non-linear modelling using additional information such as the vine vitality.

Acknowledgements

This work is conducted under the framework of the ECSEL AI4DI "Artificial Intelligence for Digitising Industry" project. The project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826060. The JU receives support from the European UnionâĂŹs Horizon 2020 research and innovation programme and Germany, Austria, Czech Republic, Italy, Latvia, Belgium, Lithuania, France, Greece, Finland, Norway. We also would like to thank the ROMEO Computing Center of the University of Reims Champagne-Ardenne.

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