Recognition of white grapes hidden in high-density vineyard canopies by CNN

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State of the art

Precision viticulture relies heavily on expert evaluation of grape yield and quality, which can be resource-intensive and sometimes unreliable. Several works (Tello 2014, Tello et al. 2015, Tello and Ibáñez, 2018) review various indices for assessing grape bunch compactness, also studying morphoagronomic variables affecting grape bunch and canopy compactness; those papers also face influencing factors on compactness descriptors.

Machine vision and image analysis have improved production management in viticulture. The LPF-TAGRALIA group has developed methods for classifying vineyard images and improving segmentation accuracy (Herrero-Langreo et al. 2010, Correa et al. 2012, Diago et al. 2012). Patents by Tardáguila Laso (2016) and Tardáguila and Laso (2015) describe automated processes for estimating vineyard porosity and determining grape cluster compactness using RGB images.

Recent AI methodologies like YOLO, Faster R-CNN, SSD, and RetinaNet are being used to predict grape yield, involving preprocessing, image normalization, and feature extraction. Semantic segmentation aims to improve grape and leaf identification accuracy, though it faces challenges with raw images (Su et al. 2022, Lucas Mohimont et al., 2022).

These efforts highlight ongoing research to enhance grape cluster identification under high leaf density conditions.

Material and Methods

The trial vineyard plot entitled La Bergonza locates at 40.1534278N Latitude, -4.2207311 Longitude, and it belongs to the winery González-Byass, a Spanish company renowned for its wines and spirits. The vineyard, planted in 2018 with the Airén variety (3.3m x 2m), is dedicated to high-intensity wine grape production, with yields between 30 and 40 t/ha, an extraordinarily high value. The single cordon vineyard training system shows a very dense grape-cluster area, with compact bunches and leafy but porous canopy development; considering a vine with a vine spacing of 2m along the row, the expected vine productivity is very high: 20-26.5 kg/ vine, amounting 77-103 bunches of grapes weighing a median of 256g from 175 analyzed; an average soluble solid content of grapes of 15.8 ± 4.0 ºBrix.

Results

Different equalizations have been used to train detection models, evaluating the impact of each technique on training quality and model accuracy. Techniques include CLAHE (Contrast Limited Adaptive Histogram Equalization) applied to the green channel, Gray level images Histogram Equalization, and Global RGB Channel Histogram Equalization applied to the three-color channels (red, green, and blue). The evolution of the F1 (x-axis) and Recall (y-axis) metrics as the number of epochs run by the YOLO models on grey_eq, RGB, and augmented data increases (Figure 1). The maximum values achieved for the metrics (Figure 1) Recall-Precision, F1, Precision, and Recall over the epochs and for the models mentioned. The model that achieves the best position is the model on augmented data, where only for precision it is significantly surpassed by Gray eq.

Also, other metrics: fitness, recall, map50, and mapAP50-95 have been computed, concluding that the best model corresponds to the augmented dataset applied to RGB equalized images. The best results attain a maximum score in predicted box of 0.998, minimizing both false positives and false negatives (197 and 111 respectively).

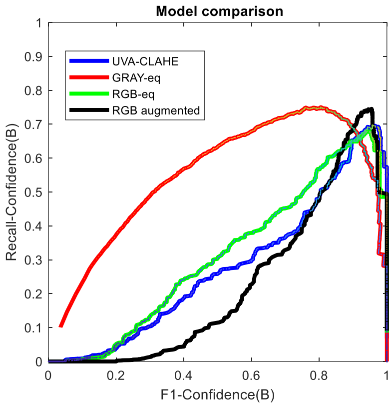

Figure 1, plot of metrics according to the neural network epochs evolution: F1 (x-axis), and Recall (y-axis), for the YOLO V8 models run on the CLAHE, GRAY_eq, RGB_eq, and RGB augmented data.

The results of our in-field segmentation can readily be used within the scheme of patent ES25053330 (2015) authorized by Tardáguila and collaborators (Universidad Politécnica de Valencia and Universidad de la Rioja), aiming at the automatic quantification of the number of grapes per bunch together with the estimation of individual bunch weight.

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