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# A smart system for the automatic evaluation of green olives visual quality in the field

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**Keywords:** image analysis, supervised training, maturity index, weight estimation, affordable tool, decision making

## Abstract

Monitoring some of the parameters that affect the quality of table olives for green processing is fundamental in a farmer's decision making. This work develops an affordable system for in-the-field evaluation of fruit calibre, ripeness and bruise index. The system consists of an illuminated cube that takes photographs acquires images of fruit samples and generates an instantaneous report, using computer vision techniques implemented in software. To do this, it was necessary to determine models of fruit weight and size and also the colour regions (RGB colour space) involved in olive maturity indexes. Moreover, supervised training models were created to perform image segmentation (background and bruising areas). Error in the estimation of fruit weight was very low ( $R^2=0.9$ ), and prediction of the maturity index (MI) was quite good, with an accuracy of 0.66 and 0.91 for manually sorted olives in MI0 and MI1 respectively (green processing). Prediction of MI2 had lower precision (0.48) when the fruit was changing to black-purple and the bruising spots were confused with fruit area because of determined similarities in colour. The error in the estimated bruise index was lower for MI0 (RMSE=2.42) than for MI1 (RMSE=3.78), both of which are suitable for an estimation of quality in the field. Overall, the system's performance reveals promising results for a quick, easy and accurate evaluation of the external parameters that define the quality of olives. The models obtained could be useful for other purposes.

## 27 **Introduction**

28 The world production of table olives is approximately 2.9 million metric tons per year (IOC, 2018). The  
29 Spanish style, which is one of the most popular preparation methods for olive consumption, requires green  
30 olives harvested during the ripening cycle when they have reached a determined size, but prior to colour  
31 change. Certain parameters like ripeness, size or defects define the commercial category to which olives will  
32 be assigned (FAO, 2013). These parameters therefore influence olive processing, and consequently the final  
33 product price.- Farmers control some of the parameters, which involve decision-making about fundamental  
34 growing practices such as determination of the optimal harvest time, the choice of harvesting procedure to  
35 reduce damage, or the selection of the most suitable trees to harvest. Hence, monitoring olive ripening, size  
36 and defects in the field becomes crucial so as not to compromise the final quality of table olives. Monitoring  
37 often employs destructive analyses in controlled laboratories with what can be relatively sophisticated  
38 equipment.

39 Colour is the principal determinant of the development stage of olive ripeness. For Spanish style processing,  
40 it is important to control the development of ripening to reach “green-ripe olives”. Normally, olive colour is  
41 determined according to different classes established long ago (Ferreira, 1979) or maturity index groups  
42 (Guzman, 2015) that consider the percentage of green, yellow, purple and black colour on the fruit.  
43 However, there is a lack of values to determine the proper colour for sorting, which is in fact often performed  
44 visually by experienced operators in the field or in the processing units. However, this method presents  
45 drawbacks. Some authors have designed algorithms to predict olive class or maturity index (MI) based on  
46 colour channels (Diaz 2000; Furferi, 2010; Dumanay 2016) with promising results.

47 In addition, the size of olives is determined in industry considering the number of fruits contained in one  
48 kilogram, and this operation is usually performed using mechanical screening or sorting machines based on  
49 image analysis. The estimation of fruit weight by determining its geometry using image analysis has given  
50 good results for citrus fruit (Omid, Khojastehnazhand, & Tabatabaeefar, 2010) and olives (Ponce, Aquino,  
51 Millán, & Andújar, 2018). The application of weight-size regressions could even be carried out automatically  
52 by techniques that predict the variety of olive samples (Martinez et al, 2018).

53 Defects in table olives affect their commercial value (Riquelme et al., 2008) and can mean that some olives  
54 may be discarded for green processing. Other than biotic agents or unfavourable climatic conditions, defects  
55 may also occur during the manual or mechanical harvesting process, causing spots that undergo an oxidation  
56 process and generate browning in the impacted zone (bruising). The level of damage can be estimated by the  
57 ratio of bruised area to total fruit area (bruise index) (Jiménez-Jiménez et al., 2013). Determination of  
58 bruised area is a difficult task to perform automatically with traditional image analysis techniques. This is  
59 due to both the complexity of spot shapes and their colour, which that can be confused with that of certain  
60 stages of olive ripeness. Machine learning techniques may be applied to extract some olive parameters or  
61 grading with good results (Díaz et al., 2004) and could also be used in industrial applications (Jodar Lazaro  
62 et al., 2020).

63 There are several studies and reviews that have researched the technologies available for assessing fruit and  
64 vegetable quality (Arendse et al., 2018; Bhargava & Bansal 2018; Ortaç- et al., 2016; Srivastava et al., 2018;  
65 Tsouvaltzis et al., 2020; Zhang et al., 2018), but also for olive quality (Navarro-Soto et al., 2018) and  
66 specifically for table olives (Campus et al., 2018). In recent years, the industry has implemented all these  
67 advances in automated fruit inspection using powerful commercial equipment (Cayuela 2010; Serranti, 2018)  
68 specifically designed for product analysis according to the criteria of the target market. However, the  
69 evaluation of fruit in the field is still a challenge, although new developments have arisen that are able to  
70 perform the estimation of certain fruit parameters from terrestrial mobile platforms (Kohno et al., 2011;  
71 Cubero et al., 2014) or from drones (Méndez et al., 2019; Apolo-Apolo et al., 2020).

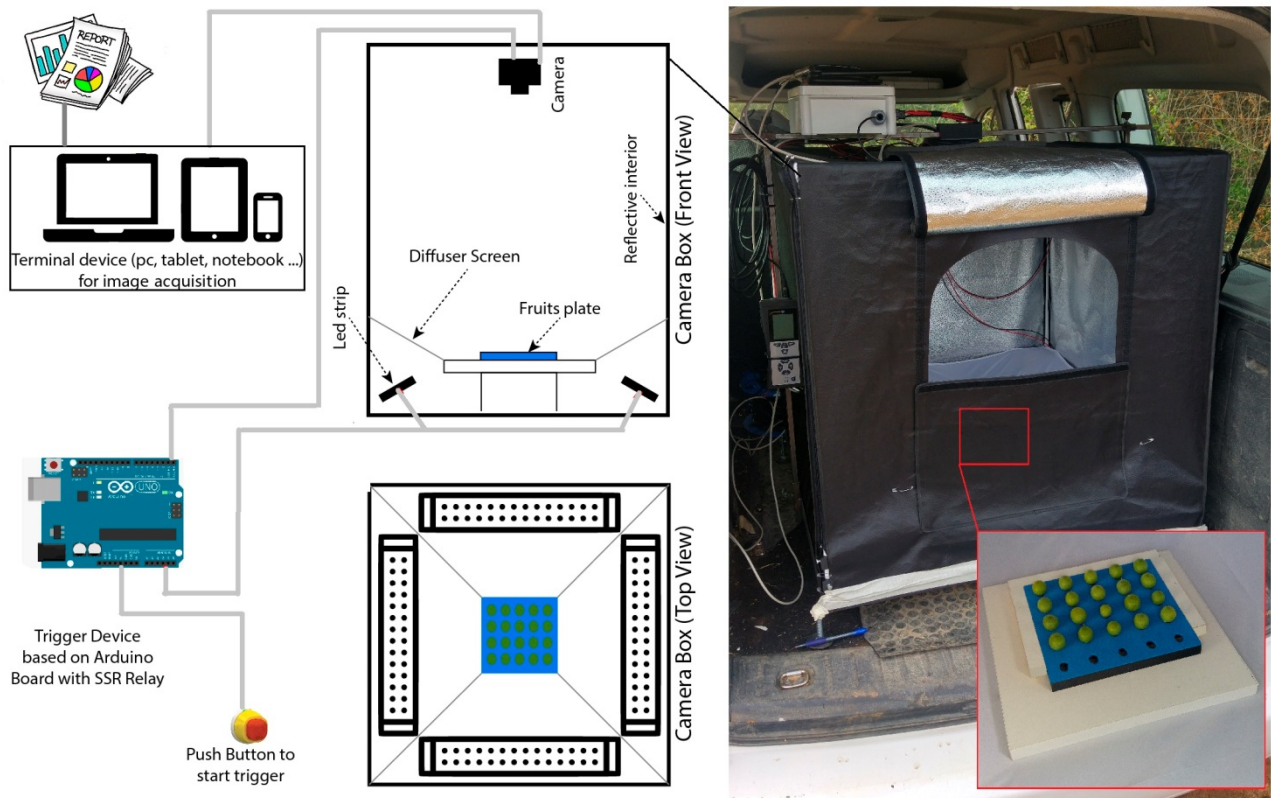
72 Considering the above, our work investigates the feasibility of a device based on a computer vision system  
73 for the automatic evaluation in the field of external parameters such as ripening, size and bruises. Such a  
74 device will be a ready-to-use tool for farmers or technicians that would avoid the need for expensive  
75 instruments or low-accuracy manual procedures. For ripening assessment in particular, the proposed method  
76 aims to identify a threshold colour for each maturity class and sort the analysed olives according to class. In  
77 addition, the study proposes shape recognition based on particle analysis to determine the main diameters of  
78 the fruit (fitted ellipse), and the estimation of its weight and calibre by applying a previously determined  
79 model. Regarding bruises, this work aims to determine the bruised area and bruise index of fruits by applying  
80 different training models according to their previously determined maturity class. Overall, this work aims to

81 develop a portable, affordable system for the automatic evaluation of green table olive quality in the field,  
82 assess its suitability, and generate the necessary models required to achieve this purpose.

### 83 **Materials and Methods**

#### 84 *Development of the system for the evaluation of olive parameters*

85 A system for the automatic evaluation of olive quality of (SAEQQ) has been developed (Figure 1). It is a  
86 portable device of 0.8 x 0.8 x 0.8 m, and weighs 5 kg, which allows the image acquisition of fruit samples  
87 ~~photographs to be taken~~ in the field. The box consists of a tubular PVC chassis covered with a reflective  
88 plastic fabric that blocks out external lighting conditions. Inside the box there is a housing for blue foam,  
89 0.18 m square trays that have perforations to hold 20 olive samples. Under the housing, covered by the  
90 diffuser screen, 4 LED bars of 5500°K ((HPB-60xd) are positioned at an orientation of 30° to the horizontal  
91 plane. These bars emit a constant level of illumination of 13.95±0.57 lux in the area of the tray. There is a  
92 support 0.85 m above the tray to place a conventional digital camera. This work used an AD-130 GE DE  
93 (JAI) camera with a low resolution of 1.3Mpx, however, any low-cost camera could be employed. The  
94 camera was synchronized using an Arduino Nano system and SSR relays with lighting (0.3 s exposure) via a  
95 trigger button. The images were automatically acquired from a laptop (IdeaPad Z510, Lenovo, China) that  
96 runs a specific software designed for the acquisition and automatic analysis of the images.



98

99

Figure 1. Device (SAEQO) developed for automatic image acquisition and analysis

#### 100 Development of the software for image analysis

101 We designed and implemented software in the terminal device connected to (SAEQO) to analyse the images.  
 102 Several field tests were conducted to programme the software. First, it was necessary to determine the  
 103 models to implement in the software, and then validate the system. The final configuration of the software's  
 104 main stages was determined from the experimental test results, and the description of these steps follows.  
 105 Figure 2 shows some examples of the outputs that the algorithm would report after each stage.

- 106 A) Image acquisition: The camera captures the image, which is loaded by the software.
- 107 B) Image processing: A Gaussian Smoothing filter (window: 5 px, sigma: 1) is applied to create a slight  
 108 defocusing that smooths the image without losing detail and removes possible noise (Haff et al.,  
 109 2013). Subsequent application of the Kuwahara filter (windows 9 px, sigma: 1) allows removal of  
 110 gradients and highlights the edges without the loss of important information (Djurovic, 2017).  
 111 Finally, an HSL (Hue, Saturation, Lightness) adjustment is performed to reduce possible shadows on  
 112 the fruits and adjust the lighting of the image to that of the colorimeter used (6500 K) for later  
 113 comparison.

- 114 C) Fruit segmentation: A Random Forest algorithm (Breiman, 2001) is applied. This is based on loading  
 115 a supervised learning model (TM\_Fruit) trained to remove the background. The remaining pixels are  
 116 then identified as belonging to the fruit.
- 117 D) Calculation of fruit size and calibre: Each fruit image is cropped and fitted to a rectangle that  
 118 circumscribes the shape of the fruit. A calibration factor (pixels per mm) is then applied. The  
 119 dimensions of the rectangle are considered as fruit diameter (width) and fruit length (height) (mm).  
 120 Fruit area (mm<sup>2</sup>) is the conversion of the total number of pixels by their distance. A mathematical  
 121 formula obtained from field tests (data shown in results section) is then applied to estimate fruit  
 122 weight fruit according to fruit size, and therefore to estimate its calibre. If the fruit belongs to the  
 123 calibre class that contains more than 420 fruit in a kilogram (small calibre), it is labelled with the  
 124 category of disposable fruit, as industry would discard this calibre.
- 125 E) Calculation of Colour: The colour of each pixel in the red, green and blue channels (RGB.R, RGB.G,  
 126 RGB.B) is calculated.
- 127 F) Calculation of Maturity Index (MI): Each fruit pixel is assigned to a colour group according to the  
 128 thresholds calculated previously from field test results (data shown in results section). Any pixel  
 129 outside these thresholds was identified as undefined and was not considered for the calculation. The  
 130 fruit is then categorised into a maturity index group ([Equation 1](#)) following one of the most common  
 131 sorting systems in industry (Guzman, 2015):

$$f(x) \equiv \left\{ \begin{array}{l} MI0, \text{ if } \left( \sum_{dg=1}^n x_{dg} > \sum_{yg=1}^n x_{yg} \right) \&\& \left( \sum_{rp=1}^n x_{rp} = 0 \right) \&\& \left( \sum_{b=1}^n x_b = 0 \right) \\ MI1, \text{ if } \left( \sum_{dg=1}^n x_{dg} < \sum_{yg=1}^n x_{yg} \right) \&\& \left( \sum_{rp=1}^n x_{rp} = 0 \right) \&\& \left( \sum_{b=1}^n x_b = 0 \right) \\ MI2, \text{ if } \left( \sum_{dg=1}^n x_{dg} + \sum_{yg=1}^n x_{yg} \right) > \left( \sum_{rp=1}^n x_{rp} + \sum_{b=1}^n x_b \right) \\ MI3, \text{ if } \left( \sum_{dg=1}^n x_{dg} + \sum_{yg=1}^n x_{yg} \right) < \left( \sum_{rp=1}^n x_{rp} + \sum_{b=1}^n x_b \right) \\ MI4, \text{ if } \left( \sum_{b=1}^n x_b > \sum_{rp=1}^n x_{rp} \right) \&\& \left( \sum_{dg=1}^n x_{dg} = 0 \right) \&\& \left( \sum_{yg=1}^n x_{yg} = 0 \right) \end{array} \right. \quad \text{Eq. 1}$$

133 a. ~~MI0: Sum of deep green pixels > Sum of yellow-green pixels and without purple or black~~  
 134 ~~pixels.~~

135 b. ~~MI1: Sum of deep green pixels < Sum of yellow-green pixels and without purple or black~~  
 136 ~~pixels.~~

137 c. ~~MI2: Sum of yellow-green pixels > Sum of purple or black pixels.~~

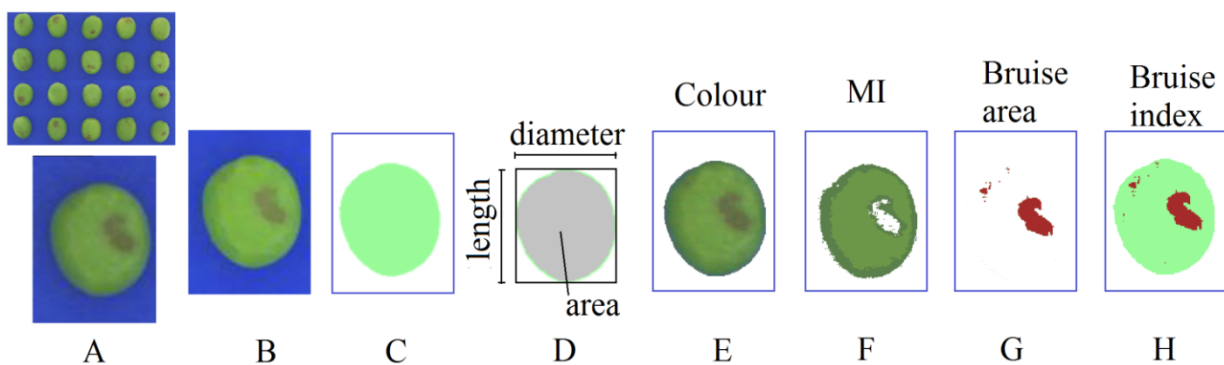
138 d.— MI3: Sum of yellow-green pixels < Sum of purple or black pixels.

139 e.— MI4 or higher: Majority of black pixels and without deep green and yellow-green.

140 where x: pixel; dp: deep green; yg: yellow-green; rp: red/purple; b: black

141 G) Bruising segmentation: A Random Forest algorithm is applied. It loads different supervised learning  
142 models, depending on whether their index is MI0 or MI1 (TM\_BrIM0, TM\_BrMI1), which have  
143 been previously trained to determine the bruising area of the fruit. Fruit with MI1 have areas with  
144 changing colour that can be confused with bruising, but this does not occur in fruit with MI0. Fruit  
145 with MI2 or higher are not analysed because they would not be considered for green olive processing

146 H) Calculation of Bruising Index (BI): The bruising index (%) is calculated based on the relation  
147 between bruise area and fruit area. The application then classifies the fruit into different categories of  
148 damage (zero, slight, moderate, severe, mutilated) depending on the bruise index (Jiménez-Jiménez  
149 et al., 2013).



150  
151 *Figure 2. Main steps of the algorithm designed for olive quality assessment*

152 All of the previously described steps are carried out thanks to an application that was developed in '.NET'  
153 language for Windows and which allows importing an image file, applying filters, loading the created  
154 training models and performing an analysis of each image to extract the main external quality parameters of  
155 the fruit (Figure 3). Several reusable libraries have been programmed for the app so that it is adaptable to  
156 different needs. The app runs whatever the machine learning algorithm used for the training and filters or for  
157 other configurations. All the cyclic processes have been programmed using multithreaded programming so  
158 that it is possible to use all processor cores, and the process can be accelerated. The application allows  
159 loading of as many images as the user wishes, and adds the results of each fruit as well as their averages to  
160 the report before exporting them to other files.

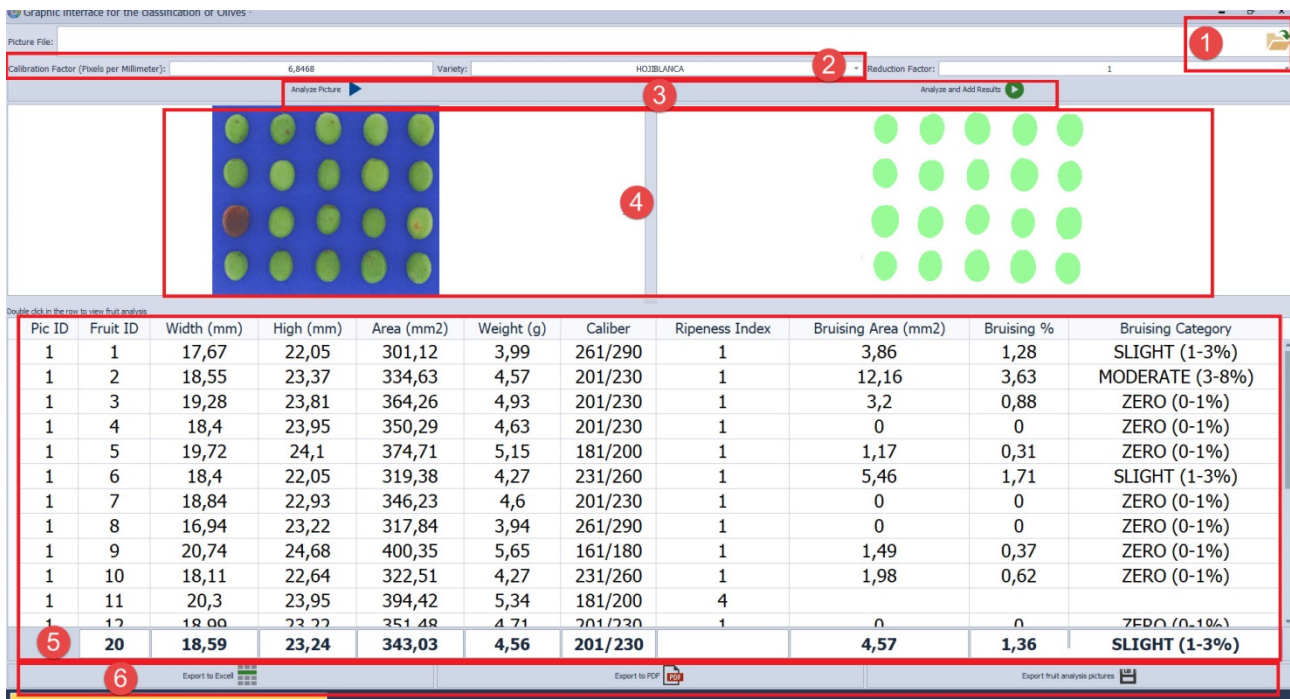


Figure 3. Interface developed for the automatic evaluation of external parameters of table olives using SAEQQ. 1: Button for loading image; 2: Calibration factor (pixels per millimetre) and selection of olive variety; 3: Buttons for analysing the image and deleting the previously analysed data or adding the data to those previously analysed; 4: Original and segmented image; 5: Data analysed; 6: Buttons for exporting the data analysed (.xls file, .pdf file) and segmented images (.tiff file)

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167 *Field test carried out for programming the software.*

168 Field tests were carried out on two different plots in the south of Spain, Almodóvar del Río (37.855472, -  
169 4.993882) planted with the Manzanilla variety, and Aguilar de la Frontera (37.457139,-4.805250) planted  
170 with the Hojiblanca variety. These are two common table olive varieties in the green processing industry. Six  
171 trials were conducted on each plot on a weekly basis from 19<sup>th</sup> September to 24<sup>th</sup> October 2019 (the season  
172 for table olive harvesting). During each trial, fruit were detached manually and mechanically using a shaker  
173 comb and a branch shaker. Random samples were taken of 760 Hojiblanca and 840 Manzanilla fruits, which  
174 had a normal distribution of maximum and minimum diameters and weights (Kolmogorov-Smirnov,  $p >$   
175 0.05). One hundred and fifty minutes after harvesting, the time during which the devolution of fruit bruising  
176 stabilizes (Jiménez-Jiménez et al., 2013), the fruit samples were placed on a tray (20 samples per tray) to  
177 take pictures with SAEQQ.

178 The data were divided into two 50/50 datasets, one dataset for training and validation and one for testing.  
179 The training and validation dataset served to train and select the models using k-5 cross validation whereas  
180 the testing dataset was used to evaluate the estimations calculated for the software. To this end, the samples  
181 were manually measured to obtain the parameters shown in Figure 3 as follows.

- 182 • Fruit length and fruit diameter: measured manually with a digital Vernier calliper (Pittsburgh 61585,  
183 USA).
- 184 • Fruit weight (w): obtained with a precision scale (Gram SPX6000).
- 185 • Colour (CIE*Lab*): determined using a colorimeter (Konica Minolta CR-400, China) as the average of  
186 two readings on different zones of the fruit. The bruising area of some of the most damaged fruit was  
187 also measured.
- 188 • Maturity index (MI): according to the classes studied by Guzman (2015), with an experienced,  
189 trained operator classifying the samples visually.
- 190 • Fruit area and bruise area: digitally determined from the pictures taken with SAEOQ by an expert,  
191 who manually marked areas (px<sup>2</sup>) of interest and scaled them using Ilastik (General Public License,  
192 Heidelberg, Germany) software.
- 193 • Bruise index (BI), calculated as the percentage of the area of fruit that was bruised. Calculations did  
194 not include spots less than 1 mm<sup>2</sup>.

195 Some of the following measurements were used to determine the models implemented in the software.

196 1) Determination of the models implemented in the software.

197 1.1. Training models

198 We obtained different training models to run the described software. An expert used the software to  
199 manually train image segmentation by selecting the pixel that corresponded to each class employed in each  
200 model (background, fruit, bruising). A data map of the selected pixel was then imported from the application  
201 to generate the models. The first model (TM\_Fruit) was used to segment the background and the fruit in the  
202 image, as well as to determine its geometry. The same number of pixels was selected for the “background”  
203 class and for the “fruit” class (approximately 3000 each) so that there was a balance of classes. The second  
204 and third model (TM\_BrIM0, TM\_BrMI1) were used to determine how much fruit was bruised. We  
205 classified fruit images visually according to different maturity indexes, selecting at least 2000 pixels for the  
206 “bruise” class and for the “fruit” class, although the balancing of classes was not so high because the “fruit”  
207 class was predominant among fruit with zero damage.

208 A Random Forest algorithm and a Naive Bayes algorithm were used as learning methods for constructing the  
209 models. As its hyperparameter, Random Forest used 200 decision trees to estimate predictions, whereas  
210 Naive Bayes employed the Gaussian classifier. The pictures acquired by SAEOQ in the field tests provided  
211 the images for training. The original images and those processed with the previously described filters were  
212 analysed with both algorithms to choose the most proper configuration with the least prediction error.

## 213 1.2. Weight and maturity index estimation.

214 Stage D (Figure 2) of the software reports a fruit calibre estimation based on fruit weight estimation. We  
215 obtained weight estimation by associating the olive weights recorded in the field with the fruit length and  
216 diameter calculated from the segmented picture. Then, a correlation was determined from the 1600 fruit  
217 samples. Differences between the two varieties studied were considered in order to properly implement the  
218 correlation obtained in the software.

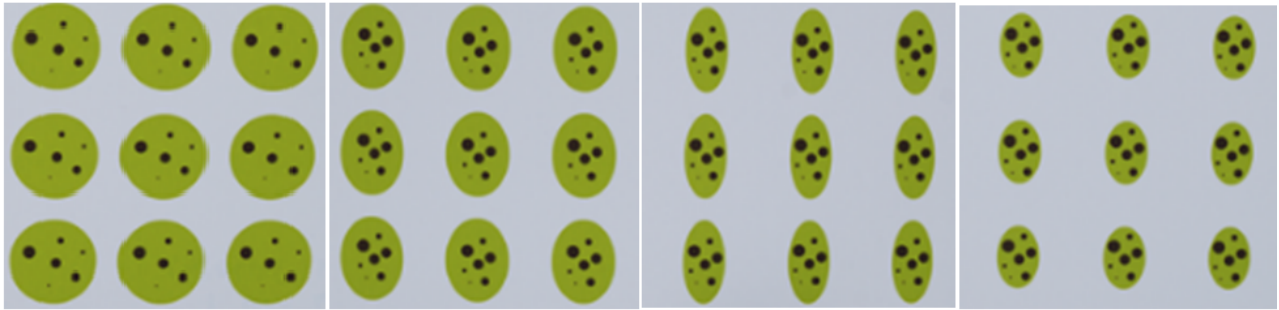
219 Stage E (Figure 2) calculates the fruit maturity index according to the colour thresholds (deep green, yellow-  
220 green, purple and black) of their pixels. To determine these colour thresholds, an expert selected the zones  
221 where these colours appeared on approximately 200 randomly chosen olives during the test. As RGB colour  
222 space is device dependent (Menesatti et al., 2012), these colour zones were also measured with the  
223 colorimeter for calibration purposes. The colour values were transformed to RGB space (the colour space  
224 used by the software). Only the Green and Red channels were used as they are the most suitable for olive  
225 segmentation (Gatica et al., 2013). Some regions were determined according to their location on the R-G  
226 chart taking into account no overlaps so as to avoid conflict in the classification software (stage E).

## 227 2) Assessment of SAEOQ.

### 228 2.1 Device performance evaluation

229 Four image templates (Figure 4) were made with several known shapes that simulate configurations of  
230 different fruit sizes and bruising. The digital images were treated with different resolutions of 72, 150 and  
231 300 dpi, and the software automatically calculated the BI to evaluate error obtained due to the algorithm  
232 itself. These images were then printed on matte canvas and placed on the flat trays for digital image  
233 acquisition with SAEOQ, in order to evaluate the error due to environmental conditions. For this last step,  
234 we installed a digital camera with a 10.2 Mpx resolution (Nikon Corporation, D80, Tokyo, Japan) on

235 SAEOQ and set it at a speed of ISO-100, with an f/9 aperture, an exposure time of 1/125 s, and a focal  
236 distance of 35 mm, with no flash. The intention was to determine the feasibility of using a low resolution  
237 with a low-cost camera.



238

239 *Figure 4. Ellipses used for the calibration setting of SAEOQ: (40x40 mm), (30x40 mm), (20x40 mm), (20x30 mm) with circular*  
240 *spots of 1-6 mm<sup>2</sup>*

241 We connected different hardware systems to SAEOQ to evaluate the system velocity for analysing the  
242 images obtained by the camera (JAI) with real fruit, with the aim of determining the feasibility of using  
243 affordable hardware in the field.

#### 244 2.2 Evaluation of external parameter prediction.

245 The manually recorded parameters and those obtained automatically with the software from 50% of the fruit  
246 images used for the training tests were compared in order to study the feasibility of this system for the  
247 automatic analysis of table olive quality in the field.

248 **Results and discussion**

249 1) Determination of the models implemented in the software.

250 1.1. Training models

251 The application of adaptive or global threshold techniques reported inaccuracy results for bruising  
 252 segmentation (data not shown) making necessary the use of machine learning algorithms. The configuration  
 253 of the Gaussian-Kuwahara-HSL filters was determined with successive tests until the configuration that gave  
 254 the highest resolution in the definition of edges, homogenization of colours and highlighting of bruising was  
 255 obtained. Table 1 shows the difference in errors obtained before and after applying filters on the raw image  
 256 captured from SAEOQ, and also between the algorithms used for the creation of the applied models (Naive  
 257 Bayes and Random Forest), by means of a cross validation using 20% of the image data in the training  
 258 models.

259 *Table 1. Mean absolute percentage error (%) of cross validation of the training models for determining the fruit (TM\_Fruit) and*  
 260 *the bruising with MI0 (TM\_BrMI0) or MI1 (TM\_BrMI1) from original and processed images. Cells marked with \* show*  
 261 *the error of the selected configuration for the software used.*

Algorithm	Classes	TM_Fruit by images		TM_BrMI0 by images		TM_BrMI1 by images	
		original	processed	original	processed	original	processed
Naive	Background	0.0	0.0	0.0	0.0	0.07	0.0
Bayes	Fruit	0.35	0.0	29.63	26.71	31.55	29.62
	Bruise	-	-	14.08	7.13	8.34	8.09
Random	Background	0.0	0.0*	0.0	0.0*	0.0	0.0*
Forest	Fruit	0.0	0.0*	4.47	1.56*	5.33	2.48*
	Bruise	-	-	10.37	6.43*	14.50	6.52*

262 The results indicate that the configuration with the least error at a global level is processed images using the  
 263 Random Forest algorithm, so this was implemented in the software described in the materials and methods  
 264 section. Fruit-background segmentation was performed out in a very precise manner in all of the possible  
 265 configurations. For bruising segmentation in MI0 or MI1, there was not a large difference in the use of filters  
 266 with Naive Bayes. Accuracy improves approximately 21% with the use of Random Forest, reducing error by  
 267 almost half in both the fruit and bruise class with the use of filter settings, as noted by Kumar Dash and

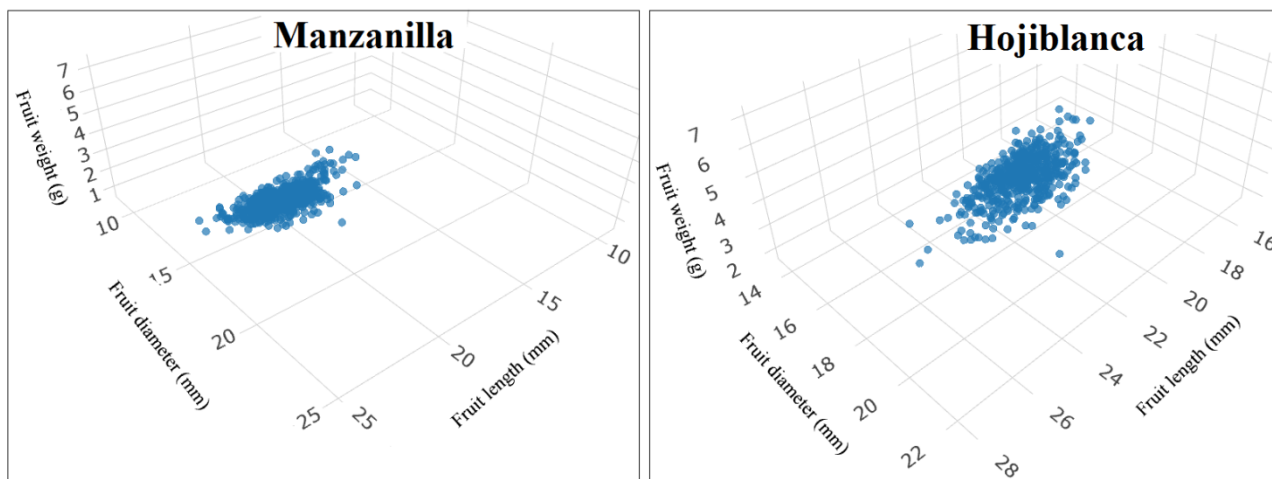
268 Panda (2016). It is highly advisable to produce the least possible error with the TM\_Br models to predict the  
269 pixel that belongs to the bruise class. However, the error obtained in the sorting (Table 2), which was around  
270 7%, could provide low accuracy predictions when estimating real bruising on fruit.

### 271 1.2.1 Weight and maturity index estimation.

272 There were significant differences in fruit diameter, length and weight between Manzanilla and Hojiblanca  
273 varieties (T-student test,  $p < 0.05$ ). This suggests that the software should include the variety to predict fruit  
274 weight (Figure 3, number 2). Therefore, multiple linear regressions were obtained between the fruit weight  
275 and the fruit diameter and length for Manzanilla ( $R^2 = 0.90$ , Equation 1) and for Hojiblanca ( $R^2 = 0.91$ ,  
276 Equation 2) (Figure 5). The high adjustment of the linear correlations obtained ensures a good estimation of  
277 fruit calibre within the tolerance that regulations allow.

278 Estimated weight (g) = - 7.175 + 0.225 \* Fruit length (mm) + 0.352 \* Fruit diameter (mm) Equation 1

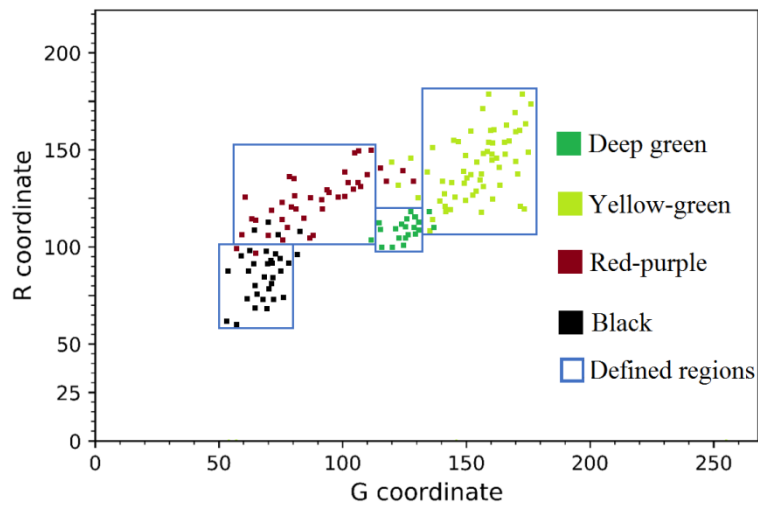
279 Estimated weight (g) = - 6.780 + 0.171 \* Fruit length (mm) + 0.397 \* Fruit diameter (mm) Equation 2



280  
281 *Figure 5. Correlation obtained to estimate fruit weight based on fruit diameter and fruit length*

### 282 1.2.2 Maturity index estimation

283 Figure 6 represents the RGB.R and RGB.G colour values measured on different fruit zones, and their  
284 classification into groups. It is possible to sort and delimit these groups by defined regions so as to avoid  
285 overlaps between them and fit them around the majority of the represented points (Table 2). The results  
286 obtained must be taken with great caution because even if the equipment were the same as that employed for  
287 this paper, the values or regions might vary depending on different lighting conditions when using the  
288 CIE*Lab* scale.



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Figure 6. Colours measured (RGB.R and RGB.G) in areas of the fruit and defined regions that fit the majority of the same group points

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Table 2. RGB.R and RGB.G values of the defined regions of colours obtained for the maturity index sorting

Colour	R min.	R max.	G min.	G max.
Deep green	97	120	118	135
Green-yellow	105	182	136	182
Red-purple	103	157	58	117
Black	55	102	52	86

293

## 2) Assessment of SAEOQ.

294

### 1.1 Performance of the device

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Table 3 shows the relative error between the bruise index estimated with the software and calculated

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theoretically with the known fruit-spot geometry from the image templates (Figure 5). The results are

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compared according to the different resolutions without any substantial differences between the resolutions

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of 150 dpi and 300 dpi. Thus, the average resolution seems to be acceptable for the application presented in

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this paper because the mean resolution of the images acquired in the field tests with the JAI camera was 173

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dpi. Moreover, the use of a higher resolution would involve a higher processing speed for the software and

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more powerful hardware.

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The error of 0.4 % due to the algorithm increases to 3.1 % when the template images are used, due to the

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effect of operating conditions such as lighting, camera lens, fruit location, etc. on the images. This suggests

304

that to reduce the error, improvements could be made in environmental conditions, such as the homogeneity

305 of lighting. Moreover, as other authors have indicated (Tu, 2009), lighting conditions influence colour  
 306 perception and this factor must also be considered, which makes it necessary to correct the regions obtained  
 307 with this method (Figure 7). Other possible corrective measures consist of enhancing the flatness of the  
 308 camera lens, although this would prove difficult for a low-cost application. The shadows produced between  
 309 the tray and fruit produce a degraded colour around the fruit perimeter that it is also possible to correct,  
 310 although this implies creating adaptive holes, which is technically difficult to implement.

311 *Table 3. Relative error of the bruise index between the theoretical calculation from known shapes (fruits and spots) and that*  
 312 *calculated by the software from original images and from template photos.*

Digital images	Resolution (dpi)	Fruit sizes in templates (diameter x length) (mm)				
		20x30	20x40	30x40	40x40	Average
originals	72	2.8 %	2.7 %	2.7 %	2.4 %	2.7 %
	150	0.5 %	0.5 %	0.5 %	0.2 %	0.4 %
	300	0.1 %	0.1 %	0.1 %	0.2 %	0.1 %
from templates	150	3.4 %	3.0 %	3.7 %	2.7 %	3.2%
photos	300	3.0 %	2.9 %	3.9 %	2.4 %	3.1 %

313 Table 4 shows the average time that several hardware configurations employed to analyse the images taken  
 314 from *SAEOQ* in the field test, reporting results of less than a half minute for each 20 sample fruits when  
 315 using a low-cost system such as hardware D.

316 *Table 4. Average time employed by some hardware configurations to analyse the images (n= 10) acquired from SAEOQ*

Hardware configuration	A	B	C	D
<b>Processor:</b>	Intel Core I9- 9900K 3.60 Ghz	Intel Core I7-7700 HQ 2.80 Ghz	Intel Pentium G645 2.90 Ghz	AMD A6-6400K APU 3.90 Ghz
<b>Cores</b>	8	4	2	1
<b>Logical processor</b>	16	8	4	2
<b>RAM:</b>	32 Gb – 2666Mhz DDR4	16 Gb – 2400 Mhz DDR4	8 Gb – 1600 Mhz DDR3	12 Gb – 1600Mhz DDR3
<b>Average time</b>	<b>4.0 s</b>	<b>8.4 s</b>	<b>12.0 s</b>	<b>27.4 s</b>

317

318 1.3 Evaluation of the estimated parameters.

319 Table 5 shows the errors generated by the device in estimating geometrical parameters. The estimation of  
 320 weight by fruit diameter and length is very precise and requires distinction between varieties (Ponce et al.,  
 321 2018).

322 *Table 5. MAE (Mean Absolute Error), RMSE (Root Mean Square Error) and R squared determined between the olive size and*  
 323 *weight values calculated by the software and with manual measurement*

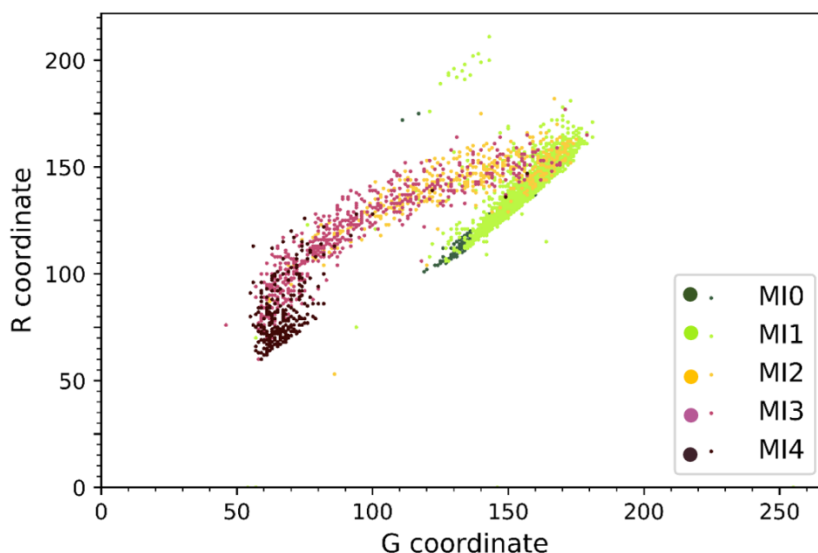
Variety	Parameter	R squared	MAE	RMSE
Manzanilla	Diameter	0.82	0.43 (mm)	0.69 (mm)
Hojiblanca	Diameter	0.84	0.39 (mm)	0.61 (mm)
Manzanilla	Length	0.91	0.41 (mm)	0.55 (mm)
Hojiblanca	Length	0.81	0.54 (mm)	0.91 (mm)
Manzanilla	Weight	0.91	0.23 (g)	0.32 (g)
Hojiblanca	Weight	0.89	0.20 (g)	0.30 (g)

324 Table 6 sets out the statistical parameters calculated for the prediction of the tested fruit's maturity index. The  
 325 precision indicates that the quality of the model is quite good in predicting MI1, but relatively poor for MI0.  
 326 This may be a problem given that such a limitation can affect bruising estimation when it comes to applying  
 327 the different models. In MI0 only one third of the real fruit that belonged in the category was identified,  
 328 whereas in MI4 almost all the fruit predictions belonged to the category the expert had specified. On  
 329 combining precision and recall, we obtain more balanced values for the different categories. It should be  
 330 taken into account that although the estimation seems to have good accuracy, we should not consider this  
 331 parameter because there is an imbalance with a greater number of samples in MI1 than in MI0.

332 *Table 6. Statistical parameters calculated to predict the maturity index according to the percentage of fruit pixels of each*  
 333 *defined colour group.*

Maturity Index	Precision	Recall	F1 score	Accuracy	Specificity
<b>MI0</b>	0.16	0.34	0.21	0.66	0.99
<b>MI1</b>	0.97	0.98	0.97	0.91	0.85
<b>MI2</b>	0.48	0.47	0.47	0.72	0.97
<b>MI3</b>	0.93	0.40	0.56	0.69	0.99
<b>MI4</b>	0.65	0.99	0.78	0.98	0.97

334 It is worth mentioning that the data from the classification made by the expert is taken as real. However, the  
 335 habitual criteria for sorting is highly subjective as it takes into account both colour and percentage of colour  
 336 on a fruit, and we must stress the difficulty of ensuring the true accuracy of the algorithm without a criterion  
 337 that establishes more quantitative data. Figure 7 shows the location of the colour in RGB.R and RGB.G  
 338 coordinates of the fruit measured with the colorimeter. Ripening tendency can be appreciated with an  
 339 evolution of colour that goes from left to right and from bottom to top in the transition from MI0 to MI1, and  
 340 similarly, from right to left and from top to bottom in the transition from MI1 to MI4. This evolution is quite  
 341 coherent with the colour threshold obtained in this work (Figure 6), suggesting the ability of computer  
 342 vision-based systems to substitute conventional methods of colour evaluation, even if different maturity  
 343 index groups overlap (Figure 7) making it difficult to automatize the classification criterion used with  
 344 extremely high accuracy.



345

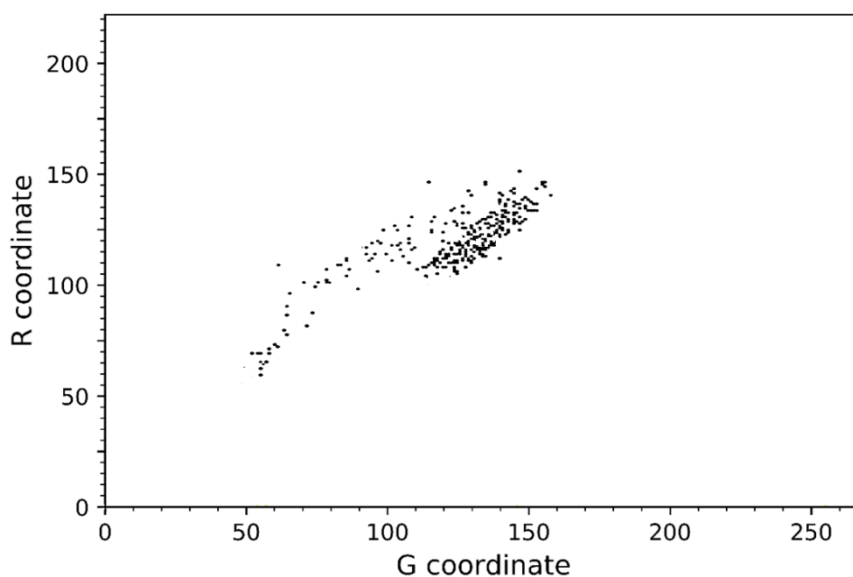
346 *Figure 7. Location of fruit colour measurements (two per fruit) in red-green channels with the colorimeter and their manual*  
 347 *sorting into the maturity index groups*

348 The values of the RGB.B blue coordinate measured were very constant during the development of ripeness  
 349 and had very low dispersion with values of  $68.4 \pm 7.0$ ,  $77.3 \pm 7.9$ ,  $84.6 \pm 8.9$ ,  $78.1 \pm 9.4$ ,  $68.5 \pm 5.83$  for MI0, MI1,  
 350 MI2, M3, and MI4, respectively. This relates with the findings of Gatica et al. (2013) and is the reason why  
 351 a blue background, as used in this work, was beneficial for fruit segmentation, achieving very high results  
 352 (Table 1).

353 The gap obtained in the RGB.G coordinate between the yellow-green and red-purple colour regions (Figure  
 354 6) was important to distinguish between MI2 and MI3 because the difference between these maturity

355 categories is simply the percentage of pixels of each colour. Figure 8, where the categories completely  
356 overlap, illustrates this. Moreover, MI2 also overlaps with MI1, which means it is very complicated to make  
357 the distinction without using a percentage of colour pixel estimation. This implies that many pixels are not  
358 categorized in each colour region, and are not therefore considered when determining MI. However, this is  
359 decisive to avoid error when estimating the maturity group. Similarly, we observed that MI0 and MI1 fruits  
360 seem to overlap in the RGB.R - RGB.G coordinate, so only the percentage of pixels of each colour region  
361 needs to be considered.

362 The error generated in determining the bruise index differs widely, depending on whether the olives are  
363 classified by the algorithm as MI0 (MAE=1.44, RMSE=2.42), or MI1 (MAE=1.96, RMSE=3.78). The mean  
364 error obtained in an analysis of 90% of the fruit was approximately 5.6 % but this error significantly  
365 increased when the remaining 10% of fruit, with the highest bruise index, were introduced in the analysis,  
366 probably because these pixels are incorrectly classified as bruising. This final low precision in the bruising  
367 estimation, mainly for MI1, is due to several errors that are carried over from earlier phases in the  
368 calculation, such as lighting, MI sorting, etc. First, correctly assigning the maturity index to fruit is decisive  
369 when applying the different models and this, in turn, is conditioned by the colour calculation and by the  
370 filters used. Secondly, a large number of pixels, most of which correspond to ripening development in MI2  
371 and MI3, are wrongly calculated as bruising due to their similarity in colour with ripe regions (Figure 8).



372

373

*Figure 8. Location of the bruising colour measurements in the red-green channels*

374 In general, the system developed allows the estimation of interesting global parameters for determining the  
375 quality of fruit (Opara and Pathare, 2014). It reports good performance and has an intelligent black box that  
376 determines these parameters without the need for more complex and sophisticated evaluation procedures.  
377 The tool can be used for a variety of purposes, such as agronomic decision-making in the field (Li et al.,  
378 2018) or the evaluation of harvest or post-harvest systems (Morales-Sillero et al., 2014; Sola-Guirado et al.,  
379 2020). Multi-objective evolutionary optimization techniques would enhance the algorithm obtained to  
380 produce a higher accuracy tool which would provide farmers and agricultural technicians with software tools  
381 to help them make the right decision (Chavez et al., 2019).

## 382 **Conclusions**

383 The developed system was manufactured with simple, inexpensive materials using a low-resolution camera  
384 and regular hardware, which make it an affordable system for any farmer. The device is portable and easy to  
385 use, capable of being transported in a vehicle and powered by the vehicle's battery. The software designed  
386 for the application has a simple interface that allows the automatic analysis of sample fruit images taken in  
387 the field at any moment. All of these elements mean that is an affordable system for farmers or researchers in  
388 comparison with other sophisticated, complicated industrial equipment because processing allows analysis of  
389 as many samples as the user wishes and the system provides a valuable report for other research purposes or  
390 for decision making.

391 The system allows fruit size, weight and calibre to be obtained with high accuracy. Although the system was  
392 studied with two varieties, it could incorporate other size-weight correlations for other varieties. The  
393 estimation of this parameter would be of value to control fruit growth and consequently to adjust agronomic  
394 actions such as fertigation. Farmers could also calculate the market value of their production.

395 Estimation of calibre may be of interest if combined with maturity index estimation. The proposed  
396 application provides reports that are accurate enough to determine the optimum harvest time for green olives,  
397 or even for olives destined for oil production. The colour calculation of each fruit pixel makes the application  
398 flexible for the estimation of maturity based on other criteria such as colour average. In fact, the estimation  
399 made with the criterion used in this work presents serious problems because it requires previous adjustments  
400 of the colours and subsequent calculation of their percentage. The results demonstrate that there was  
401 overlapping in colour values within the same maturity categories. Nonetheless, the rapid estimation of fruit

402 maturity that this system provides could be valuable to control the progression of crop readiness on a farm  
403 and adequately prepare the means necessary for harvesting.

404 It was only possible to estimate the bruise index with a medium level of precision, and our work showed that  
405 the bruise spot can be difficult to segment, principally due to the similarities between its colour and that of  
406 the ripe regions of fruit belonging to groups MI1 and MI2. For this reason, the two training methods obtained  
407 were valuable to reduce errors in less ripe fruit. The errors obtained could be better enhanced in the earlier  
408 sorting phases, in addition to modifying some device conditions such as the trays or the lighting.  
409 Nonetheless, it is still challenging to achieve high accuracy results by employing techniques that use the  
410 visible spectrum. Fast bruise index estimation is extremely useful and difficult to estimate manually, so this  
411 method offers a great advantage in this regard. Valuable information could be extracted from these results  
412 such as the assessment of the damage caused by different harvesting systems or the evaluation of fruit  
413 defects in trees caused by meteorological phenomena.

414 In general, the “all in one” system developed allows a quick, easy, accurate evaluation of the main external  
415 parameters that define the quality of olives for green processing. The method used for developing the final  
416 configuration of the device can be improved by updating new training models or incorporating new models  
417 that allow adaptation for a wider range of varieties, or even adaptation of the procedures for other crops. The  
418 tools provide valuable information with a great potential for use by farmers, researchers or insurance agents.

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