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Non-destructive and contactless quality evaluation of table grapes by a computer vision system

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ABSTRACT

Quality rating is currently accomplished by non-destructive and subjective sensory evaluation or by objective and destructive analytical techniques. There is a strong need of an objective non-destructive contactless quality evaluation system to monitor fruit and vegetable along the whole supply chain. This paper proposes a Computer vision system to satisfy this request. Image processing and machine learning techniques have been combined to develop a Computer vision system whose configuration and tuning has been strongly simplified: that makes easier its deployment in real applications. The system has been verified on two white table grape cultivars (Italia and Victoria) against three different classification tasks. The first considered five quality levels (5, 4, 3, 2, 1); the second separated the higher fully marketable quality levels (5 and 4) from the boundary (3) and the waste (2 and 1); the third separated the higher fully marketable quality levels (5 and 4) from the other three (3, 2 and 1). The system achieved a cross-validation classification accuracy up to 92% on the cultivar Victoria and up to 100% on the cultivar Italia for binary or binomial classification between fully marketable and residual quality levels. The obtained results support its capability of powerfully, flexibly and continuously monitoring the quality of the complete production along the whole supply chain.

1. Introduction

Table grape (*Vitis vinifera* L.) is a non-climacteric fruit subject to serious quality loss after harvest, mainly due to water loss, which cause stem browning and sensitivity to microbial decay. Rachis browning is the most important physiological disorder of table grapes post-storage, while the primary pathological spoilage problem is decay caused by *Botrytis cinerea* (Lichter, 2016).

Colour characteristics, firmness (skin, pulp and whole berry), chemical and volatile composition are the main sensory attributes evaluated by consumers. Usually, a green rachis is an indicator of freshness and hence a brown rachis can be a cause of consumer rejection and fruit waste. Generally, the quality level of table grape is determined through sensory and subjective determination combined to analytical and destructive techniques, which are time consuming and sometimes may require sophisticated equipment. Research has been focused on developing non-contact, rapid, environmental-friendly and accurate methods for non-invasive evaluation of quality in fruits and vegetables (Liu et al., 2017). Among these, Computer vision systems (CVSs) may be applied to extend quality prediction and discrimination along the whole supply chain from harvesting up to consumers. CVS combines mechanics, optical instrumentation, electromagnetic sensing and digital image processing technology (Patel et al., 2012). Computer vision systems are widely used to accomplish quality control on fruit and vegetables (Blasco et al., 2017). As reported by many Authors, CVS was used to assess quality and marketability of tomatoes (Arias et al., 2000), artichokes (Amodio et al., 2011), fresh-cut nectarines (Pace et al., 2011), fresh-cut lettuce (Pace et al., 2014), fresh-cut radicchio (Pace et al., 2015) and rocket leaves (Cavallo et al., 2017). Moreover, assessment of solid soluble content of table grape was also conducted using the hyperspectral imaging systems with the scatter mode by Baiano et al. (2012). In addition, Bahar et al. (2017) evaluated quality

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of table grape measuring rachis browning through no destructive image analysis. Pothen and Nuske (2016) proposed a vision-based system to evaluate the ripeness of grapes with the aim to monitor the temporal evolution of vineyard and the spatial map of fruits to support the decision about harvest dates and locations. The system uses the H component of the Hue Saturation Value (HSV) colour space to be independent on spectrally uniform illumination change. The thresholds on the H information that separate the considered classes of ripeness are set empirically by the designers of the system. Unfortunately, the illumination often changes in its spectral distribution both indoor and outdoor: it is therefore generally better to check the constancy of colour measures and to correct them whenever needed as the proposed system does using a colour reference in the scene. Rodrìguez-Pulido et al. (2012) used image analysis to evaluate the maturation of grapes and the cultivar by analyzing the seeds and the berries. A colour-chart and a carefully controlled set-up are used to make consistent the acquisition process and manually set thresholds are used to separate the classes of interest. Raban et al. (2013) developed a statistical method of image analysis to measure rachis browning in four table grape cultivars in growth or storage. In Rahman and Hellicar, 2014, a classification of mature grape bunches was shown. Their work consists of a segmentation step to detect circles (berries) in the scene, RGB and HSV colour features extraction and SVM classifiers training to predict mature grape bunches and undeveloped grape bunches. Nogales-Bueno et al. (2014) presented a hyper-spectral imaging system to predict, on grape skin, total phenolic concentration, sugar concentration, titratable acidity and pH using Modified Partial Least Squared Regression (MPLS). Diago et al. (2015) developed an image analysis system to predict yield components (berry weight, number of berries per cluster and cluster weights) by means of contour extraction and circle detection. These predicted variables are key components and have an impact on cluster architecture and compactness. Aquino et al. (2018a) use image analysis, on an android-smartphone platform, to assess the number of berries in grapevine bunches at a phenological stage between berry-set and cluster-closure. Their system requires a dark background box to be placed behind the cluster to isolate the cluster, to enhance its separation from the background and to prevent mutual reflections between adjacent bunches. The RGB image are converted to the CIELAB colour space before any processing. Maximum light reflection points and morphological processing identify and select potential berries. False positives are discarded by a neural network trained on a proper set of berry descriptors. Mean and standard deviation of the a and b components in the CIELAB colour space are used as colour descriptors. Moving the CVS on a portable hardware platform such as a smartphone certainly extends its applicability along the supply chain but require further efforts to solve all the problems related to weaker constraints on the acquisition set-up (background, geometry and lighting). In Aquino et al. (2018b) a non-invasive and in-field yield prediction was presented. This research involves several stages as input images pre-processing, identification of berry candidates and neural network training in yield components prediction. Sollazzo et al. (2018) have verified the correlation between colour and chemical compound related to the assessment of grapes ripeness using colour measures obtained by a colorimeter or subjectively evaluated using a properly designed colour chart. On the other hand, our system has been designed to reduce the manual interventions in both configuration and tuning of the algorithms to enhance the performance and to simplify its application to different products. The aim of the proposed system is to achieve contactless and no destructive quality evaluation of table grape during cold storage using a colour reference in the scene: the system fully exploits image analysis and machine learning techniques to reduce human intervention in configuration and tuning to the minimum. This significantly simplifies its deployment and application in several points of the supply chain extending the quality monitoring and improving the product management.

2. Materials and methods

2.1. Plant material and experimental setup

Table grapes (*Vitis vinifera* L., cvs *Italia* and *Victoria*) were provided by a farm (Ermes snc, Noicattàro, Bari, Italy) in two harvests (September and October) at the same maturity stage (total soluble solid content of 16° Brix, according to OIV, 2008) and were transported within 1 h from harvest to the Postharvest laboratory. One hundred bunches for each cultivar were placed in open polypropylene bags (25 × 30 cm, 30 µm, Carton Pack, Rutigliano, Italy), each one containing 1 bunch (about 1 kg of product) and stored at two different temperatures (5 and 10 °C) for 25 and 20 days respectively for cv *Victoria* and 37 and 27 days respectively for cv *Italia*. The length of storage was defined as the number of days needed to reach the lowest quality level (QL) at each temperature.

Thus, during storage, for each cultivar and storage temperature, 10 table grape bunches were evaluated by 8 panellist, in order to assign a QL using the following subjective scale: 5 = very good (rachis green, firm berries, no signs of decay), 4 = good (rachis green with slight symptom of dehydration, firm berries), 3 = limit of acceptability or marketability (rachis moderately browned, firm berries slightly brown), 2 = poor (evident signs of browning of rachis, loss of firmness of berries), and 1 = very poor (unacceptable quality due to decay). Thus, 100 bunches of Italia and 100 bunches of Victoria were used for the QL assessment. The QL3 was considered the minimum threshold of acceptance for sale or consumption (Cefola et al., 2018), therefore values below 3 indicated a waste product (Fig. 1).

2.2. Workflow of the proposed approach to predict the quality level of table grape bunches

The proposed approach to contactless and non-destructive evaluation of quality of table grapes by a Computer vision system (CVS) involves different tasks: acquisition of a dataset of calibrated colour images annotated with the QL of the corresponding table grape; proper pre-processing of the acquired images; colour features identification and extraction; training, tuning and testing a Random Forest Classifier (RFC). This workflow is graphically represented in Fig. 2.

2.2.1. Data acquisition and pre-processing

Calibrated colour images were acquired and processed for each cultivar (Italia and Victoria); in total, for each cultivar, the data set was composed by 400 images, obtained acquiring each bunch 4 times in different position. Images (for each QL from 5 to 1) were acquired using the set-up previously reported (Cavallo et al., 2017, 2018; Pace et al., 2015, 2017) using a 3CCD (Charged Coupled Device) digital camera (JAI CV-M9GE) with a dedicated CCD for each colour channel. The optical axis of the Linos MeVis 12 mm lens system was perpendicular to the black background. Eight halogen lamps (divided along two rows placed at the two sides of the imaged area) were oriented at a 45° angle with respect to the optical axis. The images were saved using the uncompressed TIFF format. A small X-Rite colour-chart with 24 patches was placed into the scene to estimate colour variations due to environmental conditions and sensor characteristics by comparing the expected numerical values released by X-Rite with the measured ones. The colour-chart was automatically detected regardless its position and orientation. Its white patch was used to white-balance the image: a correction coefficient was evaluated (dividing the reference value by the measured value) and multiplied to each band to reduce the distance between the measured white and the reference one. Noisy pixels, for which at least one channel was greater than the maximum allowed value in the colour space (i.e. 255) after the white balance, were removed. The CVS automatically separated the product at hand (foreground) from the background using two thresholds automatically derived from the analysis of the whole image in the HSV colour space,

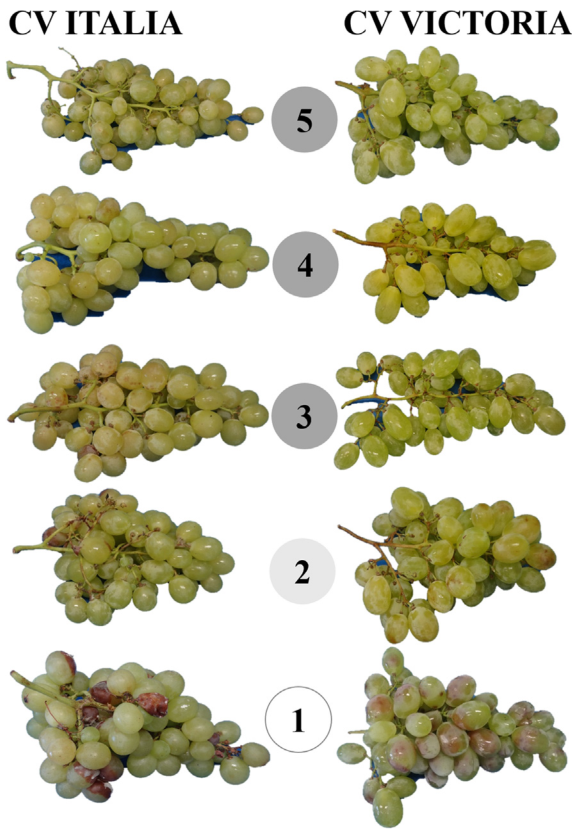

Fig. 1. Quality level rating scale for table grapes of cultivars Italia and Victoria. 5 = very good (rachis green, firm berries, no signs of decay), 4 = good (rachis green with slight symptom of dehydration, firm berries), 3 = limit of acceptability or marketability (rachis moderately browned, firm berries slightly brown), 2 = poor (evident signs of browning of rachis, loss of firmness of berries), and 1 = very poor (unacceptable quality due to decay). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

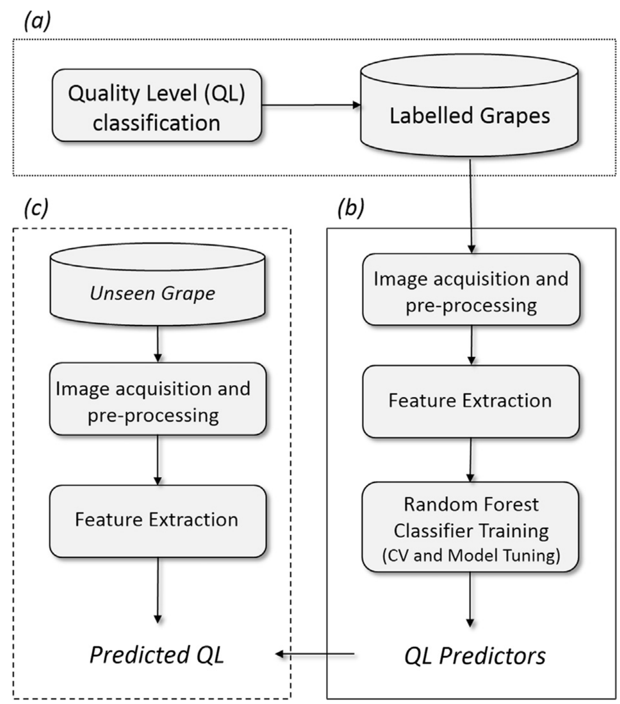

Fig. 2. The three phases of the proposed approach: (a) all the table grapes were classified by experts according to 5 quality level (QL) where the fresh product corresponds to quality 5 and the worst product (waste) to quality 1; (b) all the classified table grapes were acquired and processed by the CVS, 14 numerical features were identified and an ensemble Random Forest classifier was trained, tuned and tested using the training set; (c) the validated model was used to classify unseen table grapes.

without any human intervention. The segmentation was used only to identify the region belonging to the product (to be further processed) and not to separate different parts of the table grape. The segmentation approach was conservative: thresholds were derived to discard all the background pixels even at the cost of removing some peripheral parts at the borders of the product.

2.2.2. Feature extraction

From every calibrated image related to each QL and cultivar suitable features were extracted. Specifically, two set of features were used: the first one was represented by statistical measures evaluated over the whole foreground on the channels in the CIELAB colour space (Cavallo et al., 2017); the second one was derived by a centroid-based colour segmentation algorithm (Pace et al., 2015).

To evaluate the first set of features all the pixel belonging to the foreground were converted from the device dependent RGB space into the device independent CIELAB colour space in which the $L*$ channel expresses the lightness dimension (in the range [0, 100]) while $a*$ and $b*$ represent respectively the green-red and blue-yellow colour components (both in the range $[-127, 128]$). Mean and standard deviation (std) of each colour channel (L^*, a^* and b^*) were computed. Moreover, mean($a*$)*mean($b*$), mean(L^*)*mean(a^*), mean(L^*)*mean(b^*), mean (a^*)/mean(b^*), mean(a*)/mean(L^*) and mean(b^*)/mean(L^*) were considered. All these features were normalized using the min–max method to balance their influence on the final results: the obtained 12 normalized features were all positive and in the range [0,1].

To automatically obtain the second set of features, a hierarchical clustering algorithm was applied to the calibrated colour images. This unsupervised machine learning algorithm yields a structure called dendrogram that hierarchically groups all the colours according to a chosen distance metric. This structure can be cut at different depth providing, at the k^{th} level, k clusters. The Euclidean distance was used as distance metric and the dendrogram was cut at the 2nd level providing two clusters. Two centroids were identified to represent these two clusters: they were therefore used to segment each image into two different regions. Specifically, all pixels belonging to the foreground were converted into CIELAB space and assigned to the nearest identified centroid using Euclidean distance (colour segmentation). Finally, the two percentages p1 and p2 of pixels belonging to the two clusters were used as further features to describe colour changes of the product surface due to senescence. In Fig. 3 is shown an example of centroid-based image segmentation carried out on table grapes labelled as QL5 and QL1. The image shows the difference between the two quality levels in terms of percentages of pixels belonging to the two relevant colours: it is important to note that even if they are roughly associated to green and brown they are chosen freely and automatically by the system to represent the colorimetric characteristics of the product at hand and are not constrained to mimic what humans consider to be relevant for the desired task. Statistical features and percentages produce a vector with 14 basic elements. Moreover, additional polynomial features where composed by combining these basic features to further improve the expressivity of the feature vector. Nonlinear functions are often very difficult to fit and polynomial features can improve models' accuracies. Anyway, high polynomial degrees should be avoided to prevent undesirable effects (overfitting, curse of dimensionality). A proper combination of polynomial features and tuning of their degree must be found to maximize effectiveness.

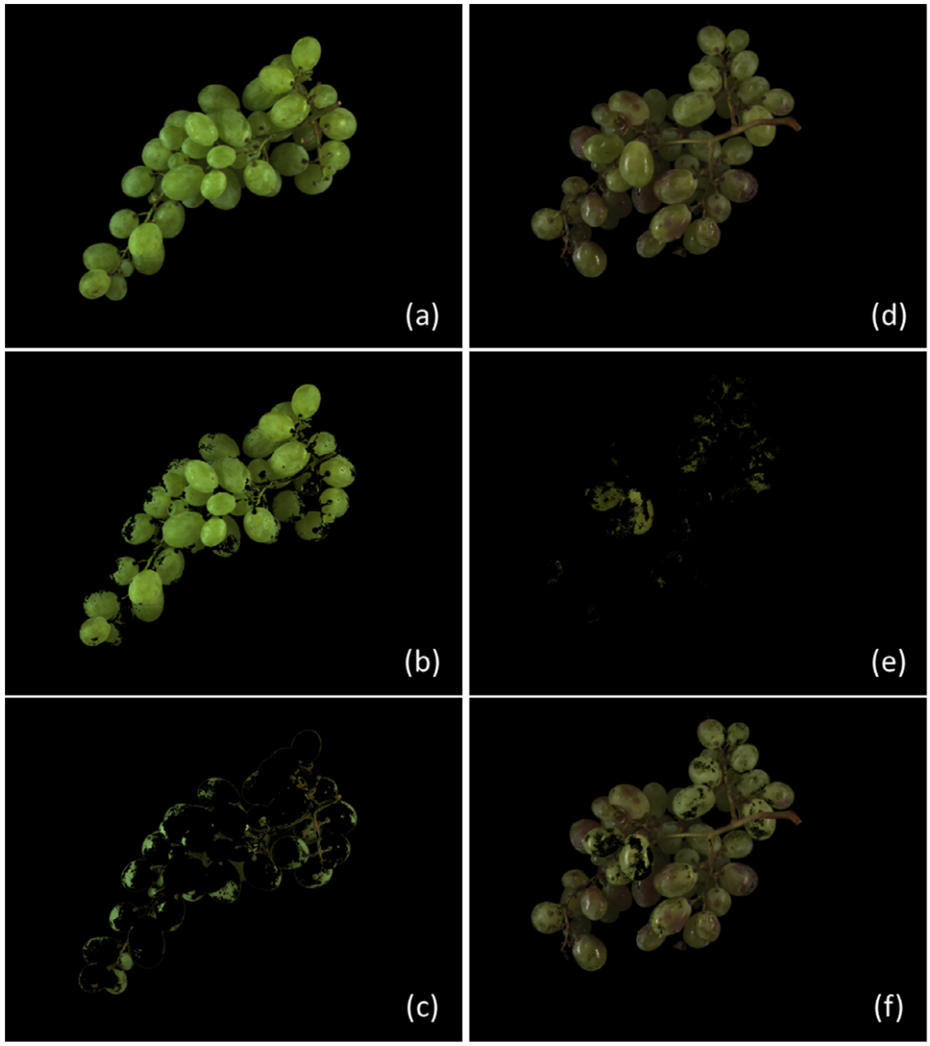

Fig. 3. An example of centroid-based segmentation of images of table grapes (cv Italia) belonging to QL 5 (a, b, c) and QL 1 (d, e, f). A hierarchical clustering unsupervised technique was applied on a set of pixels representing the whole dataset. Then, each image was segmented by these centers and the number of pixels (for each segment) was used to identify percentage-based features.

2.2.3. Random forest models

Random Forest has been chosen as the supervised classification model to predict the QL of table grapes. This ensemble model is composed by multiple predictive trees whose combination achieves a predictive performance greater than each single component. Specifically, Random Forest, also called decision forest, consists of an ensemble of decision trees with feature and sample bagging: each tree is built on a sample (bootstrap) of the training set using a random feature subset instead of the whole feature space. This technique entails two main advantages: (*i*) in spite of a slight bias growth, variance (overfitting) is drastically reduced and (*ii*) the predictive performance (obtained by averaging the answers of the different trees) is generally improved.

Since the target variable (QL) is a discrete variable that can assume five possible values (from QL5 to QL1) each decision tree is a classification tree. Nonetheless an equivalent regression ensemble model could be used with numerical response variables using regression trees as shown in Cavallo et al. (2017). Two cross-validation schemes were nested to implement this model. An external 5-fold cross-validation was applied to the available samples (and to their associated feature vectors) to evaluate the predictive performance of the complete Random Forest model; an internal 10-fold randomized search was exploited to find the best configuration of the parameters (model tuning) at each iteration of the external cross-validation scheme.

To evaluate the efficacy of the automatic feature selection approach, each run was repeated working also on a set of manually selected features. Specifically, on the base of the visualization of bivariate graphics showing the relationship between predictors and target, three features (“mean of a^* ”, “mean of b^* ” and centroid-based colour percentage) were chosen. The comparison of performances obtained using these two different sets of features was used to assess the effectiveness of the automatic feature selection.

Furthermore, three different resolution of classification of QL were checked. QL5 and QL4 represent the higher fully marketable qualities, QL3 represents the limit of acceptability or marketability while QL2 and QL1 represent only wastes. Therefore, the following classification tasks were verified:

(a) 5 classes classification: QL5 vs QL4 vs QL3 vs QL2 vs QL1;
(b) 3 classes classification: {QL5, QL4} vs QL3 vs {QL2, QL1};
(c) 2 classes classification: {QL5, QL4} vs {QL3, QL2, QL1}.

The task a is the most informative but proved to be slightly less robust. The task c is the less detailed but was much more robust and can timely alert about the achievement of the limit of acceptability or marketability: this can activate special marketing policy or can send the product toward alternative recycling paths to reduce waste. Two different approaches were compared during the modelling phase: in one of them features were manually selected before running the machine learning pipeline; in the other case features were automatically identified by the learning algorithm. Some of the parameters of the Random Forest classifier were manually set while other were optimized during the model tuning using an inner cross-validation randomized search. The following parameters were manually set: the gini-index (used to measure the quality of splits), the square root of the number of total features (adopted as the maximum number of features for each classification tree), the minimum number of samples required to split an internal node (set to the value 2), the minimum number of samples required for a leaf node (set to 1). Bootstrap samples was used (in addiction to bootstrap features): that is samples were drawn with replacement. The generalization accuracy was estimated by using out-of-bag (oob) score: this method avoids the need of a separate test set by considering, for each training instance *i,* the average error made by classifying using only the trees of the random forest that do not contain the instance *i* in their bootstrap samples. The following parameters were optimized by model tuning: number of trees (in the range [25,50]), maximum depth of trees (in the range [5,10]) and degree of polynomial features (in the range of [2,6]). Because tuning parameters requires a validation set, a nested cross-validation was used: the internal cross-validation used for tuning split the training data used by the outer cross-validation.

3. Results and discussion

To manually select the features by evaluating the relationship between target and predictors, features were visualized using bivariate plots. A strong correlation was observed between centroid-based percentage features p1 and p2 and QLs of the cultivar Italia. It was possible to separate higher QLs table grapes belonging to QL5 and QL4 from QL3, QL2 and QL1. This interesting relationship is shown in Fig. 4. Similarly, a good correlation was observed between channel features (mean of L^*, a^* and b^*) and table grapes QLs.

The performances of the predictive models were measured using classification accuracy (correct predictions/total predictions) averaged over the results of the outer 5-fold cross-validation. In fact, model tuning was performed by an inner 10-fold cross-validation, while outer 5-fold cross-validation was used only to evaluate learned models. Each fold was composed by stratified sampling to guarantee that each QL was properly represented in each fold. The same pipeline was repeated twice: one with manually chosen features and one with automatic selected features.

In Table 1 predictive performances for the three different classification tasks between manual feature selection and automatic feature selection are compared on both the cultivars Italia and Victoria. The performance on the cultivar Italia was better than the one on cultivar Victoria. Probably this is related to the fact that in cv Italia, the loss of quality is mainly due to the colour change of berries, while in Victoria this is less discriminant and needs to be integrated by other quality traits (such as berry dehydration, rachis browning and desiccation) to characterize the QLs.

The separation of all the five classes can be achieved with lower robustness. On the other hand, to separate the two first QLs (5 and 4) is not relevant in real applications. Even the separation of the last two QLs (2 and 1) is often not significant because they both correspond to products that cannot be sold anymore. Along the supply chain is generally important to detect the achievement of QL3 because it represents the limit of marketability (Amodio et al., 2007). The system has been able to separate the highest QLs (5 and 4) from the other (from QL3 to QL1) with an accuracy of 100% on cultivar Italia and of 92% on cultivar Victoria. Similarly, the same CVS, applied to fresh-cut lettuce, resulted able to discriminate the acceptable product (ranging from QL5 to QL3) from the waste (QL = 2 or 1), starting from features based on colour parameters and also to provide an accurate estimate of the ammonium content, giving a non-destructive evaluation of a chemical and objective parameter (Pace et al., 2014).

The experiments showed that the automatic feature selection was able to outperform the manually selected features. The ensemble model achieved better scores regardless the cultivar or the specific classification tasks. This is important because the configuration of the system can be done automatically by feeding in the system a quite large set of potential features, leaving to machine learning tools the task of selecting how many and which characteristics are better suited to achieve the classification task at hand. This makes the extension of the system to other products or cultivar much easier and achievable even by non-expert users. The proposed models are based on a complex combination of factors extracted from digital images which allow to predict the sensory quality with good performance. This overcomes the limits of linear models (Baiano et al., 2012) that were able to predict the intrinsic characteristics (i.e. pH, soluble solid content, titratable acidity) but that proved to poorly estimate sensory parameters of table grape such as visual quality.

In addition, to average cross-validation classification accuracy on training and test sets, Tables 2 and 3 show the confusion matrices

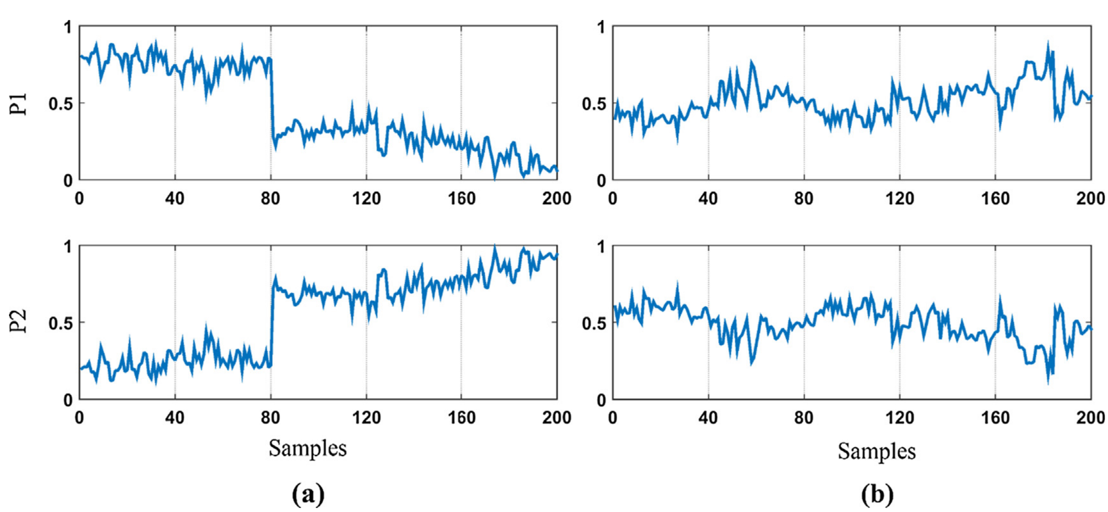

Fig. 4. These graphs show on the y-axis the percentages of colour 1 (P1) and of colour 2 (P2) for table grapes of cultivar Italia (a) and Victoria (b) stored at 10 °C. The digital images of bunches are ordered along the x-axis from left to right from the highest quality (QL5 5) to the lowest (QL1). QL 5 goes from 1 to 40, QL 4 from 41 to 80, QL3 from 81 to 120, QL2 from 121 to 160, QL1 from 161 to 200. Features P1 and P2 are much more significant in the case of the cultivar Italia. The same trends were observed in the samples stored at 5°.

Table 1
Cross-Validation classification accuracy for the cultivar Italia and Victoria obtained using the Random Forest model verified on 3 different classification tasks: 5 classes, 3 classes and 2 classes. Moreover, its performance has been checked on both manually selected features ("Mean(L^*,a^*,b^*), p1, p2") and automatically selected features. The results assess the efficacy of our approach using a self-configuring and mostly automatic CVS.

Feature Selection	Classification task	Cross-Validation classification accuracy	
		cv Italia	cv Victoria
Mean(L^*, a^*, b^*), p1, p2	QL5 vs QL4 vs QL3 vs QL2 vs QL1	0.72	0.6
Automatically selected features	QL5 vs QL4 vs QL3 vs QL2 vs QL1	0.74	0.71
Mean(L^*, a^*, b^*), p1, p2	{QL5, QL4} vs QL3 vs {QL2, QL1}	0.91	0.78
Automatically selected features	{QL5, QL4} vs QL3 vs {QL2, QL1}	0.94	0.83
Mean(L^*, a^*, b^*), p1, p2	{QL5, QL4} vs {QL3, QL2, QL1}	1.0	0.92
Automatically selected features	{QL5, QL4} vs {QL3, QL2, QL1}	1.0	0.92

Table 2
Further data about the performance of the Random Forest model (with automatic feature selection) on the cultivar Italia for all the three considered classification tasks: the average Cross-Validation (CV) Accuracy observed on both the training and test sets and the confusion matrix on the test set. In the confusion matrix, the columns represent the classification made by the CVS while the rows express the true class of the samples. Therefore, the number of samples belonging to each class is given by the sum of the values on each row.

Classification task	CV classification Accuracy		Confusion Matrix (test)					
	Training	Test	QL1	QL2	QL3	QL4	QL5	
QL5 vs QL4 vs QL3 vs QL2 vs QL1	0.99	0.75	49	24	7	0	0	QL1
			15	51	14	0	0	QL2
			3	9	68	0	0	QL3
			0	0	0	63	17	QL4
			0	0	0	10	70	QL5
{QL5, QL4} vs QL3 vs {QL2, QL1}	0.99	0.94	151		9	0		QL1
								QL2
			16		64	0		QL3
			0		0	160		QL4
								QL5
{QL5, QL4} vs {QL3, QL2, QL1}	1	1	240			0		QL1
								QL2
								QL3
			0			160		QL4
								QL5

Table 3
Further data about the performance of the Random Forest model (with automatic feature selection) on the cultivar Victoria for all the three considered classification tasks: the average Cross-Validation (CV) Accuracy observed on both the training and test sets and the confusion matrix on the test set. In the confusion matrix, the columns represent the classification made by the CVS while the rows express the true class of the digital images acquired on table grape bunches. Therefore, the number of images belonging to each class is given by the sum of the values on each row.

Classification task	CV Classification Accuracy		Confusion Matrix (test)					
	Training	Test	QL1	QL2	QL3	QL4	QL5	
QL5 vs QL4 vs QL3 vs QL2 vs QL1	0.99	0.71	72	5	2	1	0	QL1
			9	57	12	2	0	QL2
			0	17	45	9	9	QL3
			0	3	11	46	20	QL4
			0	0	4	11	65	QL5
{QL5, QL4} vs QL3 vs {QL2, QL1}	0.99	0.83	141		14	5		QL1
								QL2
			20		44	16		QL3
			2		13	145		QL4
								QL5
{QL5, QL4} vs {QL3, QL2, QL1}	1	0.92	223			17		QL1
								QL2
								QL3
			17			143		QL4
								QL5

obtained by the classification model using automatically selected features. This more detailed information can be useful to judge the kinds of errors made by the system and their relevance to the specific application needs. Different errors can correspond to different costs and this information can be used to judge the economic impact of errors and tune the classification strategy according to the required economic risk.

The experiments showed that it is possible to use a CVS to non-destructively and contactless evaluate the quality of table grapes by developing classification model that are specific for single cultivars. The performance of the system on each cultivar does not depend on the storage temperature making it practically useful in real context where the temperature can be confined into specific range but cannot be kept constant.

Further experiments have been planned to try to understand the source of the different performances on different cultivars. Globally, the system appears to be able to provide an effective answer to the request of a non-destructive and contactless method to grade completely the production in a more objective and reliable way with respect to human made visual evaluation. In addition, the system compares favourably with costs and time required by the destructive analytical tests made in the laboratory.

4. Conclusions

A Computer vision system for the non-destructive and contactless evaluation of quality of table grapes has been presented. It has been verified on two white table grape cultivars (Italia and Victoria). It showed good performance on the task of checking and detecting when the product reaches the QL 3, that represents the limit of marketability and therefore require specific management actions to be assumed. The best results were obtained in the binary classification between fully marketable and residual products. The Computer vision system uses image processing techniques to process and analyse colour images and achieve the required classification. It also exploits a few machine learning methodologies to simplify the configuration and tuning of the algorithms avoiding human intervention as much as possible without performance loss. On the contrary, the experiments showed that automatic features selection outperformed manually selected features. This assisted configuration makes easier to extend its application to different situations along the supply chain and to different cultivars. The Computer vision system represents a suitable tool to solve the request for a quality evaluation tool that can be applied to the whole production and provide an objective answer with lower cost in terms of time and money with respect to the destructive tests in laboratory.

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