Comparison of ROC feature selection method for the detection of decay in citrus fruit using hyperspectral images

D. Lorente[1], J. Blasco[1], A.J. Serrano[2], E. Soria-Olivas[2], N. Aleixos[3], J. Gómez-Sanchis[2*]

[1]Centro de Agroingeniería. Instituto Valenciano de Investigaciones Agrarias (IVIA). Cra. Moncada-Náquera km 5, 46113 Moncada (Valencia), España.

[2]Intelligent Data Analysis Laboratory, IDAL. Electronic Engineering Department. Universitat de València. Avda. Universitat s/n, 46100 Burjassot (Valencia), España.

[3]Instituto en Bioingeniería y Tecnología Orientada al Ser Humano. Universitat Politècnica de València. Camino de Vera s/n, 46022 Valencia, España.

Abstract

Hyperspectral imaging systems allow to detect the initial stages of decay caused by fungi in citrus fruit automatically, instead of doing it manually under dangerous ultraviolet illumination, thus preventing the fungal infestation of other sound fruit, and consequently, the enormous economical losses generated. However, these systems present the disadvantage of generating a huge amount of data, which is necessary to select for achieving some result useful for the sector. There are numerous feature selection methods to reduce dimensionality of hyperspectral images. This work compares a feature selection method using the area under the Receiver Operating Characteristic (ROC) curve with other common feature selection techniques, in order to select an optimal set of wavelengths effective in the detection of decay in citrus fruit using hyperspectral images. This comparative study is done using images of mandarins with the pixels labelled in five different classes: two types of healthy skin, two types of decay and scars, obtaining that the ROC technique generally provides better results than the other methods.

Keywords Computer vision, citrus fruit, decay, non-destructive inspection, hyperspectral imaging, ROC curve, feature selection.

1. INTRODUCTION

Decay caused by fungi is among the main defects affecting the post-harvest and marketing processes of citrus fruit. Infected fruit can be neither stored for a long time nor long-term transported during exportation since a small number of decay fruit can infect a whole consignment. Thus, fungal infections generate great economic losses to the citrus industry if damaged fruit are not early detected, being *Penicillium sp.* the fungi that lead to the most post-harvest loses in citrus packinghouses (Eckert and Eaks 1989). In current packing lines, the detection of decay fruit is made visually by trained operators

examining the fruit as it passes under ultraviolet (UV) light. Nevertheless, this method is subjective and potentially dangerous for human skin. The use of automatic machine vision systems is a possible solution for preventing these drawbacks.

Technology based on colour cameras has spread rapidly for the detection of skin damage of fruit and vegetables (Zude 2008; Cubero et al. 2011), being a common technique for the inspection of citrus fruit. For instance, Kondo et al., (2000) studied the possibility of detecting sugar content and acid content of oranges 'Iyokan' using a machine vision system and neural networks. Slaughter et al. (2008) developed a non-contact method of detecting freeze-damaged oranges based on UV fluorescence, and López-García et al. (2010) used multivariate image analysis to detect peel diseases in citrus fruit. Nevertheless decay lesions are difficult to detect using standard artificial vision systems since they are hardly visible to the human eye and, therefore, by standard colour cameras (figure 1). Blasco et al. (2007) used visible computer vision to detect different types of damages in citrus fruit including decay by green mould. While the success in other defects was high, the detection of decay was lower than 60% because the damages caused for this disease in the citrus skin are not clearly visible before sporulation. On the other hand, following the fluorescence technique used in the industry to detect decay by humans, Kurita et al. (2009) tried to detect decay in citrus using two lighting systems (visible and UV) changing between them while the fruit is under the view of the camera.
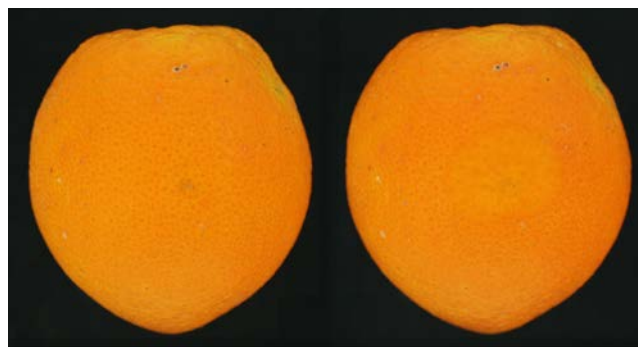
Figure 1: Sound orange (left) and the same fruit showing decay caused by *P. digitatum* (right)

Hyperspectral sensors have been used successfully as an alternative to detect non visible damages on fruit (Lorente et al. 2012). In the particular case of citrus fruit, different works have been carried out to detect decay lesions (Qin et al. 2009 & 2012; Gómez-Sanchis et al. 2012). A hyperspectral image consists of a large number of consecutive monochromatic images of the same scene in each wavelength becoming very important to select only those bands with the most relevant information, while discarding those that do not contribute in any significant way to improve the results, containing redundant information or

59 exhibiting a high degree of correlation. There are numerous feature selection methods to reduce

60 dimensionality that retain most of the original information in fewer bands.

61 For example, Gómez-Sanchis et al. (2008) evaluated four feature selection methods with the aim of

62 selecting an optimal set of wavelengths in the range 460-1020 nm for detecting decay in citrus fruit. Xing

63 et al. (2005) used Principal Component Analysis (PCA) to reduce data from a hyperspectral imaging

64 system (400-1000 nm) for detecting bruises on 'Golden Delicious' apples. PCA was also used by Liu et

65 al. (2005) to obtain spectral features for the detection of chilling injury in cucumbers imaged using a

66 hyperspectral system (447-951 nm). More recently, Li et al. (2011) have used PCA to select most

67 discriminant wavelengths in the range 400-1000 nm for detecting various common skin defects on

68 oranges. Partial Least Squares (PLS) or Artificial Neural Networks (ANN) are another techniques

69 commonly used for feature selection purposes. ElMasry et al. (2008) determined some important

70 wavelengths for detecting bruises in 'McIntosh' apples using PLS on hyperspectral images in the range

71 400-1000 nm and ElMasry et al. (2009) used ANN to classify apples into injured and normal classes, and

72 to detect changes in firmness due to chilling injury by selecting optimal wavelengths.

73 **2. OBJECTIVE**

74 The method used by Lorente et al. (2011) to select most spectral relevant features for detecting decay in

75 citrus fruit was based on the area under the Receiver Operating Characteristic (ROC) curve, which is a

76 promising method to measure the quality of a binary classifier. A novel approach was presented to extend

77 its use to multiclass problems, as is the automatic discrimination of decay lesions in citrus fruits, which is

78 a problem still under research and very important from the agricultural point of view since the damages

79 caused by fungi are hardly visible to the naked human eye and standard vision systems, and can be

80 quickly spread to other sound fruits during storage. This work aims to compare our novel approach of the

81 ROC feature selection method with other common feature selection techniques for agricultural multiclass

82 classification problems. We use the detection of decay in citrus fruits using hyperspectral imaging as a

83 benchmark problem by selecting an optimal set of wavelengths effective in the discrimination between

84 common defects and decay lesions in citrus fruit. The comparison of different feature selection techniques

85 is aimed at knowing if the ROC method is a promising technique in multiclass classification problems

86 relative to other commonly used methods in terms of classification accuracy.

87 **3. MATERIAL AND METHODS**

3.1. Image acquisition

The hyperspectral imaging system used was based on liquid crystal tunable filters (LCTF; e.g. Lorente et al., 2011). The system consists of a monochrome camera (CoolSNAP ES, Photometrics, Tucson, USA), a lens providing a uniform focus in the working range (Xenoplan 1.4/17MM, Jos. Schneider Optische Werke GmbH, Bad Kreuznach, Germany), and two LCTF (CRI Varispec VIS07 and NIR07, United Kingdom) sensitive to the visible (400 nm - 720 nm) and NIR (650 nm - 1100 nm), respectively. The scene was illuminated by halogen lamps placed inside an aluminium hemispherical domo.

For hyperspectral images, a total of 240 'Clemenules' mandarins (*Citrus clementina* Hort. ex Tanaka) collected from a local producer company were used, including 60 without visible damages, 60 presenting external scars, 60 inoculated with spores of *P. digitatum* and 60 inoculated with spores of *P. italicum*. The inoculation was performed using a suspension of spores with a concentration of 10^6 spores/ml for both fungi, which is sufficient to cause infestation in laboratory conditions (Palou et al., 2001). The images were acquired by presenting manually the damage on the fruit to the camera. A total of 240 hyperspectral images were taken in the range of 460 nm - 1,020 nm, with a 10 nm spectral resolution. Each sample pattern in the labelled set consisted of 74 spectral features associated to each pixel (reflectance level for each acquired band –grey level in each monochromatic image– and several spectral indexes) and a class label assigned manually by a human expert. Five different classes were considered in this work: green sound skin (GS), orange sound skin (OS), defective skin by scars (SC), decay caused by *P. digitatum* (PD) and decay caused by *P. italicum* (PI).

3.2. Feature selection methods

The performance of the method based on the area under the ROC curve is compared with other common feature selection methods. The methods included in this comparative study are: Correlation Analysis (CA) (Rodgers and Nicewander 1988), Mutual Information (MI) (Bonnlander and Weigend 1994), Fisher's Discriminant Analysis (FDA) (Venables and Ripley 2002), T-Test (TT) (Li et al. 2006), Wilks' Lambda (WL) (Ouardighi et al. 2007), Bhattacharyya Distance (BD) (Choi and Lee 2003), Minimum Redundancy Maximum Relevance difference criterion (MRMRd) (Ponsa and López 2007), Minimum Redundancy Maximum Relevance quotient criterion (MRMRq) (Peng et al. 2005) and Kullback-Leibler Divergence (KLD) (Kullback 1987; Abe et al. 2000). These feature selection techniques have been chosen because they are commonly applied to the analysis of hyperspectral imaging in the fields of

4

117 pattern recognition and remote sensing although they have not been used before for automatic fruit or

118 vegetable inspection using computer vision. Therefore it will also be studied if they are suitable and

119 accurate methods for this kind of problems.

120 In order to get a feature selection for each method, two steps were followed: 1) to obtain a ranking of

121 features ordered according to the discriminant relevance of the features, and 2) the selection of an optimal

122 number of features from the feature ranking. The feature selection methods and the classification

123 procedure used in this work were implemented using Matlab 7.9 (The Mathworks, Inc., Natick, USA).

124 **Step I: Obtainment of a feature ranking**

125 The obtainment of a feature ranking for each class is the initial step to follow. The feature selection

126 techniques studied are intended for binary classification problems but this work deals with problems with

127 more than two classes. Therefore, the *one vs. all* approach (Rifkin and Klautau 2004) is employed to

128 obtain a feature ranking for each class, which maximizes the separation between that class and the others.

129 The second step consists in obtaining a single global feature ranking for each method that is achieved

130 from the relevance values corresponding to the partial rankings for each class. These relevance values are

131 weighted in proportion to the relative importance of the class in the problem, and combined using Eq.1.

$$\bar{r}_j = \frac{\displaystyle\sum_{k=1}^{N} r_{jk} \cdot w_k}{\displaystyle\sum_{k=1}^{N} w_k} \tag{1}$$

132 where $\bar{r}_j$ is the global relevance of feature x_j; N is the number of different classes; r_{jk} is the relevance

133 value of feature x_j from the partial ranking for the k-th class; and w_k is the weight for the k-th class.

134 After obtaining the global relevance of each feature, each input feature is ranked.

135 **Step II: Selection of an optimal number of features**

136 Once the global feature ranking has been obtained, a minimum number of features leading to a saturation

137 trend in the success rate of classification is chosen for each method. The success rate is calculated using

138 the first features in the ranking, then successive features are added in an iterative process until the

139 increment of the success rate is lower than a certain threshold (1%). The *n* features that satisfy this

140 condition are then selected.

141 **3.2.1. Area under ROC curve**

5

142 The ROC curve is a graphical plot of the true positive rate vs. false positive rate for a binary classifier, as

143 its discrimination threshold is varied, this value being defined as that from which a positive class

144 prediction is made (Fawcett 2006). The area under a ROC curve (AUC) is used as a global measure of

145 classifier performance that is invariant to the classifier discrimination threshold and the class distribution

146 (Bradley 1997). Maximum classification accuracy corresponds to an AUC value of 1, while a random

147 guess separation involves an AUC value of 0.5. Basically, the ROC feature selection method for binary

148 classification problems consists in calculating a z statistic from the discriminant relevance of each

149 feature x_j, defined as the difference between the AUC of a classifier using all the features (AUC_0) and

150 the AUC of a classifier without taking into account the effect of feature x_j (AUC_j) (Serrano et al. 2010).

151 **3.3. Classifier**

152 The classifier used in this comparative study is a multilayer perceptron (MLP) with a single hidden layer,

153 being a type of ANN (Plaza et al. 2009). MLP can use a wide range of learning techniques for

154 determining the network parameters, the most commonly used being backpropagation. In these classical

155 learning methods, the parameters of the ANN are usually tuned iteratively, thus entailing several

156 disadvantages, such a high computational complexity and convergence to local minima (Shih 2010). To

157 avoid this the MLP used in this work avoids these problems by being trained using Extreme Learning

158 Machine (ELM; Huang et al. 2006), in the same way as that used in Lorente et al. (2011), which is a new

159 learning algorithm that determines the MLP parameters analytically in a faster way instead of tuning them

160 iteratively providing a good generalization performance at an extremely fast learning speed.

161 **3.4. Approaches to the problem of decay detection**

162 In this work, it is considered three different approaches to the problem of the decay detection in

163 mandarins, depending on the number of classes implicated and the importance of each class (Lorente et

164 al. 2011). The approach I involves the five classes described in the labelled set, all of them having equal

165 importance or weight. Therefore, the weights of all the classes were considered to be equal when

166 obtaining the global relevance.

167 It is, however, realistic to assume that the classes belonging to decaying skin should be more important

168 for decay detection. Hence, approach II gives more importance to decay classes (wPD = wPI = 15),

169 medium to the scar class ($w_{SC} = 5$) and less to sound classes ($w_{GS} = w_{OS} = 1$). Furthermore, since the

170 actual objective of a potential inspection system would be to detect decay, it is also important to study the

6

171 detection of just infected fruit, leading to a binary problem: the separation between infected or not

172 infected fruit (approach III).

173 **3.5. Methodology of comparison**

174 Two different tests were carried out in order to compare the different selection techniques with the ROC

175 feature selection method. The comparison, in both tests, is based on the performance evaluation of the

176 classifier using the different sets of features provided by the methods. The first test (test I) consists in

177 selecting an optimum number of features for each method and for each approach. Therefore, for each

178 method will be obtained a different number of features that maximises the classification. A different way

179 to make the comparison is using a fixed number of features for all methods (test II). For this test, we have

180 chosen the number of features obtained for the ROC method for each approach.

181 **4. RESULTS AND DISCUSSION**

182 The classification obtained using the ROC method is in general better than the obtained for the other

183 methods in all cases but MRMRd and MRMRq using the third approach. These results could be expected

184 since the MRMR criterion is recognised as one of the most powerful techniques for feature selection

185 (Peng et al. 2005; Ponsa and López 2007). The success of ROC approach is similar to that obtained using

186 the rest of the methods tested. The differences are not significant and therefore we can´t say that our

187 approach is better than the others in terms of decay detection accuracy. It is, however, important to

188 highlight that the best results are achieved using the ROC method for all tests and all approaches. This

189 result should to be taken into account because it is probably due to the fact that this method not only

190 evaluates the features selection but also optimises the performance of the classifier. Therefore, having

191 similar results, ROC method can achieve slightly better scores.

192 Table 1 shows the results of the classifier performance evaluation using the different sets of features

193 provided by the feature selection methods, described above, corresponding to the test I. The accuracy,

194 achieved with the ROC method, is higher than that obtained with the other methods, except for MRMR in

195 approach III. However, on one hand minimal redundancy methods try to extract the features with a high

196 degree of relevance, avoiding those features with redundant information. On the other hand, ROC is a

197 method that provides those bands that used in a classification problem get fit a classifier in much robust

198 way in terms of accuracy and significance of the model.

Table 1. Results of the classifier performance evaluation using the features selected by the different methods for each approach, but being possible a different number of features for each case (test I)

Selection method	Approach I		Approach II		Approach III	
	Success rate (%)	Selected features	Success rate (%)	Selected features	Success rate (%)	Selected features
CA	85.94	5	82.44	3	95.02	2
MI	85.53	5	84.87	4	93.08	4
FDA	86.65	5	82.21	3	95.02	2
TT	85.67	5	79.43	2	95.00	2
WL	85.96	5	82.43	3	95.03	2
BD	83.61	3	81.59	4	94.34	3
MRMRd	85.69	5	85.58	5	96.06	2
MRMRq	85.39	4	88.30	7	95.86	3
KLD	85.55	5	87.48	7	95.43	4
ROC	87.46	6	89.07	7	95.52	4

In general, the rest of the methods saturate the criterion of success with fewer bands than those selected by the ROC. This, in theory, means that to reach more approximate results than ROC, the number of bands needed by these methods should be higher. Therefore, the test II was used In order to check the performance of the ROC method using the same number of bands, being six for the first approach, seven for the second approach and four for the third one. As shown in Table 2, the ROC feature method provides higher scores than most of the feature selection methods used in this study. As it happens in test I, the only two methods surpassing the ROC are MRMRd and MRMRq for the third approach. This fact shows that, in the most pessimistic scenario for ROC method (permitting an increase of the number of features for the rest of the methods), it obtains better results than the others except in the case of MRMR methods in approach III. Even though the differences with the other methods are small since all of them are good feature selection methods, in the case of the approach II, which is probably the most realistic scenario in the real-world, the ROC method is clearly the one that obtains better accuracy.

Table 2 Results of the classifier performance evaluation using the features selected by the different methods for each approach, but always employing the same number of features for each method (test II)

Selection method	Approach I (%) (6 features)	Approach II (%) (7 features)	Approach III (%) (4 features)
CA	86.48	83.39	95.09
MI	85.88	87.50	93.08
FDA	86.78	84.12	95.10
TT	85.72	82.92	95.10
WL	86.56	83.39	95.11
BD	85.18	83.59	94.93
MRMRd	86.72	86.37	97.18
MRMRq	86.53	88.30	96.42
KLD	85.77	87.48	95.43
ROC	87.46	89.07	95.52

5. CONCLUSIONS

218 In the first test, the classification average success rate obtained using the ROC method is greater than that

219 obtained for the other methods in almost every case, except for MRMRd and MRMRq using the third

220 approach.

221 When we use the same number of features for all the methods, the ROC feature method provides

222 generally better results than most of the feature selection methods used in this comparative study, being

223 the average success rate for ROC almost always greater than that obtained for the other methods, only

224 being surpassed by the MRMR methods for the third approach.

225 Therefore, the ROC feature selection method is a suitable feature selection technique that can be applied

226 with success to multiclass classification problems with a huge amount of features such as the

227 segmentation of hyperspectral images to detect decay in citrus fruit, having at least similar results than

228 other recognized feature selection methods but with the advantage of to optimise, by its nature, the

229 performance of the classifier.

236 **REFERENCES**

237 Abe N, Kudo M, Toyama J & Shimbo M (2000) A divergence criterion for classifier independent feature
238 selection. *Lecture Notes in Computer Science. Advances in Pattern Recognition*, 1876, 668–676.

239 Blasco J, Aleixos N, Gómez J & Moltó E (2007) Citrus sorting by identification of the most common
240 defects using multispectral computer vision. *Journal of Food Engineering* 83(3), 384-393.

241 Bonnlander BV & Weigend AS (1994) Selecting input variables using mutual information and
242 nonparametric density estimation. In: *Proceedings of the 1994 International Symposium on Artificial*
243 *Neural Networks* (ISANN'94), Tainan, Taiwan, pp. 42-50.

244 Bradley AP (1997) The use of the area under the ROC curve in the evaluation of machine learning
245 algorithms, *Pattern Recognition*, 30(7), 1145–1159.

246 Choi E & Lee C (2003) Feature extraction based on the Bhattacharyya distance. *Pattern Recognition*
247 36(8), 1703 – 1709.

248 Cubero S, Aleixos N, Moltó E, Gómez-Sanchis J & Blasco J (2011) Advances in machine vision
249 applications for automatic inspection and quality evaluation of fruits and vegetables. *Food and*
250 *Bioprocess Technology*, 4(4), 487-504.

251 Duda R, Hart P & Stork D (2001) Pattern Classification. John Wiley Sons, INC, second edition.

252 Eckert J & Eaks I (1989) Postharvest disorders and diseases of citrus. *The citrus industry*, University
253 California Press, CA, USA.

254 ElMasry G, Wang N, Vigneault C, Qiao J & ElSayed A (2008) Early detection of apple bruises on
255 different background colors using hyperspectral imaging. *LWT* 41, 337–345.

256 ElMasry G, Wang N & Vigneault C (2009) Detecting chilling injury in Red Delicious apple using
257 hyperspectral imaging and neural networks. *Postharvest Biology and Technology*, 52, 1–8.

258 Fawcett T (2006) An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861-874.

259 Gómez-Sanchis J, Gómez-Chova L, Aleixos N, Camps-Valls G, Montesinos-Herrero C, Moltó E &
260 Blasco J (2008) Hyperspectral system for early detection of rottenness caused by *Penicillium digitatum* in
261 mandarins. *Journal of Food Engineering*, 89(1), 80-86.

262 Gómez-Sanchis J, Martín-Guerrero JD, Soria-Olivas E, Martínez-Sober M, Magdalena-Benedito R &
263 Blasco J (2012) Detecting rottenness caused by *Penicillium* in citrus fruits using machine learning
264 techniques. *Expert Systems with Applications*, 39(1), 780-785.

265 Huang GB, Zhu QY & Siew CK (2006) Extreme Learning Machine: Theory and applications.
266 *Neurocomputing*, 70, 489–501.

267 Kondo N, Ahmad U, Monta M & Murase H (2000) Machine vision based quality evaluation of Iyokan
268 orange fruit using neural networks. *Computers and Electronics in Agriculture*, 29, 135–147.

269 Kullback S (1987) The Kullback-Leibler distance. *The American Statistician*, 41, 340–341.

270 Kurita M, Kondo N, Shimizu H, Ling P, Falzea PD, Shiigi T, Ninomiya N, Nishizu T & Yamamoto K
271 (2009) A double image acquisition system with visible and UV LEDs for citrus fruit. *Journal of Robotics*
272 *and Mechatronics*, 21(4), 533-540.

273 Li S, Liao C & Kwok J (2006) Gene feature extraction using T-test statistics and Kernel Partial Least
274 Squares. *Lecture Notes in Computer Science. Neural Information and Processing*, 4234, 11–20.

275 Li J, Rao X & Ying Y (2011) Detection of common defects on oranges using hyperspectral reflectance
276 imaging. Computers and Electronics in Agriculture, 78(1), 38-48.

277 Liu Y, Chen YR, Wang CY, Chan DE & Kim MS (2005) Development of a simple algorithm for the
278 detection of chilling injury in cucumbers from visible/near-infrared hyperspectral imaging. *Applied*
279 *Spectroscopy* 59(1), 78-85.

280 López-García F, Andreu-García A, Blasco J, Aleixos N & Valiente JM (2010) Automatic detection of
281 skin defects in citrus fruits using a multivariate image analysis approach. *Computers and Electronics in*
282 *Agriculture*, 71, 189–197.

283 Lorente D, Aleixos N, Gómez-Sanchis J, Cubero S & Blasco J (2011) Selection of optimal wavelength
284 features for decay detection in citrus fruit using the ROC curve and neural networks. *Food and*
285 *Bioprocess Technology*, DOI: 10.1007/s11947-011-0737-x.

286 Lorente D, Aleixos N, Gómez-Sanchis J, Cubero S, García-Navarrete OL & Blasco J (2012) Recent
287 advances and applications of hyperspectral imaging for fruit and vegetable quality assessment. *Food and*
288 *Bioprocess Technology*, 5(4), 1121-1142.

289 Ouardighi A, Akadi A & Aboutajdine D (2007) Feature selection on supervised classification using Wilks
290 lambda statistic. In: *International Symposium on Computational Intelligence and Intelligent Informatics*
291 *ISCIII07*, 1, pp. 51–55.

292 Palou L, Smilanik J, Usall J & Viñas I (2001) Control postharvest blue and green molds of oranges by hot
293 water, sodium carbonate, and sodium bicarbonate. *Plant Disease*, 85, 371-376.

294 Peng H, Long F & Ding C (2005) Feature selection based on mutual information: criteria of max-
295 dependency, max-relevance, and min-redundancy. *IEEE Transactions on Pattern Analysis and Machine*
296 *Intelligence*, 27(8), 1226–1238.

297 Plaza A, Benediktsson JA, Boardman JW, Brazile J, Bruzzone L, Camps-Valls G, Chanussot J, Fauvel M,
298 Gamba P, Gualtieri A, Marconcini M, Tilton JC & Trianni G (2009) Recent advances in techniques for
299 hyperspectral image processing. *Remote Sensing of Environment*, 113 (1), S110-S122.

300 Ponsa D & López A (2007) Feature selection based on a new formulation of the minimal-redundancy-
301 maximal-relevance criterion. *Lecture Notes in Computer Science. Pattern Recognition and Image*
302 *Analysis*, 4477, 47–54.

303 Qin J, Burks TF, Ritenour MA & Bonn WG (2009) Detection of citrus canker using hyperspectral
304 reflectance imaging with spectral information divergence. *Journal of Food Engineering*, 93, 183–191.

305 Qin J, Burks TF, Zhao X, Niphadkar N & Ritenour MA (2012) Development of a two-band spectral
306 imaging system for real-time citrus canker detection. *Journal of Food Engineering*, 108(1), 87–93.

307 Rifkin R & Klautau A (2004) In defense of one-vs-all classification. *Journal of Machine Learning*
308 *Research*, 5, 101–141.

309 Rodgers JL & Nicewander AW (1988) Thirteen Ways to Look at the Correlation Coefficient. *The*
310 *American Statistician*, 42(1), 59-66.

311 Serrano AJ, Soria E, Martín JD, Magdalena R & Gómez J (2010) Feature selection using ROC curves on
312 classification problems. In: *International Joint Conference on Neural Networks, IJCNN 2010*. 28th-30th
313 July 2010. Barcelona, Spain. Proceedings, pp. 1980-1985

314 Shih FY (2010) Image processing and pattern recognition: fundamentals and techniques. Wiley-IEEE
315 Press, New York, EE.UU.

316 Slaughter DC, Obenland DM, Thompson JF, Arpaia ML & Margosan DA (2008) Non-destructive freeze
317 damage detection in oranges using machine vision and ultraviolet fluorescence. *Postharvest Biology and*
318 *Technology* 48, 341–346.

319 Venables WN & Ripley BD (2002) Modern Applied Statistics with S (4th ed.). Springer Verlag.

320 Xing J, Bravo C, Jancsók PT, Ramon H & De Baerdemaeker J (2005) Detecting bruises on 'golden
321 delicious' apples using hyperspectral imaging with multiple wavebands. *Biosystems Engineering*, 90(1),
322 27-36.

323 Zude M (ed) (2008) Optical monitoring of fresh and processed agricultural crops. CRC Press, Boca
324 Raton, USA.