

This is the peer reviewed version of the following article:

Development of a flexible Computer Vision System for marbling classification / Barbon, Ana Paula Ayub da Costa; Barbon, Sylvio; Campos, Gabriel Fillipe Centini; Seixas, José Luis; Peres, Louise Manha; Mastelini, Saulo Martielo; Andreo, Nayara; Ulrici, Alessandro; Bridi, Ana Maria. - In: COMPUTERS AND ELECTRONICS IN AGRICULTURE. - ISSN 0168-1699. - 142:(2017), pp. 536-544. [10.1016/j.compag.2017.11.017]

Terms of use:

The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

04/03/2025 09:39

(Article begins on next page)

Development of a flexible Computer Vision System for marbling classification

Ana Paula A. C. Barbon^{a,*}, Sylvio Barbon Jr.^b, Gabriel Fillipe Centini Campos^b, José Luis Seixas Jr.^b, Louise Manha Peres^a, Saulo Martielo Mastelini^b, Nayara Andreo^a, Alessandro Ulrici^c, Ana Maria Bridi^a

^a*Department of Zootechnology, Londrina State University (UEL), Londrina 86057-970, Brazil*

^b*Department of Computer Science, Londrina State University (UEL), Londrina 86057-970, Brazil*

^c*Department of Life Sciences, University of Modena and Reggio Emilia (UNIMORE), Reggio Emilia 42122, Italy*

Abstract

Traditional marbling meat evaluation is a tedious, repetitive, costly and time-consuming task performed by panellists. Alternatively, we have Computer Vision Systems (CVS) to mitigate these problems. However, most of CVS are restricted to specific environments, configurations or muscle types, and marbling scores are settled for a particular marbling meat standard. In this context, we developed a CVS for meat marbling grading, which is flexible to different muscle colour contrasts and grading standards. Essentially, the proposed method segments an image pre-processed by illumination normalisation and contrast enhancement, analyses visible intramuscular fat pixels and attributes a score based on a desired meat standard defined in the learning step. Learning approach is an instance-based system making use of k -Nearest Neighbours algorithm (k -NN) to attribute a score from segmentation results. The algorithm classifies the new samples based on scores assigned by panellists. We investigated the optimal number of samples for modelling, focusing on the smallest number leading to acceptable accuracy, and considering two different animal species: bovine and

24 swine. The CVS led to accuracy values equal to 81.59% (bovine) and to 76.14% (swine),
25 using only three samples for each marbling score.

26 *Keywords:* Beef, Image analysis, *k*-Nearest Neighbours, Machine learning, Pork

27 1. Introduction

28 Traditional evaluation process of meat quality is tedious, laborious, highly repetitive,
29 costly, time-consuming and requires trained specialists (Sun, 2011, 2012; Qiao et al., 2007;
30 Chen and Qin, 2008; Jackman et al., 2009; Liu et al., 2012; Huang et al., 2013). Several
31 studies have highlighted marbling as an important meat quality parameter; however, the
32 traditional evaluation approaches can be influenced by the subjective visual and sensory
33 criteria adopted by the involved specialists (Xiong et al., 2014).

34 Marbling consists in visible portions of intramuscular fat and it influences other meat
35 attributes such as tenderness, flavor and texture. Furthermore, marbling level influences
36 consumers choice, since a high marbling degree indicates a superior meat quality (Faucitano
37 et al., 2005; Killinger et al., 2004).

38 In general, specialists determine marbling scores based on a visual assessment supported
39 by standard meat images. Meat standards are labelled according to numerical scales re-
40 lated to the visible amount of intramuscular fat. Several standards have been defined for
41 marbling classification according to country, meat type and animal species, such as the

*Corresponding author

Email addresses: apbarbon@gmail.com (Ana Paula A. C. Barbon), barbon@uel.br (Sylvio Barbon Jr.), camposg@uel.br (Gabriel Fillipe Centini Campos), jlseixasjr@gmail.com (José Luis Seixas Jr.), louise_mp@zootecnista.com.br (Louise Manha Peres), mastelini@uel.br (Saulo Martielo Mastelini), nayarandreo@hotmail.com (Nayara Andreo), alessandro.ulrici@unimore.it (Alessandro Ulrici), ambridi@uel.br (Ana Maria Bridi)

Preprint submitted to Computers and Electronics in Agriculture

November 3, 2017

42 Japanese standard, the Australian standard, the Canadian standard and the USDA stan-
43 dard. Therefore, a generalised approach capable of handling various types of meat and
44 different standard scales could constitute a valuable help to facilitate meat marbling assess-
45 ment (Cheng et al., 2015).

46 Liu et al. (2012) described several research works focused on objective marbling assess-
47 ment in specific species, mainly dealing with colour contrast differences. Several Computer
48 Vision Systems (CVS) were proposed, that are however designed for specific marbling stan-
49 dards and animal species. This implies that various parameters and thresholds need to
50 be tuned depending on the specific problem at hand, i.e., based on the considered marbling
51 standard and on the particular animal species that is evaluated.

52 CVS has been widely used in food industry for food quality evaluation and control
53 (Jackman et al., 2012). Marbling assessment can be performed by a CVS by means of a
54 digital camera, which is inexpensive and widely available. However, a general approach that
55 can lead to good results independently of muscle colour, contrast, standard or species is still
56 a challenge. This challenge can be tackled using a CVS approach combined with machine
57 learning algorithms. In (Qiao et al., 2007; Jackman et al., 2009; Huang et al., 2013), CVS
58 has been used for marbling assessment, leading to satisfactory results. However, these works
59 report expensive solutions based on quite controlled environments, costly equipments and
60 parametrised algorithms for image processing.

61 In Jackman et al. (2009) a marbling segmentation algorithm has been proposed. Ac-
62 tually, in this paper the Authors did not calculate a marbling score after the segmen-
63 tation phase. However, they suggested the use of artificial intelligence based processes

64 that could learn from the panellists assessments, in order to gain more advanced levels
65 of adaptability. Furthermore, in this paper as well as in other research works dealing with
66 similar issues (Chen and Qin, 2008; Peña et al., 2013), the image acquisition step requires
67 to consider a controlled environment, often using specific camera models and configurations
68 (exposure compensation, aperture, lens and ISO). These issues cause difficulties in CVS
69 reproduction and industrial application.

70 Some CVS need to deal with nonlinearities between the image features and the marbling
71 score of interest, making use of sophisticated modelling techniques from artificial intelligence.
72 Furthermore, specific parametrisation and thresholds could lead to scarcely reproducible so-
73 lutions. Thus, in order to implement a robust CVS able to cope with more complex scenarios,
74 it is recommended to apply machine learning algorithms. Machine Learning (ML) is an ef-
75 fective tool for exploratory data analysis and is widely employed for various applications,
76 including Computer Vision. (Ropodi et al., 2016).

77 The application of ML algorithms for food evaluation has been widely investigated (Du
78 and Sun, 2006; Balasubramanian et al., 2009; Chen et al., 2010; Valous et al., 2010; Wang
79 et al., 2012; Liu et al., 2013; Papadopoulou et al., 2013; Prevolnik et al., 2014; Muñoz
80 et al., 2015), demonstrating that ML can be applied to uncover non-trivial relationships by
81 automatically learning from a set of training data, thus producing knowledge which in turn
82 can be used to interpret new data.

83 The choice of the most proper machine learning algorithm is related to its properties
84 and to the set of assumptions used by the learner to estimate the output for those ex-
85 amples that have not been considered in the training phase (which is known as induc-

86 tive bias); these aspects are mainly related to data representation and local-versus-global
87 learning (García et al., 2008). In particular, in the present work we aimed at considering
88 the smallest possible number of instances enabling to predict classes (marbling score val-
89 ues) with acceptable accuracy. For this reason, k -Nearest Neighbour (k -NN) classifier was
90 considered, since it is a simple supervised learning scheme which classifies unknown instances
91 by finding the closest previously observed instances (Brighton and Mellish, 2002). Learners
92 which apply this classification method are named Instance-Based Learners.

93 O’Farrell et al. (2005) compared k -NN usage to ANN (Artificial Neural Networks), more
94 precisely to a MLP (Multi-layer Perceptron), in order to verify whether a simple classifica-
95 tion technique like k -NN could fit for quality control in food industry. The Authors, citing
96 also several research works on food matrices, concluded that k -NN may be entirely satisfac-
97 tory and is computationally very simple. In Barbon et al. (2016), the performance of k -NN
98 to predict pork storage time was compared to seven other algorithms (Random Forest, MLP,
99 Support Vector Machine, J48 and Naïve Bayes, and two different Fuzzy methods), leading to
100 the second best accuracy values.

101 In this context, this paper contributes to the current research in the field by presenting
102 a method to perform marbling grading based on image analysis, designed in a way to be
103 able to handle different muscles of various animal species, and to be adaptable to diverse
104 marbling standards. In particular, our CVS is based on dynamic thresholding, illumina-
105 tion normalisation, adaptive contrast enhancement and instance-based decision for marbling
106 grading. The performance of the proposed method was evaluated considering meat samples
107 from two different animal species (beef and pork), each one with its own marbling standard.

108 **2. Materials and Methods**

109 The overall proposed method is exhibited in Figure 1, which shows the main stages
 110 numbered as 1, 2 and 3. Stage 1 refers to the establishment of desired meat standard and
 111 exemplification of each level by tagging some image examples. Details of how we conduct
 112 this step and data sets used in experiments are available in Section 2.1. The results of this
 113 stage are applied to instance-based modelling and automatic grading of the new samples.
 114 Stage 2 is marbling segmentation kernel, performed by applying a series of image processing
 115 steps, which are described in Section 2.2. Finally, Stage 3 (Section 2.3) is focused on the
 116 instance-based marbling score by k -NN, regarding advantages of the selected algorithm, how
 117 it can be applied and evaluation criteria.

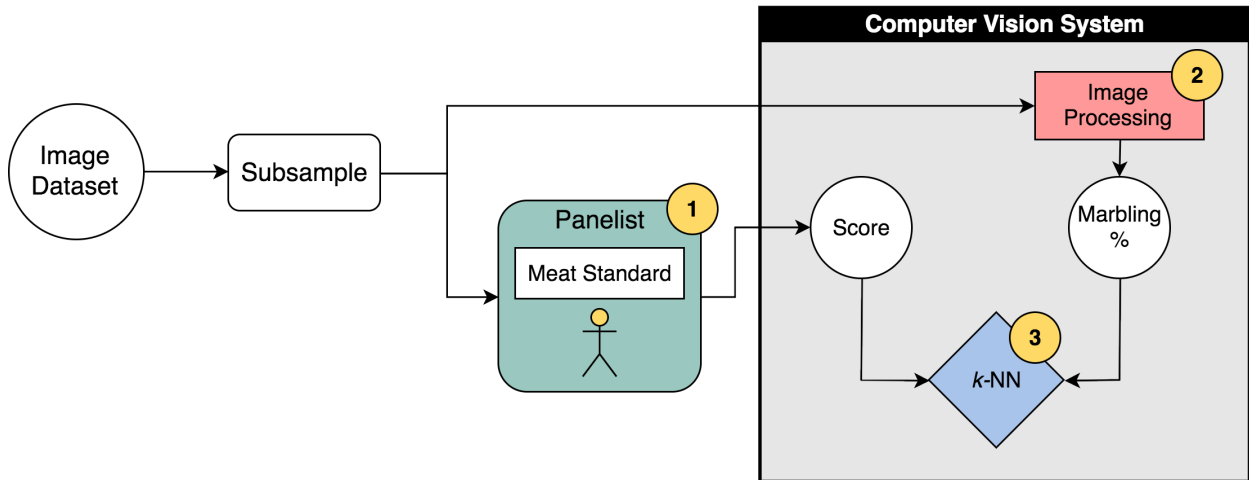


Figure 1: Proposed method and main stages: Panelist tasks (1), Image Processing (2) and k -NN (3)

118 *2.1. Samples and Panelist Analysis*

119 A requirement of instance-based learning is the availability of labelled instances to per-
 120 form supervised learning. In other words, some samples must be tagged with appropriate

121 marbling score to build a relation between marbling score and image properties. A panellist
122 performs this task through a conventional approach, which is tedious and time consuming.
123 For this reason, we proposed the usage of few samples from each grade to reduce the number
124 of samples required for the labelling process. Furthermore, our approach was designed to
125 carry out this stage only once per each standard. In particular, two different muscle foods
126 were considered, each one labelled by the relevant standard scale. Images of pork and beef
127 samples were acquired at 24 hours *post mortem* and were used to construct the k -NN model
128 and for panellist task.

129 Image sampling was performed at the Food Analysis Laboratory (LANA), State Univer-
130 sity of Londrina. The image acquisition setup was placed in an uncontrolled environment,
131 which was illuminated by ambient daylight and cool white fluorescent artificial lighting.

132 Three hundred thirty-five (335) pork samples and forty-five (45) beef samples were
133 used, both from *longissimus thoracis* muscle removed between penultimate and last ribs
134 of the left half carcass. Beef samples came from *Nelore* breed animals, fed on pasture
135 and slaughtered at a federally inspected abattoir. Pork samples came from commercial ge-
136 netics provided by a local company, and were transported under refrigeration to LANA
137 immediately after slaughtering.

138 Pork and beef samples images were acquired using a digital single-lens reflex camera,
139 model Nikon SLR D7000 (Nikon Co. Ltd., Japan), equipped with a 16.2 megapixels image
140 sensor and with a high-quality lens, which was optimally engineered to gather more light.
141 The digital camera was configured with automatic settings. A tripod supported the device
142 at 37cm above samples, which were placed on a blue paper sheet used as image background.

143 After acquisition and according to Figure 1, pork images were analysed subjectively by
144 experts using traditional marbling methodology based on NPPC photographic standard.
145 A marbling score was assigned to each image, ranging from 1 (devoid) to 10 (abundant)
146 (National Pork Board - NPB, 2015).

147 Similarly, all beef images were analysed subjectively by experts following the same method-
148 ology used for pork images evaluation, but based on USDA photographic standard. This
149 methodology consists in a subjective analysis based on beef marbling intensity, leading to
150 score values defined according to the following scale: 1 = devoid, 2 = practically devoid, 3
151 = traces, 4 = slight, 5 = small, 6 = modest, 7 = moderate, 8 = slightly abundant and 9 =
152 moderately abundant (Tan, 2004).

153 Panellists were trained using digital images, not fresh samples. We consider that assess-
154 ment based on digital images did not compromise accuracy, since this task was performed
155 as in Tan (2004) and possible distortions or divergences between real and image-based eval-
156 uation were avoided by standard based calibration.

157 *2.2. Marbling Segmentation*

158 All the image processing steps followed to implement marbling segmentation are shown
159 in Figure 2.

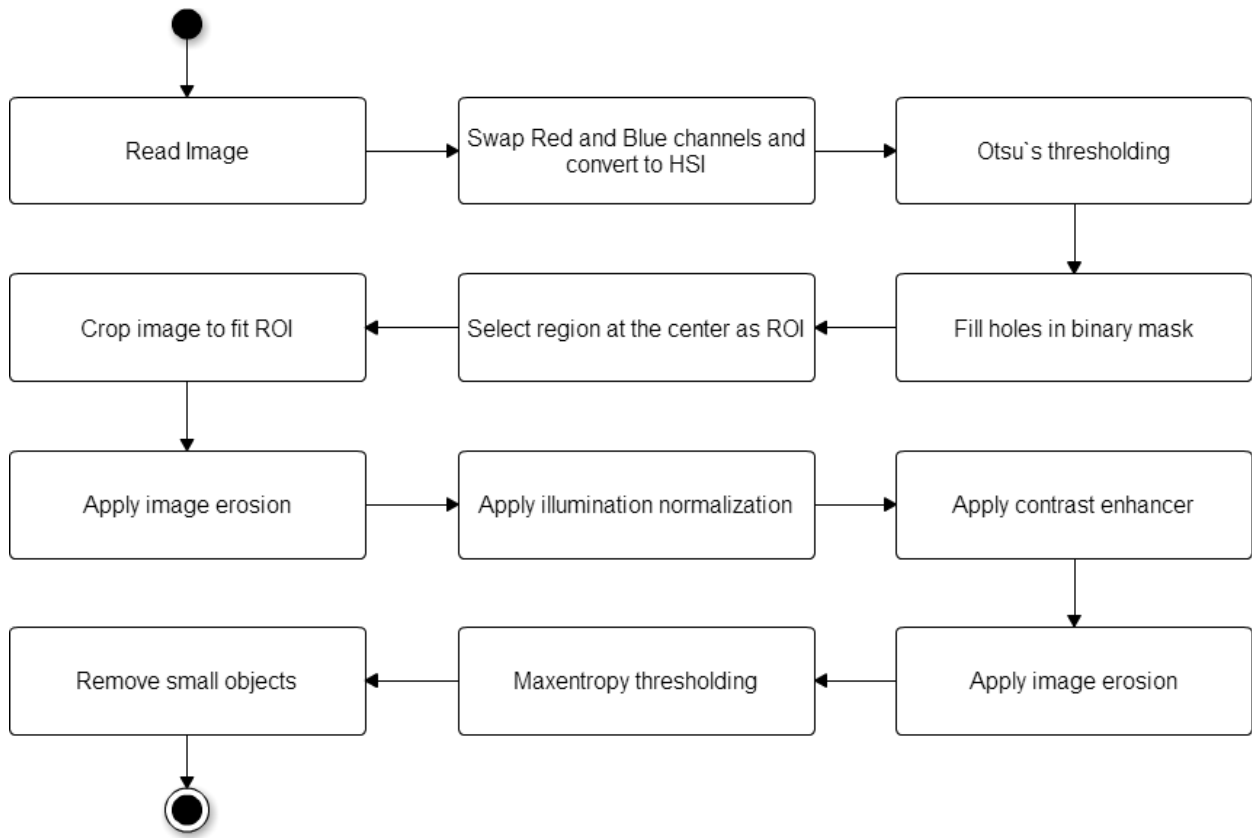


Figure 2: Proposed approach for marbling segmentation.

160 The first goal of this marbling segmentation method is background removal, keeping the
 161 Region of Interest (ROI) only. To achieve this, red and blue channels (from RGB colour
 162 space) of the original image were swapped. According to Jackman et al. (2009), this helps to
 163 remove blue backgrounds using image thresholding in Hue channel of HSI (Hue, Saturation
 164 and Intensity) colour space. This threshold value was selected using Otsu's method (Otsu,
 165 1979) since it is one of the most accurate and widely used methods for image segmentation
 166 (Sahoo et al., 1988). Since this image thresholding step may erroneously lead to the removal
 167 of some pixels of the ROI, all the holes in the image were filled using a connectivity approach.

168 At this point, the obtained image mask is similar to the one reported in Figure 3b,

169 where the blue background region has been removed, but some non-interesting regions are
170 still present. Since the ROIs of our samples were always in the image centre, it was possible
171 to easily remove these non-interesting regions by selecting the central region with a region
172 growing algorithm, leading to an image mask like the one reported in Figure 3c.

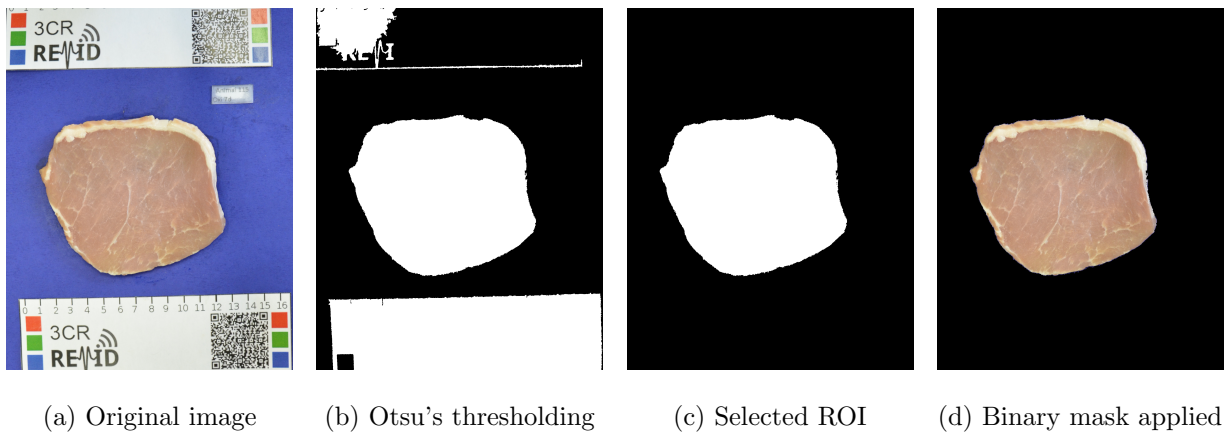


Figure 3: Background removal, keeping the Region of Interest (ROI) only.

173 Once the image ROI was defined, the original image was cropped to fit the ROI. Then,
174 an erosion filter with a disk size equal to 6% of the image dimension was applied to remove
175 the possible presence of fat in the sample border, as it frequently happens both in pork and
176 in beef.

177 Furthermore, often the imaged samples have dark or light spots, due to sample prepara-
178 tion issues, as it can be seen in Figure 4a. These spots can compromise contrast enhancement
179 methods and also hinder to find a proper threshold value for marbling segmentation. To
180 solve this problem, we applied an illumination normalisation method described in Barbin
181 et al. (2016), which is exemplified in Figure 4. This figure shows that for pork image the
182 illumination normalisation led to a less intense image, while for the beef sample the result-

183 ing image it was possible to observe a intensity enhancement. This aspect can be better
184 appreciated by looking at the intensity (frequency histograms) reported in the top-right of
185 each sub-figure.

186 Illumination normalisation method starts with a Gaussian blur filtering over a copy of the
187 original image. This action spreads light spots increasing their radius, and creating a gradi-
188 ent of intensity starting from the spots centres. A colour compensation of the blurred image
189 is then performed, so that the spots become darker. The resulting image is then converted
190 to the HSL colour space, and the L (Lightness) channel is selected. In the L image, the inten-
191 sities of spread light spots are then reversed, so that they can be combined with the original
192 image to attenuate lighter regions. An Overlay blend operation between processed lightness
193 representation and original image is then performed to lead to an illumination normalised
194 image. The Overlay blend is given by equation (1):

$$E = \frac{I}{255} \times \left(I + \frac{2 \times M}{255} \times (255 - I) \right) \quad (1)$$

195 Where E is the resulting image , I is the original image and M is the L channel
196 of the blurred image. As a result, dark regions become darker and light regions become
197 lighter. Based on the processed lightness image, light spots are attenuated, while regions
198 with homogeneous illumination are less changed.

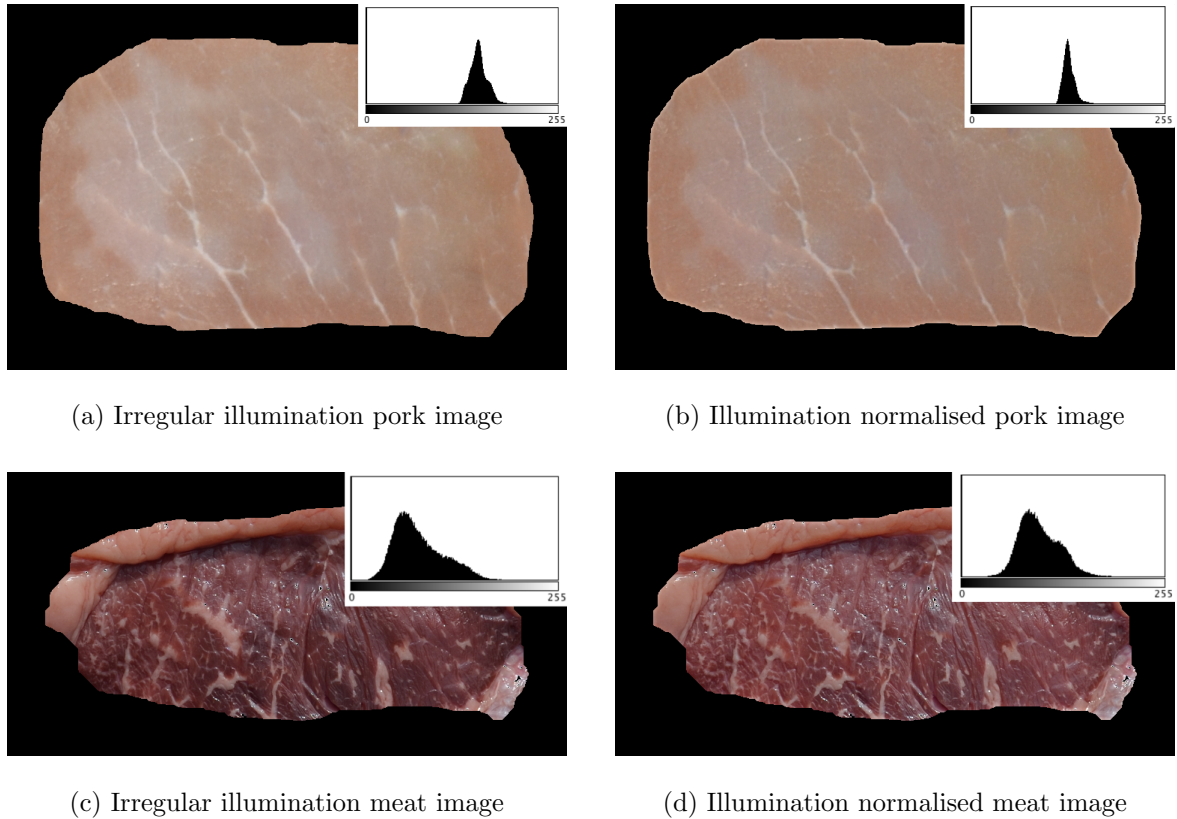


Figure 4: Example of illumination normalisation in pork sample

199 Channel Subtraction was then applied to enhance contrast. Using the HSV colour space,
 200 the contrast-enhanced image was obtained by subtracting the Saturation (S) channel from
 201 the Value (V) channel. The effect of this process can be seen in Figure 5, where figures 5a
 202 and 5e are the input images, figures 5b and 5f are the grey-scale input images (for comparison
 203 only), and figures 5c and 5g are the contrast enhanced images for pork and meat samples,
 204 respectively. The contrast difference between original and enhanced images can be observed
 205 also by comparing the frequency histograms at the top-right of figures 5b - 5c and of figures
 206 5f - 5g for pork and beef, respectively.

207 By performing illumination normalisation and contrast enhancement steps, the robust-

208 ness of our solution was increased. It made the approach less susceptible to acquisition
209 problems, like colour and light variations or camera settings.

210 Erosion method was then applied to eliminate fat coverage, by removing the border pixels
211 from the region of interest (Hansard et al. (2014)), as it can be seen in Figures 5d and 5h.

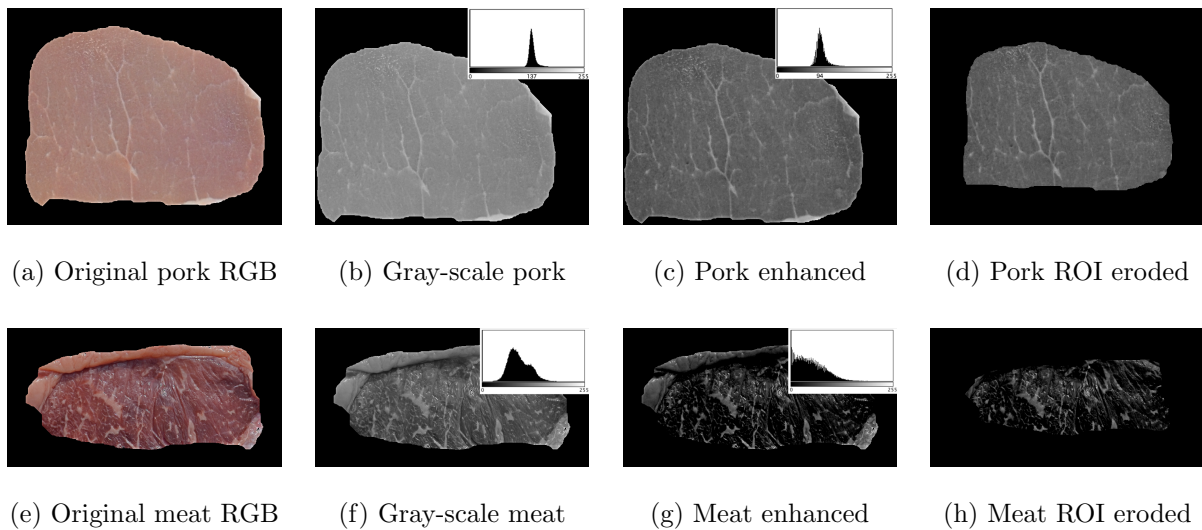


Figure 5: Contrast enhancement and ROI erosion of pork and meat samples

212 At this stage, image is ready for thresholding, which will segment marbling from muscle.
213 After the thresholding step (max-entropy), small objects (smaller than 0.01% of image's size)
214 were removed to avoid noise, due e.g. to specular reflection, as proposed by Jackman et al.
215 (2009). The effect of thresholding and noise removal on two sample images can be observed
216 in Figure 6 for pork and beef, respectively.

217 Even though these correction steps during preprocessing may slightly modify the mar-
218 bling pixels, the machine learning algorithm builds a model able to deal with the modifica-
219 tions caused in the previous stages of our Computer Vision System.

220 The final result (marbling) can be calculated by the pixel ratio number. For exam-

221 ple, in the case of the pork image reported in Figure 6, this value is calculated as the ratio
222 between the number of pixels of Figure 6c and the number of those of Figure 6a.

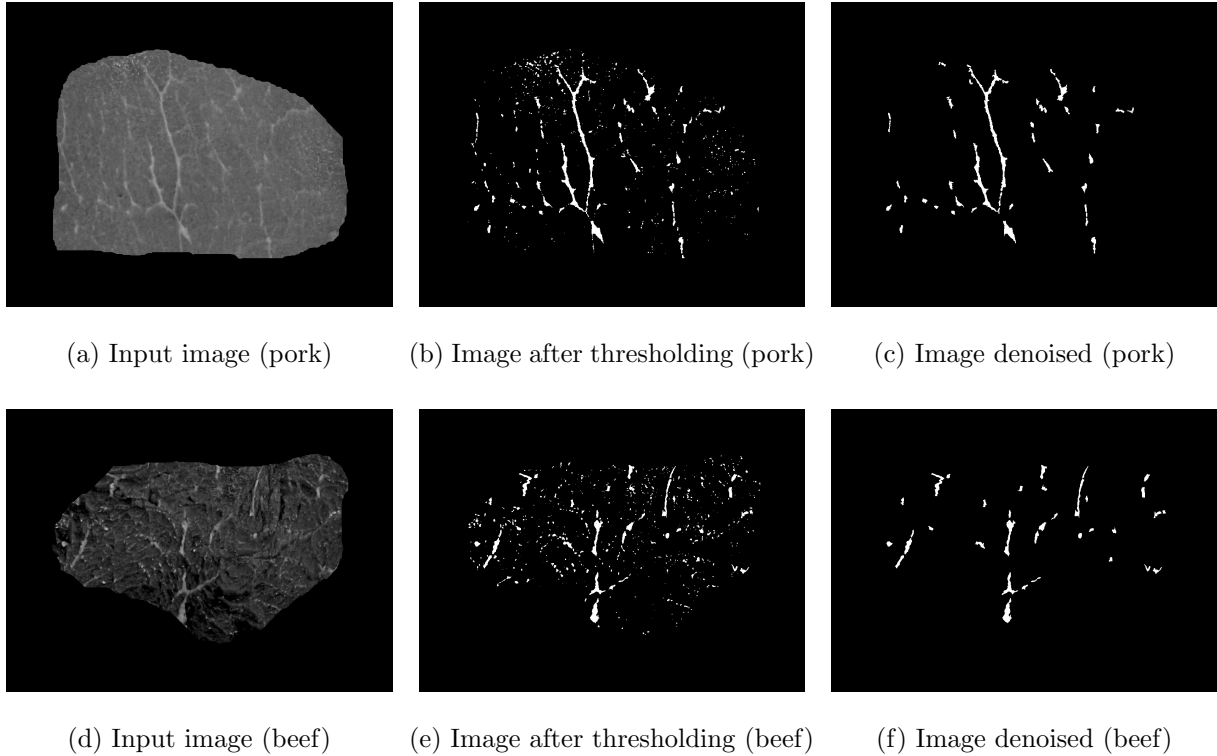


Figure 6: Thresholding and noise removal of pork and beef samples ROI

223 2.3. Instance-Based Marbling Grading

224 In this manner, it is possible to quantify for each sample the pixels percentage that rep-
225 resents sample marbling. However, this value is not related to any marbling meat standard
226 model.

227 As Aggarwal (2014) states, there is a set of algorithms that do not need a complete
228 rebuild in cases instances amount changes. Even when some instances are added to the
229 former dataset, none computational processing would be required. Aggarwal (2014) called
230 them instance-based learners.

231 Differently from common supervised learning algorithms, instance-based learners do not
232 need a training step to build a model. Instead, all computational effort is focused on clas-
233 sification step. Such characteristic is also a double edge: a) it is possible to change dataset
234 at will, however b) the classification step might be costly (Aggarwal, 2014).

235 k -NN, an instance-based learner, predicts a sample value by finding its k nearest neigh-
236 bours. Once k neighbours are found, a mean value is calculated among neighbours and
237 attributed as prediction value to an unknown instance. One advantage of using such algo-
238 rithm in our solution is that no model is rebuilt as the dataset is updated. In fact, as stated
239 before, no model is returned.

240 Also, k -NN is very simple and intuitive considering its parameters. Settings of such
241 algorithm include: number of neighbours to be found (k), metric to be considered to compare
242 neighbours (e.g., Euclidean Distance), and weighted neighbor application ¹ ².

243 In our approach, Euclidean Distance was used as metric, neighbour weighting was
244 based on $1/distance$, and both the number samples, n , and the number of neighbours,
245 k , were optimised in order to find the minimum value leading to acceptable accuracy in
246 classification. In particular, different values of the k parameter of k -NN were tested in the
247 $1 \leq k \leq (n - 1)$ range, where n is the number of samples considered as a reference for each
248 marbling score value.

249 k -NN was evaluated by holdout 70/30 stratified with 100 repetitions. Statistical evalua-
250 tion was performed to evaluate CVS performance and to compare it with human assessment.

¹<https://cran.r-project.org/web/packages/FNN/FNN.pdf>

²<http://www.mathworks.com/help/stats/classificationk-NN-class.html>

251 This evaluation has been performed separately for pork and beef. k -NN from R packages
252 was used in this work, and the results were expressed in terms of Accuracy.

253 3. Results and Discussion

254 Regardless of the analysed species, a panellist took about eleven seconds (11 s) to grade
255 a sample, while CVS can take less than one second ($< 1 s$) with no breaks. This evaluation
256 corroborate CVS as a solution to tackle a time-consuming task like this one.

257 The results are presented in the following order: the exploration of the optimal n sample
258 number considered as a reference for each marbling score is reported in subsection 3.1 for
259 pork dataset and in subsection 3.2 for beef dataset. Then, the identification of the best value
260 of the k parameter is discussed in subsection 3.3. Finally, in subsection 3.4 the advantages
261 of the proposed CVS method over other approaches dealing with similar tasks are discussed.

262 3.1. Pork

263 Results showed that in 100% of images, 335 samples, the maximum absolute difference
264 between CVS score and panellists mean score was lower than one marbling score.

265 Comparing each marbling score, level one achieved the better accuracy. Figure 7 shows
266 that, using two samples ($n = 2$) for modelling, marbling score one achieves an average of
267 90.09% with outliers presence that results in a high standard deviation (0.20). By increas-
268 ing the n , the average accuracy values of marbling score one were equal to 94.59% ($n = 3$),
269 94.32% ($n = 4$) and 93.57% ($n = 5$). Using just one sample ($n = 1$), the average accuracy value
270 of score one resulted equal to only 32.78%.

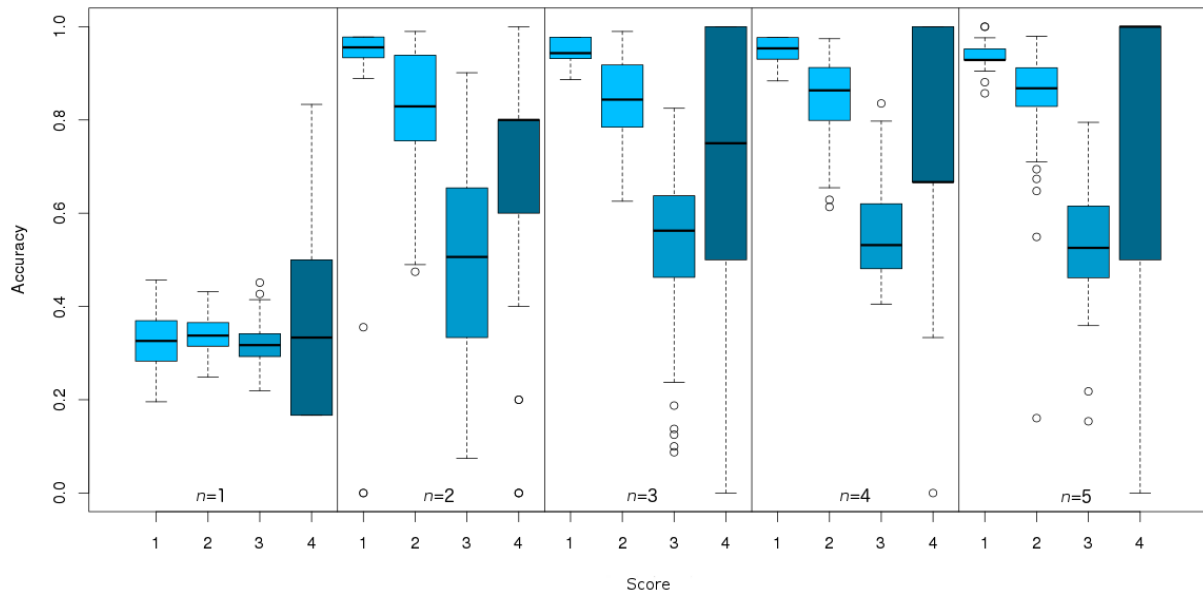


Figure 7: Accuracy of k -NN algorithm for pork prediction models built with increasing number of samples (n from 1 to 5): boxplots of the four different marbling score values.

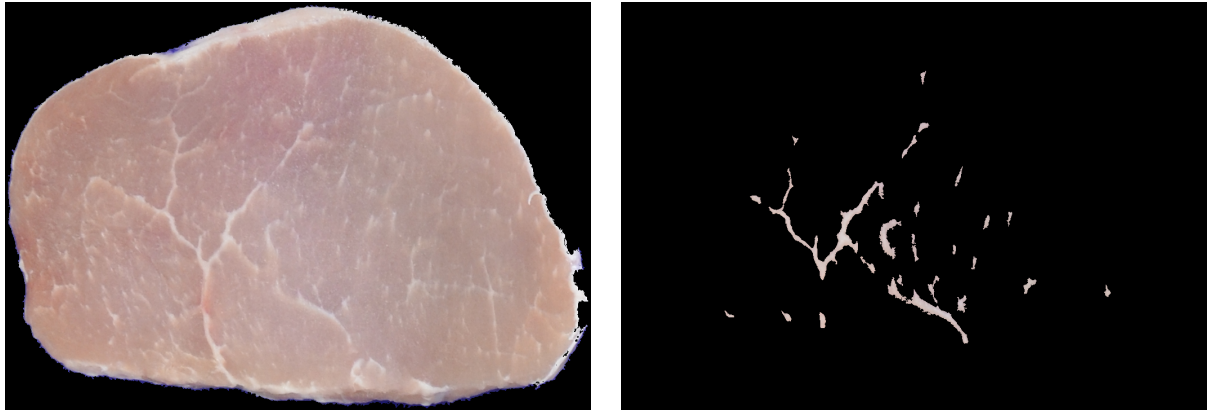
271 Concerning the accuracy in the estimate of the different marbling score values, in gen-
 272 eral the best accuracy was obtained for score one, followed by two and three. The score
 273 four presented the largest boxplots, across the whole range of samples (n). This occurs
 274 due to the fact that the number of available samples with score equal to 4 was lower than
 275 the number of samples with the other score values.

Score	$n=1$		$n=2$		$n=3$		$n=4$		$n=5$	
	ACC	STD	ACC	STD	ACC	STD	ACC	STD	ACC	STD
1	32.78	0.06	90.08	0.20	94.59	0.02	94.32	0.02	93.57	0.06
2	33.71	0.03	82.51	0.12	85.02	0.08	84.86	0.08	84.24	0.13
3	32.07	0.04	48.24	0.20	52.97	0.18	55.84	0.09	53.53	0.12
4	35.00	0.16	66.80	0.26	72.00	0.24	70.66	0.23	73.00	0.38
Average	33.39	0.07	71.90	0.19	76.14	0.13	76.42	0.10	76.08	0.17

Table 1: Average accuracy values (ACC) and standard deviation values (STD) for different numbers of samples ($1 \geq n \geq 5$) by different marbling scores (1, 2, 3 and 4) for the pork dataset.

276 Table 1 reports the average accuracy values of the data shown in Figure 7, together with
277 the relevant standard deviations. In general, the smallest accuracy values were always
278 obtained for score three, independent of the number n of samples. Since the accuracy values
279 were determined by comparison with the corresponding assessments made by panellists, this
280 result is not surprising. In fact, in the traditional approaches used for marbling assessment,
281 intermediate scores are those most susceptible to divergence among different assessors, due to
282 subjectivity. Figure 8 is an example of panellists subjectivity. Figure 8a shows a sample
283 ROI which was graded with score 5 by panellist 1 (P1), score 3 by panellist 2 (P2) and score
284 4 by panellist 3 (P3). After marbling segmentation (Figure 8b), CVS found 2.99% of visible
285 image marbling fat, which corresponds to score 3 according to our K -NN model.

286 According to Faucitano et al. (2004), in many cases during the attribution of the mar-



(a) ROI

(b) Marbling segmented = 2.99%

Figure 8: Panelists variation and CVS inside variation range.

287 bling score to a given sample, the panellists could face with heterogeneous distribution of
 288 intramuscular fat. In other words, the fat concentration is present in a certain region and is
 289 not distributed throughout the sample, leading to different scores among panellists. How-
 290 ever, this problem is mitigated with the use of CVS, since it considers the total muscle area
 291 independent of the way intramuscular fat is distributed.

292 3.2. Beef

293 Similar to pork dataset, the analysis of beef dataset began by searching for the the small-
 294 est number of n to be considered in the modelling step in order to obtain an adequate accu-
 295 racy. Due to the lower number of available samples in the beef dataset with respect to the
 296 pork dataset, in this case the maximum value of n was set equal to three.

297 Regarding each marbling score, Figure 9 shows that, by using only one sample ($n = 1$)
 298 in the modelling step, the median accuracy value was always lower than 50%, with outliers
 299 presence in all the scores. Using two samples ($n = 2$), only marbling score two presents

300 outliers. However, using three samples ($n = 3$), the accuracy values for score four show a
301 significant increase in terms both of the median and of the average value, as reported in
302 Table 2.

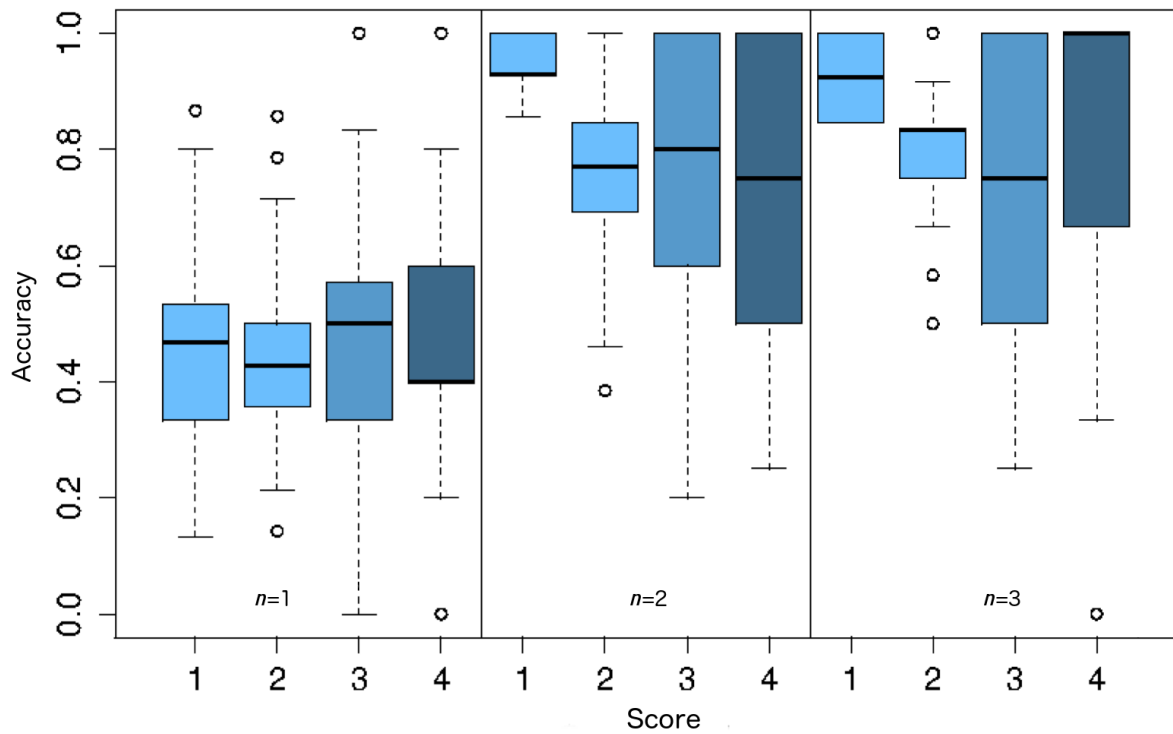


Figure 9: Accuracy of k -NN algorithm for beef prediction models built with increasing number of samples (n from 1 to 3): boxplots of the four different score values.

Score	$n=1$		$n=2$		$n=3$	
	ACC	STD	ACC	STD	ACC	STD
1	46.83	0.15	94.37	0.05	92.73	0.06
2	45.23	0.13	76.34	0.11	79.78	0.11
3	45.88	0.19	74.25	0.24	73.61	0.20
4	47.06	0.22	68.43	0.25	80.24	0.24
Average	46.25	0.17	78.34	0.16	81.59	0.15

Table 2: Average accuracy values (ACC) and standard deviation values (STD) for different numbers of samples ($1 \geq n \geq 3$) by different marbling scores (1, 2, 3 and 4) for the beef dataset.

3.3. k -NN parameter

The modelling step was performed by varying k to discover the best k -NN parameter value to build a good prediction model. Thus, this step started from $k = 1$ and increased until reaching a stable accuracy within the limit of available samples. For pork, satisfactory accuracy values were obtained starting from $k = 2$ and were almost stable from $k = 3$ to $k = 5$, as shown in Figure 10: the best performance was obtained from three to five neighbours ($3 \geq k \geq 5$), as it is also shown in Figure 12, where the average accuracy values are reported.

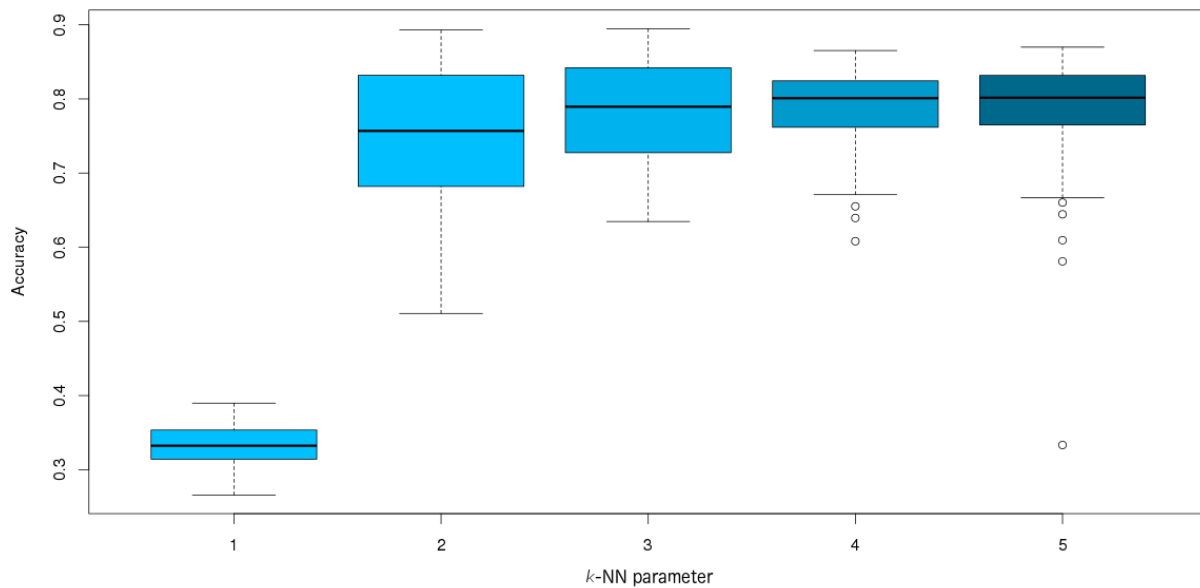


Figure 10: Boxplot of pork model accuracy obtained for different k values

310 Figure 11 shows the boxplot of the accuracy values obtained in the modelling step con-
 311 sidering one, two and three neighbours ($1 \leq k \leq 3$) for the beef dataset. The average
 312 accuracy values were equal to 46.25%, 82.18% and 81.59%, and the corresponding standard
 313 deviation values were equal to 0.17, 0.16 and 0.15, respectively.

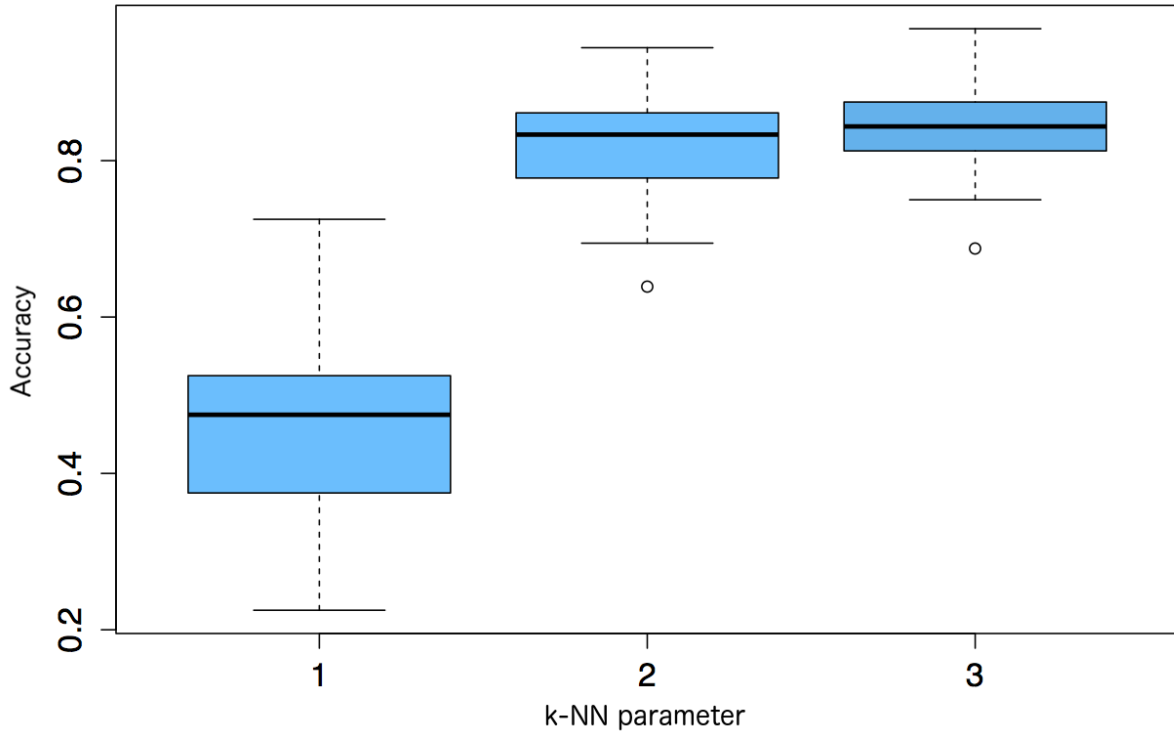


Figure 11: Boxplot of beef model accuracy obtained for different k values

314 A final consideration can be made about the optimal (k) value defined for the two con-
 315 sidered muscle foods. Our experiments showed that the best k value resulted equal to 3 for
 316 both pork and beef datasets. This is highlighted by the vertical line in Figure 12, that shows
 317 the average accuracy calculated over 20 different k values using two samples ($n=2$).

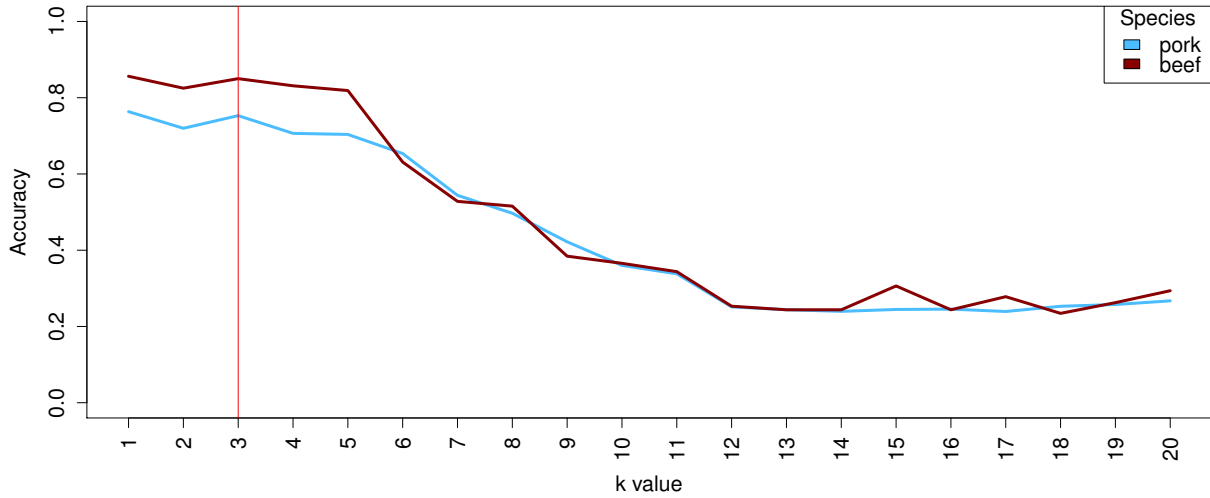


Figure 12: Comparison of near neighbours (k) evaluated in experiments for pork and beef.

318 3.4. Other issues

319 An advantage of the proposed method lies in its ability to efficiently deal with muscles
 320 with different aspect in terms of colour and contrast. For example, colour variations among
 321 different meat qualities as PSE (Pale, Soft, and Exudative) and DFD (Dark, Firm, and
 322 Dry) is automatically normalised before performing marbling evaluation. In Pang et al.
 323 (2014) it was necessary to apply a method based on homomorphic filtering to reduce uneven
 324 illumination influence and light reflection for beef accurate segmentation.

325 Other CVSs require to specify many values to properly configure the imaging system, fo-
 326 cusing on a single problem scenario and sample-based features to detect marbling. For exam-
 327 ple, Liu et al. (2012) and Huang et al. (2013) proposed tools for automatic pork marbling de-
 328 tection, while Jackman et al. (2009) and Chen and Qin (2008) proposed a specific algorithm
 329 for beef segmentation. Conversely, the proposed approach mitigates the effects of different

330 environmental setups for image acquisition and minimises the number of parameters to be
331 set.

332 4. Conclusion

333 The proposed CVS showed to be a viable alternative compared to traditional assessment
334 of meat marbling, since it is capable to reduce the dependence on human experts and
335 mitigates problems of panellists evaluation by few labelled samples.

336 Our CVS obtains marbling meat score by an objective and fast assessment, since ma-
337 chines can evaluate multiple images with no pause. This implies also lower costs in compari-
338 son to panellists, who need training and require much longer times to perform the same task.
339 This alternative is suitable to production lines in slaughterhouses, and does not require
340 that the images are acquired within a controlled environment.

341 Panellists are more susceptible to misclassification due to low marbling levels or variability
342 of fat distribution. The proposed approach performs marbling identification and score pre-
343 diction in different scenarios (low or high marbling level; dark or pale muscles) based on a
344 ML algorithm.

345 A variety of research works dealing with similar tasks applied the SVM or the ANN
346 algorithms, but for these algorithms the proper selection of the model parameters is not a
347 trivial task, and commonly is strictly related to the specific problem at hand. Alternatively,
348 looking for a simpler solution, we investigated the use of k-NN and achieved good results for
349 two different muscle foods (pork and beef), also using a limited number of samples during
350 the modelling step with respect to similar approaches already reported in the literature.

351 In fact, the results reported in the present work demonstrated that the k -NN approach can
352 correctly identify marbling score using few samples of each grade.

353 Further research work is currently aimed at verifying the device independence of the pro-
354 posed approach, by using different digital cameras and smartphones in the image acquisition
355 step .

356 5. Acknowledgments

357 The authors would like to thank CAPES (Brazilian Agency) for their financial support.

358 References

- 359 Aggarwal, C. C., 2014. Data classification: algorithms and applications. CRC Press.
- 360 Balasubramanian, S., Panigrahi, S., Logue, C., Gu, H., Marchello, M., 2009. Neural networks-integrated
361 metal oxide-based artificial olfactory system for meat spoilage identification. Journal of Food Engineering
362 91 (1), 91–98.
- 363 Barbin, D. F., Mastelini, S. M., Barbon, S., Campos, G. F., Barbon, A. P. A., Shimokomaki, M., 2016.
364 Digital image analyses as an alternative tool for chicken quality assessment. Biosystems Engineering 144,
365 85–93.
- 366 Barbon, A. P. A., Barbon, S., Mantovani, R. G., Fuzyi, E. M., Peres, L. M., Bridi, A. M., 2016. Storage
367 time prediction of pork by Computational Intelligence. Computers and Electronics in Agriculture 127,
368 368–375.
- 369 Brighton, H., Mellish, C., 2002. Advances in Instance Selection for Instance-Based Learning Algorithms.
370 Data Mining and Knowledge Discovery 6 (2), 153–172.
371 URL <http://dx.doi.org/10.1023/A:1014043630878>
- 372 Chen, K., Qin, C., 2008. Segmentation of beef marbling based on vision threshold. computers and electronics
373 in agriculture 62 (2), 223–230.

374 Chen, K., Sun, X., Qin, C., Tang, X., 2010. Color grading of beef fat by using computer vision and support
375 vector machine. *Computers and Electronics in Agriculture* 70 (1), 27–32.

376 Cheng, W., Cheng, J.-H., Sun, D.-W., Pu, H., 2015. Marbling analysis for evaluating meat quality: Methods
377 and techniques. *Comprehensive Reviews in Food Science and Food Safety* 14 (5), 523–535.

378 Du, C.-J., Sun, D.-W., 2006. Learning techniques used in computer vision for food quality evaluation: a
379 review. *Journal of food engineering* 72 (1), 39–55.

380 Faucitano, L., Huff, P., Teuscher, F., Gariépy, C., Wegner, J., 2005. Application of computer image analysis
381 to measure pork marbling characteristics. *Meat science* 69 (3), 537–543.

382 Faucitano, L., Rivest, J., Daigle, J., Lévesque, J., Gariépy, C., 2004. Distribution of intramuscular fat content
383 and marbling within the longissimus muscle of pigs. *Canadian journal of animal science* 84 (1), 57–61.

384 García, V., Mollineda, R. A., Sánchez, J. S., 2008. On the k-nn performance in a challenging scenario of
385 imbalance and overlapping. *Pattern Analysis and Applications* 11 (3-4), 269–280.

386 Hansard, M., Horaud, R., Amat, M., Evangelidis, G., 2014. Automatic detection of calibration grids in
387 time-of-flight images. *Computer Vision and Image Understanding* 121 (0), 108 – 118.

388 URL <http://www.sciencedirect.com/science/article/pii/S1077314214000149>

389 Huang, H., Liu, L., Ngadi, M., Gariépy, C., 2013. Prediction of pork marbling scores using pattern analysis
390 techniques. *Food Control* 31 (1), 224–229.

391 Jackman, P., Sun, D., Allen, P., 2009. Automatic segmentation of beef longissimus dorsi muscle and marbling
392 by an adaptable algorithm. *Meat Science* 83 (2), 187 – 194.

393 Jackman, P., Sun, D.-W., ElMasry, G., 2012. Robust colour calibration of an imaging system using a colour
394 space transform and advanced regression modelling. *Meat science* 91 (4), 402–407.

395 Killinger, K. M., Calkins, C. R., Umberger, W. J., Feuz, D. M., Eskridge, K. M., 2004. Consumer sensory
396 acceptance and value for beef steaks of similar tenderness, but differing in marbling level. *Journal of*
397 *animal science* 82 (11), 3294–3301.

398 Liu, L., Ngadi, M., Prasher, S., Gariépy, C., 2012. Objective determination of pork marbling scores using
399 the wide line detector. *Journal of Food Engineering* 110 (3), 497–504.

400 Liu, M., Wang, M., Wang, J., Li, D., 2013. Comparison of random forest, support vector machine and back
401 propagation neural network for electronic tongue data classification: Application to the recognition of
402 orange beverage and chinese vinegar. *Sensors and Actuators B: Chemical* 177, 970–980.

403 Muñoz, I., Rubio-Celorio, M., Garcia-Gil, N., Guàrdia, M. D., Fulladosa, E., 2015. Computer image analysis
404 as a tool for classifying marbling: A case study in dry-cured ham. *Journal of Food Engineering* 166,
405 148–155.

406 URL <http://www.sciencedirect.com/science/article/pii/S0260877415002587>

407 National Pork Board - NPB, 2015. Pork quality standards. <http://www.pork.org>, Accessed: 2015-04-05.

408 O'Farrell, M., Lewis, E., Flanagan, C., Lyons, W., Jackman, N., 2005. Comparison of k-nn and neural
409 network methods in the classification of spectral data from an optical fibre-based sensor system used for
410 quality control in the food industry. *Sensors and Actuators B: Chemical* 111, 354–362.

411 Otsu, N., Jan. 1979. A Threshold Selection Method from Gray-level Histograms. *IEEE Transactions on*
412 *Systems, Man and Cybernetics* 9 (1), 62–66.

413 URL <http://dx.doi.org/10.1109/tsmc.1979.4310076>

414 Pang, B., Sun, X., Liu, D., Chen, K., 2014. Beef marbling image segmentation based on homomorphic
415 filtering. *Journal of Multimedia* 9 (2), 189–195.

416 Papadopoulou, O. S., Panagou, E. Z., Mohareb, F. R., Nychas, G.-J. E., 2013. Sensory and microbiological
417 quality assessment of beef fillets using a portable electronic nose in tandem with support vector machine
418 analysis. *Food research international* 50 (1), 241–249.

419 Peña, F., Molina, A., Avilés, C., Juárez, M., Horcada, A., 2013. Marbling in the longissimus thoracis muscle
420 from lean cattle breeds. computer image analysis of fresh versus stained meat samples. *Meat science*
421 95 (3), 512–519.

422 Prevolnik, M., Andronikov, D., Žlender, B., Font-i Furnols, M., Novič, M., Škorjanc, D., Čandek-Potokar,
423 M., 2014. Classification of dry-cured hams according to the maturation time using near infrared spectra
424 and artificial neural networks. *Meat science* 96 (1), 14–20.

425 Qiao, J., Ngadi, M. O., Wang, N., Garipy, C., Prasher, S., 2007. Pork quality and marbling level assessment

426 using a hyperspectral imaging system. *Journal of Food Engineering* 83 (1), 10 – 16, future of Food
427 Engineering Selected Papers from the 2nd International Symposium of {CIGR} Section {VI} on Future
428 of Food Engineering.
429 URL <http://www.sciencedirect.com/science/article/pii/S0260877407001185>

430 Ropodi, A., Panagou, E., Nychas, G.-J., 2016. Data mining derived from food analyses using non-
431 invasive/non-destructive analytical techniques; determination of food authenticity, quality & safety in
432 tandem with computer science disciplines. *Trends in Food Science & Technology*.

433 Sahoo, P., Soltani, S., Wong, A., 1988. A survey of thresholding techniques. *Computer Vision, Graphics,*
434 *and Image Processing* 41 (2), 233 – 260.
435 URL <http://www.sciencedirect.com/science/article/pii/0734189X88900229>

436 Sun, D., 2012. *Computer Vision Technology in the Food and Beverage Industries*. Woodhead Publishing
437 Series in Food Science, Technology and Nutrition. Elsevier Science.
438 URL <https://books.google.com.br/books?id=WR5tAgAAQBAJ>

439 Sun, D.-W., 2011. *Computer vision technology for food quality evaluation*. Academic Press.

440 Tan, J., 2004. Meat quality evaluation by computer vision. *Journal of Food Engineering* 61 (1), 27 – 35,
441 applications of computer vision in the food industry.
442 URL <http://www.sciencedirect.com/science/article/pii/S0260877403001857>

443 Valous, N. A., Mendoza, F., Sun, D.-W., Allen, P., 2010. Supervised neural network classification of pre-
444 sliced cooked pork ham images using quaternionic singular values. *Meat science* 84 (3), 422–430.

445 Wang, D., Wang, X., Liu, T., Liu, Y., 2012. Prediction of total viable counts on chilled pork using an
446 electronic nose combined with support vector machine. *Meat science* 90 (2), 373–377.

447 Xiong, Z., Sun, D.-W., Zeng, X.-A., Xie, A., 2014. Recent developments of hyperspectral imaging systems
448 and their applications in detecting quality attributes of red meats: A review. *Journal of Food Engineering*
449 132, 1–13.