Using machine learning procedures to ascertain the influence of beef carcass profiles on carcass conformation scores

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Abstract

In this study, a total of 163 young-bull carcasses belonging to seven Spanish native beef cattle breeds showing substantial carcass variation were photographed in order to obtain digital assessments of carcass dimensions and profiles. This dataset was then analysed using machine learning (ML) methodologies to ascertain the influence of carcass profiles on the grade obtained using the SEUROP system. To achieve this goal, carcasses were obtained using the same standard feeding regime and classified homogeneous conditions in order to avoid non-linear behaviour in grading performance. Carcass weight affects grading to a large extent and the classification error obtained when this attribute was included in the training sets was consistently lower than when it was not. However, carcass profile information was considered non-relevant by the ML algorithm in earlier stages of the analysis. Furthermore, when carcass weight was taken into account, the ML algorithm used only easy-to-measure attributes to clone the classifiers decisions. Here we confirm the possibility of designing a more objective and easy-to-interpret system to classify the most common types of carcass in the territory of the EU using only a few single attributes that are easily obtained in an industrial environment.

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1. Introduction

The European Union (EU) has set up a bovine carcass conformation assessment system, known as the SEUROP system, to be applied in the entire EU territory for bovines from 300 kg of live weight (Regulation (EEC) No. 1026/91). The SEUROP system is described in a very broad manner. The description of conformation classes ranges from 'exceptional' to 'poor' muscular development and from 'extremely' convex to 'very' concave profiles. Some mechanical classification systems based on video image analysis and calibrated using classifiers decisions have been tested in the European beef market (Allen &

Finnerty, 2001; Borggaard, Madsen, & Thodberg, 1996). Carcass conformation is an important component of price negotiations between beef producers and market operators. Hence, the assessment of the consistency of the rules used to obtain carcass classifications is a key task in beef production.

In previous analyses, it was shown that SEUROP rules are not consistent across the whole carcass weight range in which the system is expected to be useful (Díez et al., 2003). Besides the assessment of muscular development and convexity of profiles, classifiers use other traits to carry out grading, such as those describing carcass size and body measurements (Díez et al., 2003, 2001; Goyache et al., 2001). This is especially true for immature (light) carcasses (Díez et al., 2003). The repeatability of the carcass classification tends to be low, thus affecting market confidence

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(Keane, 1999). Particularly, the need to assess profiles makes it difficult to develop objective carcass grading methodologies and is moreover a stumbling block in the clarification and standardisation of the beef market in the European Union.

Artificial intelligence (AI) techniques can be used to identify the major factors affecting conformation grading of beef carcasses. Recent studies have applied machine learning (ML) algorithms both to clone the behaviour of bovine carcass classifiers in order to obtain sound assessments as well as to assess the differences in the performance of classifiers when dealing with different types of carcasses (Díez et al., 2003; Goyache et al., 2001). As reported for other food quality assessments (del Coz et al., 2004; Díez et al., 2004), these studies point out that carcass classification presents highly non-linear behaviour. However, Díez et al. (2004) concluded that the non-linearity of quality assessments of food products is based on the heterogeneity of both the products to be classified and the way in which different classifiers use the rules to be applied. Thus, the consistency of the rules of a given carcass classification system should be tested on a homogeneous dataset designed to reduce the differences between assessment sessions, thus permitting grading scores to be considered as absolute ratings rather than relative preferences.

The aim of this paper is to test the influence of carcass profiles on the grade obtained using the official SEUROP conformation classification system. To do so, a set of 163 beef carcasses from seven Spanish native beef breeds showing substantial carcass conformation differences were studied. The animals were reared using the same standard feeding regime and slaughtered at carcass weights within the 'young-bull' commercial category, which is the most popular in the Spanish beef market. Carcasses were classified using the consensus grade of two well-reputed expert classifiers (Albertí et al., 2005). The obtained dataset was analysed using ML algorithms to ascertain the importance of the traits (attributes in AI terms) in order to explain the classification decisions and obtain sound carcass grading. Recommendations for the improvement and clarification of the carcass grading system in the EU territory may ensue from the results of the present analysis.

2. Materials and methods

2.1. Data

A total of 163 carcasses of entire males were used from seven Spanish breeds: Asturiana de la Montaña (31), Asturiana de los Valles (32), Avileña-Negra Ibérica (32), Morucha (3), Parda Alpina (4), Pirenaica (55), Retinta (3) and Rubia Gallega (3). A detailed description of the used breeds and their carcasses can be found in Albertí et al. (2005). The animals were fed ad libitum with concentrate and cereal straw in different feedlots, with feedlot size varying from 3 to 13 individuals, and slaughtered at average live-weight per feedlot varying from 330 to 550 kg. See

Albertí et al. (2005) for a detailed description of the feeding characteristics. After slaughter, the carcasses were weighed and 2% of carcass weight was automatically subtracted to determine the cold carcass weight. The carcasses were then chilled for 24 h at 4 °C. Carcass classification was carried out using the SEUROP rules. To improve the accuracy of classification, the signs + or – could be added to each conformation grade (Kempster, Cook, & Southgate, 1988). The SEUROP grades were numerically codified ranging from 1 (P) to 6 (S); the signs + and – were computed as +0.25 or –0.25 conformation points, respectively (Díez et al., 2003; Goyache et al., 2001).

Carcass traits were captured by photographing each carcass in three different positions: (a) lateral, (b) medial and (c) dorsal. A metric reference was included in each photo so as to be able to measure lengths from the pictures. The digital pictures were then processed by marking (with mouse clicks) 21 key points and 5 curve arcs so as to calculate up to 20 attribute values numerically representing the features or traits mentioned in the SEUROP specifications (Díez et al., 2003; Goyache et al., 2001). The attributes used are listed in Table 1. The applied techniques are not only useful for assessing carcass dimensions, as occurs with traditional methodologies (De Boer, Dumont, Pomeroy, & Weniger, 1974), but also for estimating differences in

Table 1

Description of the attributes used to represent bovine carcass conformation grading in 101 carcasses from seven Spanish native beef breeds included in the training set

Attribute	Mean	s.d.	Min.	Max.
Carcass weight	327.7	61.0	195.9	480.6
Thigh width	27.8	3.2	20.8	35.5
Thigh length	46.2	3.3	38.3	55.3
Hind limb length	66.5	5.5	51.3	82.5
Shoulder length	42.1	3.1	34.6	51.9
Shoulder width	28.4	3.9	18.1	37.5
Lateral shoulder height	3.5	1.2	0.2	6.9
Back length	83.2	6.7	67.6	99.2
Front width of back	14.5	3.1	7.1	22.7
Rear width of back	12.7	2.4	4.7	18.9
Lateral back width at hip	14.7	1.9	8.9	19.9
Lateral back width at chest	14.3	2.4	9.0	23.8
Carcass length	124.2	8.6	103.8	147.3
Chest depth	46.4	3.0	39.2	53.5
Belly depth	32.6	3.5	25.2	47.2
Round profile ($\times 10^{-4}$)	–8.5	2.2	–0.1	–13.4
Shoulder profile ($\times 10^{-4}$)	–8.5	3.0	–1.1	–15.0
Topside profile ($\times 10^{-4}$)	–8.9	3.2	6.0	–14.5
Hips profile ($\times 10^{-4}$)	–7.9	3.5	2.6	–14.6
Thigh profile ($\times 10^{-4}$)	–11.0	2.8	–4.0	–16.4
Neck profile ($\times 10^{-4}$)	–8.5	2.8	0.9	–14.2
Conformation score	3.7	0.9	1.75	6.0

Attributes are described in cm for distances between two given key points; profiles and ratios are described in the corresponding units; carcass weight is in kg. Curvature of the profiles is expressed in units $\times 10^{-4}$.

The conformation score was obtained following the SEUROP methodology; signs + or – were added to each conformation grade; SEUROP grades were numerically codified ranging from 1 (P) to 6 (S); the signs + and – were computed as +0.25 or –0.25 conformation points, respectively.

muscular development and carcass profiles. Single anatomical traits were easily calculated by means of the distance between key points. To represent profile convexities, we consider the curve arc that borders the profile as a variable real function k . We then compute the curvature k at a given point x_i as $k(x_i) = \frac{k''(x_i)}{(1+k'(x_i)^2)^{3/2}}$, where $k'(x_i)$ and $k''(x_i)$ are, respectively, the first and second derivatives at a point on the profile. We subsequently divide the arc by means of a sequence of points $\{x_i\}$ in $[0, a]$ that divide the interval into a given number (the same in all cases) of equal length sub-intervals. Finally, to summarise the convexity of the whole arc in the interval $[0, a]$, we compute the average curvature (K) for all $\{x_i\}$ as $K = \frac{\sum_{i=1}^n k(x_i)}{n}$. See Goyache et al. (2001) and Díez et al. (2003) for a more detailed description of the profile's curvature computation method.

Carcass traits were used as the input dataset for learning algorithms (the so-called, in AI terms, training sets). In the present case, each example is described by means of attributes that numerically represent the traits of the carcasses considered. Additionally, the examples are endowed with the consensus conformation score; we will usually refer to this score as the class of the example. Since the SEUROP system is expected to be applied to bovines from 300 kg of live weight, regardless of the sex, age or management conditions of the animal, this trait is not properly included in the SEUROP rules. However, carcass weight is likely to have an influence on grading. For this reason, this attribute was included in the training set. To differentiate the influence of carcass weight on grading, all the computations were carried out using two different initial training sets: with and without this attribute to describe the carcasses. Thus, the initial training sets to be used as independent input to ML algorithms respectively included 21 and 20 attributes describing carcass conformation (see Table 1). Throughout the paper, the training sets initially including the carcass weight or not will be referred to as the CW-set and nCW-set, respectively. Descriptive statistics of the attributes defining our training sets were computed using SAS/STAT™ (1999).

2.2. Machine learning algorithms

A detailed description of AI principles and methods and of the main characteristics of several kinds of ML algorithms focused on the food field can be found in Goyache et al. (2001) and Díez et al. (2003) and in the references cited therein. In the present analysis, a well-reputed ML algorithm, M5' (Quinlan, 1993), was first used to assess the linearity of the experimental dataset constructed for the present analysis, comparing its performance with linear regression. The algorithm M5' makes up a crisp evaluation mechanism through the induction of a set of regression rules of the form:

if   some conditions about the traits are fulfilled
then   to compute the SEUROP conformation
          score, use a given linear function

The number of functions needed by M5' to explain the computer assessments is a good measure of the linearity of the assessing task (Díez et al., 2003).

Secondly, the training sets were analysed by means of linear regression following a kind of heuristic search in order to find the best combination of attributes presenting the best ratio between the prediction error in carcass classification and the number of attributes used to learn. In other words, the relevancy (see Goyache et al., 2005) of the different attributes (and their weight) to obtain sound SEUROP conformation grading was assessed. The method employed consisted in the gradual reduction of the number of attributes. The learning process started off with all the possible attributes describing the available carcasses and removed one attribute per iteration. The description of the algorithm implemented to assess the relevancy of the attributes in this analysis is given in Fig. 1. The interpretation of the results has been done using the mean absolute distance or deviation (mad) of the function f learned by the regression method, i.e.,

$$\text{mad} = \frac{1}{|\text{TS}|} \sum |f(x) - c_{\text{class}}| \quad \forall x \in \text{TS}$$

where TS is a test set. The attribute ranking criterion is based on the mad obtained when an attribute is deleted from the data set. Thus, when a more relevant attribute is deleted, the mad obtained should be greater than if a less relevant attribute is conserved.

The accuracy of the performance of each ML algorithm was estimated through a cross validation system. Each training set was divided into 10 folders. Each of these folders was successively used as a test set while the other 9 were used for training. The prediction function obtained by the ML algorithm from the other 9 folders was then applied to each example from the test folder and then the average absolute difference with respect to the class of the example was computed. All the mad were obtained in a 10-fold cross validation.

3. Results

Table 1 presents descriptive statistics of the training sets. The analysed dataset showed substantial variation. Average carcass weight, carcass length and conformation scores for the whole dataset were 327.7 kg, 124.2 cm and 3.7, respectively. The range in which these traits varied were: from 195.9 to 480.6 kg for carcass weight, from 103.8 to 147.3 cm for carcass length and from 1.75 (O-) to 6.0 (S) for conformation score.

The results of the initial analysis carried out using M5' (Quinlan, 1993) together with the results obtained using linear regression are given in Table 2. Linear regression and M5' gave similar mad results (roughly 0.34). In fact, M5' learned to classify beef carcasses in a linear way (using only one function), thus cloning the behaviour of the linear regression.

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Let
A = Set of attributes describing each example
T = Set of training examples  $(x_1, x_2, \dots, x_{|A|}, y)$ 
L = [A] // Initially, one subset with all the attributes
While |A| > 1 do
  // Ranking attributes
  For all a  $\in A$  do
     $A = A \setminus a$  // Remove a from A
     $\omega = \sum_{i=1}^{|A|} \omega_i x_i + b$  // Compute the linear regression (10-fold cross validation)
     $mad = \frac{1}{|TS|} \sum_{i=1}^{|TS|} |\langle \omega, x_i \rangle - y_i|$  // Compute the mad (10-fold cross validation)
     $A = A + a$  // Reinsert a in A
  End for
  Sort attributes in A from less mad to more mad
   $A = A \setminus a_{|A|}$  // Delete the least relevant attribute
   $L = L + A$ 
End while
Return L // Return the ordered list of attribute subsets

```

Fig. 1. Description of the algorithm used to compute the relevancy of the attributes characterising the available dataset.

Table 2

Average absolute errors and number of functions selected to make predictions on unseen cases for linear regression and a machine learning algorithm (M5') in carcass conformation classification

Method	mad	Average number of functions used
Linear regression	0.337	1.0
M5'	0.340	1.0

Results obtained by 10-fold cross validation over the training set including carcass weight. To interpret the results, we used the mean absolute distance or deviation (mad) of the function f learned by the regression method.

Fig. 2 shows the variation in the mean absolute distance or deviation (mad) obtained when the CW and the nCW are analysed and the least relevant attribute is sequentially removed from the data set. Errors are always higher with the nCW set. The mean absolute deviation obtained when starting off with 21 attributes was, respectively, 0.337 and 0.362 for the CW and the nCW training sets (the latter including only 20 attributes). The most relevant attributes are the carcass weight and thigh width for the CW and the nCW sets, respectively, although the errors obtained using only these attributes are the highest obtained in the analyses (mad of 0.490 and 0.459, respectively). Regardless of whether carcass weight is considered or not, one attribute is removed by the ML algorithm in each step until a training set including 16 attributes is analysed. After that, our methodology fits the results well using only 10 attributes both with the CW and nCW sets. In fact, the best learning performance (assessed through the smallest mad values) was obtained with 9 attributes for the CW set (mad = 0.309) and with 10 attributes for the nCW set (mad = 0.348). These two training sets include only one carcass profile: the round profile. However, the corresponding mad remains lower than that obtained with the whole training set with 4 attributes for the CW set

(mad = 0.333) and with 8 attributes for the nCW set (mad = 0.362). These two 'best' training sets do not include any carcass profile.

Table 3 lists the attributes selected by the ML algorithm for those training sets with the lowest mad, with the smaller number of attributes obtaining a lower mad than that obtained with the whole dataset and with only two attributes. The most relevant attributes used to successfully clone carcass grading were those characterising carcass dimensions. Specifically, chest depth and hindlimb length were retained in the 'better' CW and nCW training sets including 4 and 8 attributes, respectively. However, carcass length was not retained in the nCW training sets. When carcass weight was considered for the learning process, the two attributes characterising the whole carcass (carcass length and carcass weight) were retained. However, when carcass weight was not used as an input for learning, the carcass grading was carried out by the system considering only the size and the muscular development of the leg (thigh width and hindlimb length, respectively).

4. Discussion

The measurements and weights shown in Table 1 characterise the analysed dataset as a realistic sample for the majority of the beef market in Spain. The dataset analysed here included a balanced number of carcasses from Spanish native breeds that have previously been classified as high meat producers (Asturiana de los Valles and Rubia Gallega), medium meat producers (Parda Alpina and Pirenaica) and low meat producers (Avileña, Retinta and Morucha) (Albertí et al., 2005). Although the analysed dataset presented wide variation, to attain the goals of the present analysis the dataset was required to behave linearly with respect to carcass classification performance. This was checked using a well reputed ML system: M5'

Fig. 2. Mean absolute distance or deviation (mad) with respect to the training sets including carcass weight (open circles) or not (open squares) when the least relevant attribute is removed from the data set. Results are given for the training set including carcass weight (open circles) and for the training set that did not include carcass weight.

Table 3

List of attributes (and the corresponding mean average divergence, mad) forming the training sets selected to learn how to classify beef carcasses for each of the subsets considered in the present paper (see text)

Number of attributes	Attributes used	mad
<i>With carcass weight</i>		
9	Shoulder width, front width of back, round profile, thigh width, rear width of back, chest depth, hindlimb length, carcass length and carcass weight	0.309
4	Chest depth, hindlimb length, carcass length and carcass weight	0.333
2	Carcass length and carcass weight	0.385
<i>Without carcass weight</i>		
10	Round profile, chest depth, back length, belly depth, shoulder length, thigh length, rear width of back, front width of back, thigh width and hindlimb length	0.348
8	Belly depth, back length, shoulder length, chest depth, rear width of back, thigh width, front width of back and hindlimb length	0.362
2	Thigh width and hindlimb length	0.423

The described training sets were those with the lowest mad, those with the smaller number of attributes obtaining a lower mad than that obtained with the whole dataset and those including only two attributes. Attributes were listed from less to more relevant.

(Quinlan, 1993). The linear behaviour of conformation grading in standard carcasses is consistent with previous information reporting that the conformation score is expected to increase with age and carcass weight (Kempster et al., 1988; More O'Ferrall & Keane, 1990). However, the linearity of the behaviour assessed in the training sets analysed here is more likely to be dependent on the design of a dataset that focused on avoiding most of the sources of heterogeneity of the products to be assessed and of the differences between assessment sessions (Díez et al., 2004), in our case different fattening methods and multiple classifiers.

With respect to other training sets previously used to analyse the behaviour of beef classifiers (Díez et al., 2003; Goyache et al., 2001), the experimental dataset used here shows a high internal consistency. While the above studies included both light and standard carcasses, the present dataset included carcasses that would be classified as belonging to the commercial category of (standard) 'young bull', which is the most common on the Spanish beef market (Albertí et al., 2005). Regardless of the training set (CW or nCW), the mad obtained here was always lower than 0.50. This was also true for the training sets including only a single attribute (carcass weight or thigh width for the CW and the nCW sets, respectively). Fitting in 0.50, the threshold for allowed error of a ML system, enabled us to ensure that the numerical gap between the signs + or – for each conformation grade was exceeded (Díez et al., 2003).

Although carcass weight is not properly included in the SEUROP rules, our results suggest that this trait exerts a major influence on classification performance. When the same number of attributes was included in the training sets, the obtained mad was consistently lower (roughly 0.04) for the CW than for the nCW sets. However, carcass weight cannot be the only attribute used to classify beef carcasses; the mad obtained using only carcass weight was larger than that obtained using only thigh width (0.489 vs. 0.459). Nonetheless, the importance of carcass weight cannot be ignored; conformation grading is a visual assessment of the thickness of muscle and fat in relation to the size of the skeleton (More O'Ferrall & Keane, 1990). The last two attributes retained for the CW set are those needed to compute the blockiness index (ratio between carcass weight and carcass length). The blockiness index has been repeatedly found to be relevant in obtaining an accurate carcass classification (Díez et al., 2003; Goyache et al., 2001; Vallejo et al., 1992). However, the information provided to the classifiers by the blockiness index is not sufficient to obtain accurate gradings. In an independent run, the mad obtained using only the blockiness index was 0.440, which was slightly lower than the mad obtained using only carcass weight and substantially higher than the mad obtained using carcass weight and carcass length separately (see Table 3).

The results obtained with the nCW can be interpreted in a similar way. The learning process carried out when carcass weight is not available attempts to take into account a kind of 'thigh blockiness', using attributes characterising the size and muscular development of the carcass leg (thigh width and thigh length). When the nCW sets are considered, however, 3 attributes are needed to obtain mad values lower than 0.4, which, in turn, are obtained with only 2 attributes using the CW sets. In this respect, when carcass weight is not used as input for the learning procedure, the system needs more information on carcass size, including an indicator of the size of the fore part of the carcass (chest depth). The learning process carried out with the nCW sets was expected to be consistent with the SEUROP rules, which are expected to grade carcasses according to their muscular development regardless of carcass weight. However, the cloning of carcass classification is more affected by size than by the attributes characterising the muscular development of the carcass to be assessed. In fact, only 4 of the 10 attributes used in the 'best' nCW set may be considered as muscular development attributes (round profile, thigh width, rear width of back and front width of back).

The present results contrast with others previously described (Díez et al., 2003) reporting that carcass size attributes were used by classifiers to grade light carcasses, while standard carcasses were classified more consistently with the SEUROP rules by basically using attributes characterising muscular development. The results reported here are, however, not directly comparable with those obtained in earlier papers (Díez et al., 2003; Goyache et al., 2001) because of the different training sets used pre-

viously (including areas and volumes as input attributes) and the different methodology used to assess learning performance. Moreover, the training sets used in the aforementioned studies are more heterogeneous, including different carcass types (light -veal type- and standard -young bull- carcasses) and different classifiers grading the same carcasses in different grading sessions. This heterogeneity of the employed training sets probably underlies the highly non-linear behaviour of the learning performance for carcass grading reported previously (Díez et al., 2004). In fact, when training sets formed by fewer than 6 attributes were used to predict carcass classification using regression, the prediction error tended to be 0.5 or higher (Goyache et al., 2001), showing a bad performance of the linear regression when trainings sets including light and standard carcasses and various classifiers gradings were used (Díez et al., 2003). The present analysis was developed using a training set that minimises the possibilities of non-linear behaviour of the grading process, thus being useful for assessing inconsistencies in the classification methodology. A major result arising from the present study is that, regardless of whether the classifiers are influenced by the carcass weight or not, carcass profiles are not essential to clone grading decisions. Profile information is considered non-relevant by the ML algorithm in earlier stages of the analysis. This is consistent with previous reports (Díez et al., 2003) highlighting the fact that profiles are not taken into account by carcass classifiers to a significant extent, irrespective of the type of carcass. Carcass profiles are probably considered dependent on the degree of muscular development and skeletal size, these latter traits being easier to assess without uncertainty. Furthermore, when carcass weight is taken into account, classifiers use only easy-to-measure attributes to make their decisions.

The present results confirm the possibility of designing a more objective and easy-to-interpret system to classify the most common types of carcass in the territory of the EU. This new system should take into account as few traits as possible, since single attributes are easy to obtain in an industrial environment (Goyache et al., 2001).

5. Implications

The aim of this paper was to test the validity of the official SEUROP bovine carcass classification system within the most common commercial types of beef carcass in Spain and in other important markets in European Union territory. To do so, we analysed a dataset in which the non-linear response to carcass classification behaviour is minimised, at the same time as exploiting the major advantages of employing ML techniques to ascertain the main attributes affecting carcass grading performance.

We found that carcass profiles are not essential to obtain sound carcass grading. Within a specific set of carcasses, grading is carried out using objective traits such as those related to carcass dimensions (size and weight) and thigh development (length and width). It is then possible to design

a carcass grading methodology to be applied without uncertainty, at least for the standard carcass market. Further research will be needed to: (a) establish the thresholds within which it is possible to separate different categories of carcasses; and (b) ascertain the relationship of the objective carcass traits selected to carry out grading with the amount of meat from different commercial categories that market operators can expect to obtain from a carcass of a given class.

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