Meta-recommendation of pork technological quality standards

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Pork quality classification is supported by different reference standards that are widely reported in the literature. However, selecting the most suitable standard for each type of meat samples remains a challenge, due to their intrinsic variation according to the quality parameters' interval. The usage of meta-learning was proposed to automatically recommend the most adequate standard for a determined sample collection, leading to a more accurate classification. The meta-learning procedure has emerged from the machine learning research field to solve the algorithm selection dilemma, outlining a new method for pork quality classification. The applicability and advantages of using a suitable classification standard for pork quality were addressed using the J48 Decision Tree (DT) algorithm, which serves as the meta-recommender. Experiments conducted with six pork standards revealed promising results based on a few meta-attributes (L^*, water hold capacity, and dataset entropy) as the approach successfully recommended all scenarios.

Keywords:
Classification
Computational intelligence
Decision tree
Machine learning
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1. Introduction

Meat quality is a term used to describe several meat properties that result from the interaction between ante and post-mortem muscle metabolism (Durkin, Margeta, Margeta, Kralik, & Kušec, 2009; Maltin, Balcerzak, Tilley, & Delday, 2003; Sima, Heres, Klont, & Mireşan, 2015). Evaluating meat quality is an essential task for the industry, which aims to match the consumer demands of meat and meat products from different market niches, according to their quality (Elmasry, Barbin, Sun, & Allen, 2012; Gonzalez et al., 2020; Piórkowska et al., 2020; Sosnicki,

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Abbreviations

ANN	Artificial Neural Network
DFD	Dark, Firm and Dry
DL	Drip Loss methodology
DT	Decision Tree
FPW	Filter-paper Wetness methodology
H(a*)	*a** conversion from HunterLab to CIELab*
H(b*)	*b** conversion from HunterLab to CIELab*
H(L*)	*L** conversion from HunterLab to CIELab*
ML	Machine Learning
PFN	Pale, Firm and Non-Exudative.
pH	potential of Hydrogen
pHu	ultimate potential of Hydrogen
PM	Pressing Method
PSE	Pale, Soft and Exudative.
RFN	Reddish Pink, Firm and Non-Exudative.
RSE	Reddish Pink, Soft and Exudative.
WHC	Water Holding Capacity

Pommier, Klont, Newman, & Plastow, 2003; Teixeira & Rodrigues, 2019).

From a technological perspective, pork quality could be defined by some few measurable parameters, including the pH, drip loss and colour, which are interrelated and define the quality perceived by the consumer (Lee et al., 2000). In the literature, different pork quality standards have been derived from the combination of these parameters based on their different thresholds. However, a consensus for the best combination have not been reached (Cazedey, Torres Filho, Fontes, Ramos, & Ramos, 2016). In fact, pork samples are sometimes classified into three or more categories based on a given standard.

Kušec, Kralik, Durkin, Petričević, and Hanžekl (2007) proposed a plurality of criteria to classify pork quality, such as the standards from Kauffman et al. (1993); Santos, Roseiro, Goncalves, and Melo (1994); Van Laack, Solomon, Warner, and Kauffman (1996); Warner, Kauffman, and Greaser (1997); Flores, Armero, Aristoy, and Toldra (1999); Van Laack and Kauffman (1999); Channon, Payne, and Warner (2000); Joo et al. (2000); Du and Sun (2006); Maganhini et al. (2007); Faucitano et al. (2010); Barbin, Elmasry, Sun, and Allen (2012); Bauer, Petzet, Schwagele, Scheier, and Schmidt (2013); Tomovic et al. (2014).

This multiplicity of pork quality standards reflects the lack of standardisation, in which a given sample could be classified into different classes depending on the standard selected (Cazedey, Torres Filho, Fontes, Ramos, & Ramos, 2016). Determining pork quality is fundamental for the modern food industry (Du & Sun, 2006), aiming to standardise their products according to specific niche markets, which demands specifications according to measurable parameters. However, the factors affecting these meat quality parameters, such as genetics, the ante-mortem stress, or the post-mortem carcass chilling, among others, leads to a wide variation in the measurements. Thus, to better match the demands of different market niches, considering the intrinsic variation in meat quality parameters, an automated system based on machine learning (ML) could be the solution for a smart decision making. The ML procedures could contribute to better revenues of meat companies, able to sell pork cuts and carcasses matching the market specifications and improving product homogeneity. Furthermore, ML would solve the question to whether which pork standard would be the most appropriate to classify a given pork sample, improving the accuracy in the decision making.

ML solutions have been widely applied in the area of food research for several food products, such as seeds, fruits, and meat (Barbon et al., 2016; Caballero et al., 2016; Kamruzzaman, Makino, & Oshita, 2016; Mohareb, Papadopoulou, Panagou, Nychas, & Bessant, 2016; Sanz et al., 2016; Peres et al., 2018; Pereira, Barbon, Valous, & Barbin, 2018; Castro et al., 2019).

ML algorithms can build a classification model based on the knowledge extracted from a given data set. Recommending an adequate pork quality standard for classification requires in-depth knowledge about the collected samples, called the dataset, along with the available ones from the literature. Meta-learning has thus emerged from the ML research field to solve the selection problem by assessing data and recommending the most effective solution (Aguiar et al., 2019; Campos, Barbon, & Mantovani, 2016). Following the principles of Meta-learning, we propose the use of meta-recommendation of the most appropriate pork quality standard through the decision tree (DT) algorithm.

DT has been widely chosen for classification in the literature. This is because this algorithm is considered as one of the most powerful ML algorithms due to its advantages, such as low computational cost, ability to handle missing values, as well as irrelevant resources (Harrington, 2012). Accordingly, this algorithm can be easily implemented in an industrial environment and interpreted in contrast to many "black box" solutions, such as ANN (Barbon et al., 2016).

In this work, we propose a method based on meta-learning that can be used to recommend the most appropriate classification standard to determine pork qualification based on the sample characteristics analysed. Accordingly, the number of classified samples was maximised, the demand of parameters to perform a test was verified, and confidence was obtained in the results of the classification.

2. Materials and methods

In the first step, our meta-model, which involved grouping several different datasets to describe the vast variability of sample types according to the literature's selected standards, was established. This step is described in depth in Section 2.1. In the second step, meta-features were extracted from the original datasets, which were composed of the traditional quality parameters. The meta-features are features based on Information Theory and Statistics described in Section 2.3. The meta-dataset was obtained from meta-features and was applied to create a meta-model by using the ML algorithm; the J48 DT was employed. This induction procedure is described in Section 2.4. After this step, the meta-model could be applied to a new dataset to recommend the most suitable classification standard, to ultimately automatically reduci the number of unclassifiable samples (Peres et al., 2018) and perform further classification.

2.1. Pork quality standards

Pork samples were obtained from ten different slaughterhouses, the total number of *longissimus lumborum* muscles collected was 1301. The meat quality parameters were determined at 24 h post-mortem in the collected loin samples, and included the ultimate *pH* (*pHu*), the water holding capacity (*WHC*) and lightness (L^*) of instrumental colour measurement.

The *pHu* was measured 24 h *post-mortem* using a Testo 205 pH-meter. The *WHC* was obtained by the Pressing Method (*PM*) proposed by Hamm (1960) and adapted by Wilhelm, Maganhini, Hernández-Blazquez, Ida, and Shimokomaki (2010) and the L^* value (International Commission on Illumination, 1978) was determined with a portable Minolta R colourimeter (model CR-10, illuminant D65, 8° angle of inclination - Tokyo, JP) after blooming for 30 min.

We used different methodologies to measure the *WHC* and L^* values and compare them with those obtained by Kauffman et al. (1993) and Faucitano et al. (2010). The measurements were fist standardised by means of mathematical transformations proposed by Peres et al. (2018) (Eqs. (1) and (2)) and traditional ones (3,3,4,5) enabling a comparison among the pork quality standards. *DL* and *FPW* represent drip loss and filter-paper wetness methodologies, respectively.

$$DL = 0.100707 \cdot PM \tag{1}$$

$$DL = -0.36 + 0.064 \cdot FPW \tag{2}$$

$$H(L^*) = 10\sqrt{Y} \tag{3}$$

$$H(a^*) = 17.5 \cdot \frac{(1.02 \cdot X) - Y}{\sqrt{Y}} \tag{4}$$

$$H(b^*) = 7 \cdot \frac{Y - (0.847 \cdot Z)}{\sqrt{Y}} \tag{5}$$

In Eqs. (3)–(5), X, Y, and Z are the coordinates from the CIE XYZ primary colour system used to obtain the CIELab space colour.

2.2. Datasets

To match the requirements of all classes described in the pork quality standards, we used real and synthetic datasets. The real-life dataset was composed of 1301 samples that could not represent samples for each class proposed in the literature, further demonstrating a significant difference in their number, which caused an imbalanced learning problem. The imbalanced learning problem is compromised of the performance of most learning algorithms because most assume or expect a distribution of balanced classes in the training set. Thus, these algorithms fail to correctly represent the distributional characteristics of the data and hence, provide unfavourable class accuracy (He & Garcia, 2009).

A possible solution to this type of problem is to collect more data; however, this would not guarantee a balance of samples of all classes. To overcome this drawback, an additional synthetic dataset, supported by the literature, was created to explore a vast variety of sample setups balancing the number of samples from each class. The synthetic dataset was created by running 130 random generations, where each was composed of 1000 samples grounded at intervals of six different patterns (Barbin et al., 2012; Faucitano et al., 2010; Kauffman et al., 1993; Van Laack & Kauffman, 1999; Van Laack et al., 1996; Warner et al., 1997) (Table 1). The real-life and synthetic data set are available online.[1]

2.3. Meta-dataset and meta-features

The meta-dataset is the repository used to support the induction of a meta-model (or predictor). This repository is composed of meta-features and a target related to their best match. Thus, each dataset (real-life or synthetic) had its meta-features extracted and assessed with the best pork quality standard among the six possibilities (exposed in Table 1). The adequate standard was identified by observing the most significant number of classified samples with minimal bias when compared to all standards over a given dataset.

For instance, a dataset *N* with 1000 samples, classified according to Kauffman et al. (1993) had 376 hits, Van Laack et al. (1996) - 378 hits, Warner et al. (1997) - 385 hits, Van Laack and Kauffman (1999) - 339 hits, Faucitano et al. (2010) - 341 hits; and Barbin et al. (2012) - 400 hits. Therefore, the dataset was labeled as Barbin et al. (2012), indicating Barbin et al. (2012) is the most suitable standard to classify the dataset observed. This process was thus used to label all datasets.

The extracted meta-features were decomposed into statistical moments (mean, standard deviation, skewness, and kurtosis), information theory (entropy), and a simple descriptive information (maximum and minimum values) of the original parameters (*pH*, *WHC*, L^*) as suggested in the literature (Campos et al., 2016; Mantovani, Rossi, Vanschoren, & Carvalho, 2015).

The meta-dataset was composed of 140 instances (one from each dataset), 21 meta-features, and a suitable dataset according to the identification process. In the next step, the meta-model was induced to perform the prediction of a classification standard from a new dataset.

2.4. Meta-model

The J48 DT (Quinlan, 1993) was selected to build the meta-model and generate a user-friendly model supporting ease comprehension (Barbon, et al., 2016). A DT model is characterised by branches related to a given feature and a threshold that begins from a root node; each leaf node represents a class label (e.g., pork quality standard). The first division of the *DT* occurs from the root node and the choice of the meta-feature that represents this is the meta-feature with the highest gain of information; this occurs because the higher the gain of information, the more efficient the division (Quinlan, 2014). The path from the root node to leaf represents the classification rules. A significant advantage of J48 is related to the hierarchical relationship of the meta-features, automatically selecting the ones that best explain the problem.

The environment used to create the meta-model was WEKA 3.8 (Witten & Frank, 2000). We used the standard

[1] http://www.uel.br/grupo-pesquisa/remid.

Table 1 – Standards and parameters for the classification of pork quality.

Standard	Class	pH_u	WHC		L*	
			FPW	DL	CieLab	HunterLab
Kauffman et al. (1993)	PSE	–	–	>5.0	–	>58
	RSE	–	–	>5.0	–	52–58
	PFN	–	–	<5.0	–	>58
	RFN	–	–	<5.0	–	52–58
	DFD	–	–	<5.0	–	<52
Van Laack et al. (1996)	PSE	<5.5	–	>5.0	>50	–
	RSE	<5.9	–	>5.0	43–49	–
	RFN	5.4–6.0	–	<5.0	43–49	–
	DFD	>6.0	–	<2.0	<43	–
Warner et al. (1997)	PSE	<6.0	–	>5.0	>50	–
	RSE	<6.0	–	>5.0	42–50	–
	RFN	<6.0	–	<5.0	42–50	–
	DFD	≥6.0	–	<5.0	<42	–
Van Laack and Kauffman (1999); Kauffman et al. (1993)	PSE	–	–	>6.0	>50	–
	RSE	–	–	>6.0	<50	–
	RFN	–	–	<6.0	<50	–
Faucitano et al. (2010)	PSE	<6.0	≥80	≥4.76	>50	–
	PFN	<6.0	<80	<4.76	>50	–
	RSE	<6.0	≥80	≥4.76	43–48	–
	RFN	<6.0	<80	<4.76	43–48	–
	DFD	≥6.0	<40	<2.2	<42	–
Barbin et al. (2012)	PSE	5.45 ± 0.08	–	7.0 ± 1.5	53.1 ± 1.7	–
	RFN	5.59 ± 0.15	–	3.8 ± 0.6	47.2 ± 2.8	–
	DFD	6.11 ± 0.19	–	0.6 ± 0.2	39.2 ± 1.9	–

DL (drip loss); *FPW* (filter paper wetness); DFD (dark, firm, dry); PFN (pale, firm, non-exudative); PSE (pale, soft, exudative); RFN (red, firm, non-exudative); and RSE (red, soft, exudative).

hyperparameters in the algorithm by considering the full training set as the classifier model.

3. Results and discussion

The meta-model derived to meta-recommend the adequate pork quality standard displayed a high-performance level for carrying out its task. An accuracy of 100% is related to the recommending of suitable standards for real and synthetic datasets in all cases. The coefficient of agreement (Kappa) presented the maximum value, demonstrating the trustworthiness of the model performance and validating that the result interpretation is legitimate and not by chance (Cohen, 1960). The 140 instances were correctly classified and the robustness and precision of the meta-recommendation model generated were confirmed. The meta-features selected could distinguish each standard in the literature to perform the recommendation.

Another important achievement was a concise *DT* as shown in Fig. 1. The obtained *DT* was not complex; as it is based on only 4 meta-features, it is possible to recommend a pork quality standard.

The root node was composed by the meta-feature *L** Kurtosis; this was followed by the intermediary nodes (*WHC* Skewness, *Entropy* and L* Maximum). Each leaf presented the most standard to classify the pork quality for the dataset in this study.

A possible explanation for the selection of *L** as the most important meta-feature of *DT* is its contemplation in all classification standards (Table 1). In addition, *L** is the result of the behavior of *pH* and *WHC* (Pearce, Rosenvold, Andersen, & Hopkins, 2011).

The idea of cause and consequence between parameters and their effects on pork quality is evident, as a high correlation exists between *pH* and *L** (Boler et al., 2010; Kim et al., 2016; Wyrwisz, Półtorak, Zalewska, Zaremba, & Wierzbicka, 2012).

Considering a hypothetical situation in which the *pH* decreases during postmortem metabolism, the *WHC* will be smaller. This can be explained because the *pH* condition of the pork, when approaching the isoelectric point of the myofibrillar proteins, causes the neutralisation of the positive and negative charges. This reduces the intracellular space, resulting in a greater amount of exudates on the surface of the meat (Bowker & Zhuang, 2015; Lawrie, 2006). This alteration of the myofibrillar structure affects the light scattering properties. Further, the pork becomes lighter (Hughes, Oiseth, Purslow, & Warner, 2014). Moreover, the opposite is also true.

Some insights into the pork standard behaviour were obtained by observing the DT structure. The most recent standards (Barbin et al. (2012) and Faucitano et al. (2010)) present a different split of *L** maximum from the others, based on the *L** defined threshold alone. However, the former standards (Kauffman et al., 1993; Van Laack et al., 1996; Warner et al., 1997) can be identified by observing the entropy meta-feature of a given dataset alone.

The proposed classification system is the first approach with a potential implementation scope at the industry level. According to the new definition of meat quality categories, this model should evolve according to the new definitions,

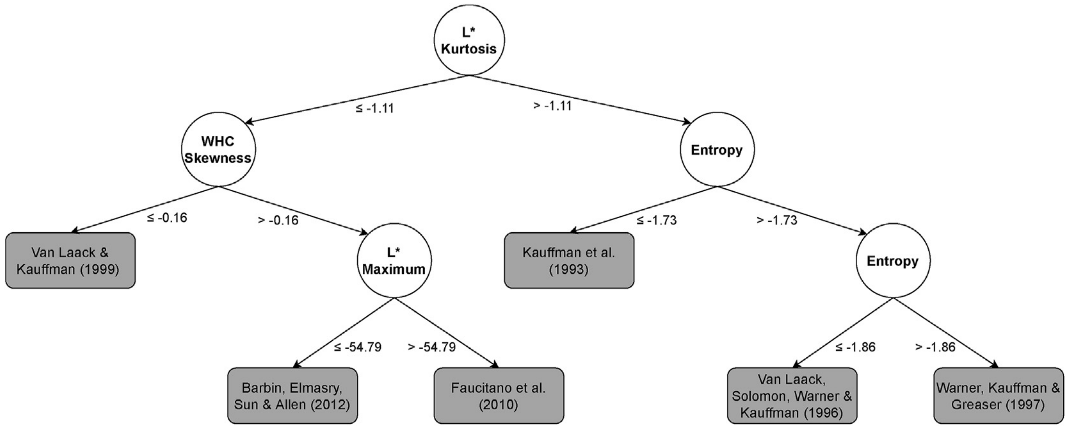

Fig. 1 – Decision Tree (J48) to recommend the most suitable pork quality standard.

adding other parameters that could improve the success in sorting carcasses and cuts according to meat quality. This could allow the meat and meat product industry to apply different models according to differences in intrinsic sources of pork variation, such as genetics, production system, or ante-mortem treatment, and match the demands from meat processors and consumers. It would also enable a better understanding of the possible causes leading to a higher incidence in low meat quality categories, enabling decisions to be made with a standardised and objective method.

Applying the meta-recommendation procedure enables a multivariate approach to quality classification in the meat industry. By integrating meat quality data with inputs related to pig genetics, the type of production system or ante-mortem treatment, among others, leads to a better match between the market and consumer demands, which affect, to an ultimate extent, the economic sustainability of the meat industry. The benefits delivered by using a suitable quality classification go beyond the optimisation of carcass classification by reducing the number of unfeasible carcasses. The suggested standard can reveal possible marketplaces and customers as each proposed standard has been established by observing the thresholds of normality grounded on a particular breed and pork marketing strategy.

Using the DT provided by the recommendation system, the industry can follow the path employed to derive the recommendation for obtaining insights about the attribute interval used to identify the suggested pattern. In other words, it is possible to comprehend the attributes that interfere with the final recommendation for managing procedures that can settle this parameter, such as pre-slaughter stress and animal welfare strategies to handle WHC and L^* values.

4. Conclusion

Meat quality evaluation is essential in the food industry. However, the following question arises: "What is the adequate technological quality standard to classify a given pork sample?". Herein, we exploited meta-learning to answer this question and provided insights into pork quality standards. Using meta-features extracted from a dataset of pork quality parameters, we could build a *DT* meta-model that could recommend, in all experimental cases (140 datasets), the right standard among the six possibilities. Furthermore, some peculiarities and assumptions of the current literature models could be made. Hence, our proposal contributes to the selection of the most suitable standard for presenting more reliable results regarding sample classification. Thus, after this first successful approach of applying a meta-grading system for meat quality classification, further research should consider the link with sensory attributes, allowing the industry to better match consumer demands with a broader scope of meat quality perception.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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