Computers and Electronics in Agriculture 150 (2018) 455–464

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Fuzzy approach for classification of pork into quality grades: coping with unclassifiable samples

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A R T I C L E I N F O

Keywords:
Classical logic
Classification
Computational intelligence
Fuzzy Logic
Meat
Pattern recognition

A B S T R A C T

Meat classification methods are commonly based on quality parameters standardized by numeric ranges. However, some animal samples from different production chains do not match the current grades proposed. These unclassifiable samples are not capable to fit into a standard created by crisp range of values due to being infeasible toward its definition. An alternative to handle this kind of sample classification is the fuzzy logic, which could deal with uncertainty and ambiguity degree like human reasoning. In this work, we compare the traditional classification method and fuzzy approaches with the objective to handle the infeasible samples. This was compared to traditional pork standards using eleven real-life datasets with a total of 1798 samples described by *pH*, water holding capacity and/or L^* value. The results demonstrated that traditional classification could not predict the unclassifiable samples. On the other hand, the fuzzy approaches improve significantly the number of classified samples. Performance of the fuzzy approaches were compared with several machine learning algorithms, but no significant statistical difference was observed. Finally, a real-life study case was explored, highlighting some advantages and further achievements of the fuzzy modeling.

1. Introduction

Meat quality has been increasingly important as a large supply chain, and it raises concerns of demanding consumers (Węglarz, 2010; Campos et al., 2014).

The widely used parameters concerning pork quality are *pH*, water holding capacity (*WHC*), color and firmness. These parameters are determined according to standards, which differ from each other as a combination of subjective and objective measurements that vary according to the markets (USA, 2003). The *pH* is one of the most important factors in the conversion from muscle to meat (Dutson, 1983). *WHC* refers to the meat ability to retain water during the application of force (compression, drip loss, shear) or external treatment (Huff-Lonergan and Lonergan, 2005; Silva Sobrinho et al., 2005) and influence meat succulence. And meat visual aspect, e.g. color intensity, also covers important features for quality evaluation as it is related to initial product choice and acceptability. Hence, color feature has a straightforward relation to consumer perceptions (Fletcher, 1999). There is a high variation in pork quality (Bauer et al., 2013), since variations have been observed between quality parameters. Thus, some experiments led to an inaccurate evaluation of the pork quality (Warriss and Brown, 1987; Van Laack et al., 1994).

Several quality standards have been proposed to evaluate pork in the industry: Barbin et al. (2012) and Tomovic et al. (2014) include three classes of pork quality, Warner et al. (1997) and Joo et al. (2000) propose four classes, Kauffman et al. (1993) and Faucitano et al. (2010) propose five classes, while Bauer et al. (2013) suggests 8 classes. The main classes described in the literature are *PSE* (pale, soft, exudative), *PFN* (Pale, firm, non-exudative), *RSE* (red, soft, exudative), *RFN* (red, firm, non-exudative) and *DFD* (dark, firm, dry), resulting from the combination of *pH, WHC* and/or L^* value.

However, even with several classification standards proposed, pork meat classification remains a challenge due to the strict values (crispness) of each quality parameter. For example, in the study of Faucitano et al. (2010), 14% of loins evaluated could not be classified according to the quality criteria used, being considered infeasible samples, because

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https://doi.org/10.1016/j.compag.2018.05.009
Received 30 August 2017; Received in revised form 21 February 2018; Accepted 7 May 2018
0168-1699/

these did not match the standard's parameters. Infeasible samples could be simply discarded, or manually converted, when possible (Chen and Li, 2010).

The problem persists even for new standards proposed (Adorni et al., 2001). All the proposed classifications are formed by rigid thresholds that are different from each standard, and use classical logic to deal with the pork samples. In other words, if a pork sample does not match a given quality class, it cannot be classified, becoming an infeasible sample. This fact increases the difficulty to classify a sample that does not adjust in the expected parameter interval.

Classical set theory establishes crisp limits. Therefore, an element may or may not belong to a determined set. In fuzzy sets, there is a membership degree of each item to a determined set, that makes a gradual transition between full membership and no membership (Jensen and Shen, 2008; Coutinho et al., 2015).

There have been several approaches to deal with this issue. The most prominent are using the fuzzy logic (Moore and Lodwick, 2003), that has been a valuable tool in the study of various physical and biological phenomena (Sunita and Deo, 2012). The fuzzy logic kernel is capable of modeling the uncertainty, handling quantitative data with ambiguity degree like human reasoning (Lodwick, 2002; Vásquez-Villalobos et al., 2015). Much of the research to date has been in the use of interval mathematics in fuzzy set theory, in particular, fuzzy arithmetic and fuzzy interval analysis (Lodwick, 2002).

Nowadays, one of the most used implementations of fuzzy algorithms is Fuzzy Rule-Based System (*FRBS*) package from R. This solution was applied with success for storage time prediction of pork meat in comparison to sophisticated machine learning (*ML*) solutions as Random Forest (*RF*), Artificial Neural Networks (*ANN*) and Support Vector Machine (*SVM*) and the results showed that, although *RF* was the best one, *FRBS* also presented significant performance, reaching 93.93% of accuracy (Barbon et al., 2016).

In the current study, we propose to evaluate three different implementations of four pork quality grading standards according to Kauffman et al. (1993), Warner et al. (1997), Joo et al. (2000) and Faucitano et al. (2010). These standards are based on *pH*, *WHC* and L^* value. The fuzzy models were built for each grade, and the classification results compared against the classical logic aiming to improve the capability of the pork quality standard to handle the infeasible samples.

There are several methods to fuzzy logic modeling (Hüllermeier, 2015). We investigated three model constructions: classical logic, fuzzy top-down and fuzzy bottom-up approaches. Classical logic is based on the grade's rule composed of crisp limits. Top-down is a manual fuzzy classification model designed by human experts, where the limits and degrees need to be designed by adapting the crisp limits. Bottom-up is the fuzzy classification model induced by a *ML* supervised approach, also called as data-driven. In this last method, the relationships, limits and degrees between dependent and independent parameters are obtained automatically based on labeled datasets.

Therefore, we introduced the fuzzy modeling to pork quality assessment capable of enhancing the number of samples classified. This was accomplished through fuzzy classification of the infeasible samples obtained from crisp grade.

2. Materials and methods

2.1. Pork quality standards

Our classification experiments were based in four standards already described in the literature: Kauffman et al. (1993), Warner et al. (1997), Joo et al. (2000) and Faucitano et al. (2010), using the *pH, WHC* and/or lightness (L^* value) parameters (Table 1).

Pork samples (n = 1798) were collected and *pH*, *WHC* and lightness (L^*) parameters were measured in the *longissimus dorsi at lumborum* muscle, between the penultimate and last ribs of the left half of cooled carcasses (2 ± 2 °C) 24 h after slaughter.

Table 1
Pork quality standards used in the experiments PSE (pale, soft, exudative); PFN (pale, firm, non-exudative); RSE (red, soft, exudative); RFN (red, firm, non-exudative); DFD (dark, firm, dry).

Standard	Class	pHu	WHC	L^*
Kauffman et al. (1993)	PSE	–	> 5	> 58
	RSE	–	> 5	52–58
	PFN	–	< 5	> 58
	RFN	–	< 5	52–58
	DFD	–	< 5	< 52
Warner et al. (1997)	PSE	< 6	> 5	> 50
	RSE	< 6	> 5	42–50
	RFN	< 6	< 5	42–50
	DFD	⩾6	< 5	< 42
Joo et al. (2000)	PSE	–	⩾6	⩾50
	RSE	–	⩾6	⩽50
	RFN	–	⩽6	⩾43
	DFD	–	⩽6	⩽43
Faucitano et al. (2010)	PSE	< 6	⩾4.76	> 50
	PFN	< 6	< 4.76	> 50
	RSE	< 6	⩾4.76	43–48
	RFN	< 6	< 4.76	43–48
	DFD	⩾6	< 2.2	< 42

Ultimate *pHu* was measured 24 h *post mortem* using a Testo 205 pH-meter; *WHC* was measured by pressing method (*PM*) proposed by Hamm (1960) and adapted by Wilhelm et al. (2010), while L^* value (lightness) was acquired with a Minolta R portable colorimeter (model CR-10 colorimeter with illuminant D65 and 8° angle of inclination - Tokyo, JP) after blooming for 30 min (CIE, 1978).

Some quality standards consider different methodologies for *WHC* and L^*. Hence, *WHC* was also converted, as Kauffman's and Faucitano's standard used pressing method (*PM*) and filter paper wetness (*FPW*), respectively. This conversion was carried out in order to compare results from different classification standards. Normalized drip loss (*DL*) parameter was performed using Eqs. (1) and (2) as proposed by Peres et al. (2011). L^* was converted from HunterLab to CIELab⁎ for Kauffman's standard as exposed in Eqs. (3)–(5). In these equations, Y represents the luminance, X and Z are the chromatic values (Billmeyer and Hammond, 1990).

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

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

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

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

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

2.2. Organization of the experiments and datasets

Three classification approaches were performed (Fig. 1): classical logic (Experiment 1), top-down considering fuzzy logic (Experiment 2) and fuzzy bottom-up and *ML* algorithms (Experiment 3). Experiment 1 was performed to obtain the classification and the number of unclassified samples. Experiment 2 was carried out to observe the behavior of fuzzy top-down approaches (designed by a specialist) for classifying all real-life datasets, mainly the unclassified samples observed in Experiment 1. Finally, Experiment 3 was carried out to observe the capacity to deal with the infeasible samples using *ML* algorithms.

For the three aforementioned experiments, we considered two dataset profiles: eleven real-life and four synthetic datasets. In total there were fifteen datasets, eleven real-life and four synthetic datasets