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Storage time prediction of pork by Computational Intelligence

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ABSTRACT

In this paper, a storage time prediction of pork using Computational Intelligence (CI) model was reported. We investigated a solution based on traditional pork assessment towards a low time-cost parameters acquisition and high accurate CI models by selection of appropriate parameters. The models investigated were built by J48, Naïve Bayes (NB), k-NN, Random Forest (RF), SVM, MLP and Fuzzy approaches. CI input were traditional quality parameters, including pH, water holding capacity (WHC), color and lipid oxidation extracted from 250 samples of 0, 7 and 14 days of post mortem. Five parameters (pH, WHC, L^*, a^* and b^*) were found superior results to determine the storage time and corroborate with identification in minutes. Results showed RF (94.41%), 3-NN (93.57%), Fuzzy Chi (93.23%), Fuzzy W (92.35%), MLP (88.35%), J48 (83.64%), SVM (82.03%) and NB (78.26%) were modeled by the five parameters. One important observation is about the ease of 0-day identification, followed by 14-day and 7-day independently of CI approach. Result of this paper offers the potential of CI for implementation in real scenarios, inclusive for fraud detection and pork quality assessment based on a non-destructive, fast, accurate analysis of the storage time.

1. Introduction

The parameters involving meat quality are of most importance for the meat processing industry. Research projects are often developed to assess improvements in measurements and quality assessments, as well as factors that influence pork quality such as environmental conditions, pre-slaughter management and purchasing decisions of consumers (Rosenvold and Andersen, 2003). A perspective of pork quality evaluation is based on the muscle to meat conversion. This process includes several enzymatic and protein denaturation processes that directly influence pH and other quality attributes (Salmi et al., 2012). These parameters are play a major role on quality and are related to post mortem period, mainly because the rate of glycolysis, affecting the technological quality of meat (Hammelman et al., 2003).

Determination of post mortem period is relevant for the industry because it allows identification of aging period and freshness evaluation, as well as indicating the consumer preferences. Another advantage is to identify potential fraud during the food storage period. Besides, it can indicate storage problems as temperature deviation in cold rooms, freezers, and refrigerators that can lead to meat deterioration and shelf-life reduction.

Nowadays, consumers are more demanding for food quality, as they are looking for clear and reliable information about product origin, production method and food preservation (Sentandreu and Sentandreu, 2014).

Fraud in the meat sector is constantly described and (Ballin, 2010) describes that fraud can be categorized according to the possibility of occurrence: origin of meat, meat replacement, and meat processing. Moreover, within each of these frauds there are subcategories: post mortem period, meat cuts, animal breed, meat freshness, among others.

However, during post mortem period, some meat quality parameters may be modified, e.g. pH, Water Holding Capacity (WHC), color and lipid oxidation (Tarsitano et al., 2013). The Meat freshness determines the choice of the product by the consumer (Xiong et al., 2015). Moreover, this assessment is also measured by quality parameters mentioned before, and depends directly on the storage time. Nonetheless, laboratory evaluation parameters are costly, time consuming, dependent on trained persons and subjective evaluation. In this context arise alternative methods and non-destructive analysis of food using computational tools (Chen et al., 2011).

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The use of Computational Intelligence (CI) for food quality classification has been widely discussed (Kodogiannis and Alshejari, 2014; Shan et al., 2015; Przybylak et al., 2015; Ravikanth et al., 2015; Zapotoczny et al., 2016). The main advantage of CI is the capacity of handling multiple parameters, facilitating the evaluation in an industrial environment; being faster; more accurate; not requiring reagents that could damage the environment and having low costs (Qiao et al., 2007).

Among the various techniques of CI for assessing the food quality, some standout, e.g. Clustering Algorithms (CA), Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Fuzzy Rule-Based Systems, Multilayer Perceptron Neural Network (MLP) and others (Liu et al., 2013).

Some of these techniques have been applied to several kinds of food quality research, mainly on prediction and classification tasks. Often combined or not, CI techniques have been widespread for evaluating spoilage, defects, fraud or predict the most important quality parameters to assess the meat (Kamruzzaman et al., 2013; Argyri et al., 2013; Liu et al., 2014; Ropodi et al., 2015).

The aim of this paper was to classify the pork storage time through the use of CI techniques (J48, Naïve Bayes, k-NN, Random Forest, SVM, MLP and Fuzzy approaches) and to investigate the most appropriated method to perform the meat quality classification by traditional parameters (pH, color, WHC and TBARS). Secondly, it was observed which quality parameters were relevant and capable to provide the identification of storage time.

This paper is organized as follow: Section 2 presents the Materials and Methods of this work, followed by Section 3 which presents experiments results and discussions they promote. Conclusions and closing remarks can be found in Section 4.

2. Materials and methods

2.1. Data samples and analytical measurements

The samples used in our experiments were obtained from pigs slaughtered in Federal Inspection and transported to the Food Analysis Laboratory (LANA) at UEL, Londrina, Brazil for further analysis. Data samples were about two hundred and fifty (250) of *longissimus dorsi et thoracis* muscle from different animals. The samples were vacuum packed and stored at 1 °C for periods of 0, 7 and 14 days.Considering the quality parameters, the pH, color (CIELab), WHC and lipid oxidation (TBARS) value were chosen to describe the samples.

The pH was measured 24 h after cooling (ultimate pH) with insertion electrodes into the meat sample using TESTO 205 pH meter (TESTO, Hampshire, UK).

After a 30 min blooming period, the color was obtained as the average of 3 consecutive measurements at random locations of samples using the Colorimeter (Konica Minolta Color reader CR10) calibrated against a standard white tile. The color was expressed in terms of values for lightness (L^*), redness (a^*), and yellowness (b^*) using the Commission Internationale de lEclairage (CIE) color system (de lEclairage, 1978; Honikel, 1998).

The evaluation of WHC was measured by water pressure loss technique according to described by Barbut (1996). In this analysis, 2 g of sample was weighed in a semi-analytical balance. This sample was placed between two paper filters and two acrylic plates and then applied a weight of about 10 kg for 5 min under the sample. After the pressing time, the weight of the sample was checked again to calculate losses.

The lipid oxidation were analyzed by the methodology indicative of thiobarbituric acid reactive substances (TBARS) described by Pikul et al. (1989).

Statistical information of traditional parameters for the Dataset is exhibited in Table 1. The Dataset was composed by 208 pale, firm, and non-exudative (PFN) samples and 42 red, firm, and non-exudative (RFN), classified based on Faucitano et al. (2010).

Table 1
Statistical summary of entire Dataset (storage times 0, 7 and 14) composed by 250 samples.

Parameter	Mean	St. Dev.	Min	Max
L	52.292	2.252	47.000	56.600
a^*	5.238	1.186	2.700	8.800
b^*	13.191	1.511	10.000	17.900
WHC	26.740	3.126	20.020	34.520
pH	5.716	0.137	5.350	6.020
TBARS	0.446	0.122	0.109	1.136

In this work, we employed statistical tests and information theory-based aiming the same. Pearson's statistical correlation was applied to depicts linear relationships, and Spearman's correlation was computed to discovering monotonic relationships, both between storage time and each parameter. Considering information's theory approaches we computed: Information Gain (*IG*), Gain Ratio (*GR*) and Symmetrical Uncertainty (*SU*), all based on Shannon Entropy (*H*) are showed in Table 2, where *P* is the parameter, *A* is the storage time and *p* the probability of *P* showing up in a specific storage time. Chi^2 was applied to test the independence between the storage time and quality parameters. Correlation Feature Selection (CFS) was used to obtain the best subset based on individual attributes using the symmetrical uncertainty based on subset merit (Yu and Liu, 2004). Subset merit, $Merit_s$, is calculated as in Table 2, where *s* is the subset composed by *k* features, r_{cf} is correlation between feature and class based on entropy, and r_{ff} is the inter-correlation between features.

2.2. Pork quality parameters

2.2.1. pH

The evaluation of pH value in fresh meat is one of the most important parameters to measure the meat quality and in many situations influence on other parameters such as WHC, color and shelf life. The rate of pH decline will dictate the final quality features during the post mortem period, and may modify the storage time meat (Liao et al., 2012).

Holmer et al. (2009) reported regression equations to predict the shelf life of pork in a certain pH range for 28 days. In this study, researchers assert that the pH might interfere with the shelf life after post mortem time and that regression equations could predict that higher pH with longer days of storage of meat had shorter shelf life.

2.2.2. CIELab color system

Color is an important attribute that relates to the first consumer perceptions about the meat quality at the time of purchase of the product (Chmiel et al., 2011).The color of the meat comes from main factors, myoglobin, hemoglobin and cytochrome C (Mancini and Hunt, 2005). In general, the color is measured objectively using a colorimeter device and the most common evaluation system is

Table 2
Entropy-based metrics and Merit for parameters evaluation.

Metric	Equation
Entropy	$H(P) = -\sum_{x=P} p(x) \log p(x)$
Information Gain	$IG(P,A) = H(A) + H(P) - H(A\|P)$
Gain Ratio	$GR(P,A) = \frac{H(A)+H(P)-H(A\|P)}{H(P)}$
Symmetrical Uncertainty	$SU(P,A) = \frac{H(A)+H(P)-H(A\|P)}{H(P)+H(A)}$
Merit	$Merit_s = \frac{k(r_{cf})}{\sqrt{k+k(k-1)(r_{ff})}}$