APPLICATION OF VISIBLE/NEAR INFRARED SPECTROSCOPY TO BEEF LONGISSIMUS TENDERNESS CLASSIFICATION BASED ON ARTIFICIAL NEURAL NETWORK

Juliana M. Balage[1], Madeline R. Mazon[1], Daniel S. Antonelo[1], Keni E. Z. Nubiato[1], Delaila J. Brigida[1] and Saulo da L. e Silva[1]

[1] FZEA/USP. Av. Duque de Caxias Norte, 225 - Campus da USP - CEP 13635-900 - Pirassununga/SP-Brazil

Abstract – The potential of beef tenderness classification from VIS/NIR spectra has been studied. Therefore, 73 carcasses were ribbed between 11th and 12th ribs and one sample of 2.5 cm thick of the *Longissimus* muscle was taken. VIS/NIR spectra were collected in the chilling room over the samples and the samples were used to Warner-Bratzler shear force (WBSF) reference analysis. Artificial neural networks (ANN) algorithm was applied to classify beef samples into tender (WBSF <50 N) or tough (WBSF ≥50 N) groups. Two ANN classification models were evaluated, one using the full spectra data set (200 wavelengths) and a reduced one, containing only the important wavelengths (25). The models were evaluated using leave-one-out cross-validation and had a classification accuracy of 90% and 92%, respectively. These results indicates that VIS/NIR spectra could be used to classify beef tenderness in the chilling room conditions.

Key Words: Meat quality, NIR.

I. INTRODUCTION

Tenderness is an important meat quality attribute and is directly linked to consumers eating satisfaction, which are the main criteria in repurchase act [1]. Brazil is an important player in the international market of beef meat and the development of a system that identifies tough and tender carcasses online can be of great importance to industry that could sort carcasses in tenderness groups and thus, increase consumer satisfaction.

In practice, tenderness is measured by means of slow and destructive methods, either by sensory profiling or by mechanical techniques [2].

Recently, the near infrared (NIR) spectroscopy has been successfully used for classification purposes in several species [3, 4, 5]. NIR has demonstrated its potential a sensitive, fast, non-destructive analytical technique for estimating quality attributes of meat [6], that with minimal or no sample preparation provides information about the molecular bonds of organic compounds and tissue ultra-structure in a scanned sample [3].

Some meat features as tenderness, are related to both linear factors (content of myofibrillar proteins) and nonlinear factors (muscle structure - connective tissue). In this case, not only linear but also non-linear methods should be used to build predictive and classification models [7]. However, it is found that most of the studies have used linear methods such as PLS and MLR to establish the models [4, 5].

Artificial neural networks (ANN) is a powerful and flexible non-linear classification algorithm and has been applied to solve classification problems of NIR spectra data [8, 9].

The objective of this study was to explore the potential of VIS/NIR spectra associated to ANN classification algorithm to classify beef samples into two tenderness groups.

II. MATERIALS AND METHODS

Sample collection

Seventy-three Nellore steers (314±7.12 kg of hot carcass weight) were slaughtered at Experimental Abattoir of Sao Paulo University, in accordance to Humanitarian Slaughter Guidelines as required by Brazilian law and carcass processing followed the common industry practices adopted in Brazil. After twenty-four hours of chilling at 2°C carcasses were ribbed between 11th and 12th ribs and one sample of 2.5 cm thick of the *Longissimus* muscle (LM) was taken, from cranial to caudal direction for reference analysis.

Warner Bratzler Shear Force Analysis

Tenderness was determined using the WBSF method, according to AMSA recommendations [10]. Samples were cooked in an electric oven to a flipped over and cooked to a temperature of 71°C. Samples were cooled to room temperature and were wrapped in plastic film and cooled in a refrigerator (2-5 °C) overnight. The WBSF was determined from six replicates (1.27-cm diameter) with fiber direction parallel to the longest dimension of the strip and perpendicular to the direction of the blade using WBSF equipment (G-R Manufacturing Co., Manhattan, KS, USA) equipped with a Warner–Bratzler blade. The WBSF value was the average of six measurements.

Spectroscopy analysis

Spectra were collected in the chilling room immediately after quartering the carcasses over the LM, between 11th and 12th ribs surface, using a portable spectrophotometer composed by two units (model EPP2000-CXR-Srs and EPP2000-InAs-512, Stellarnet Inc., Florida, USA) connected with a bifurcated optical cable resulting in a single reading from 400 to 1,395 nm. A white reflectance standard was used to create a reference for the measurements. Light was supplied by a 20-W halogen light source and a diffuse reflection. Spectral resolution was set to 5nm and the spectrometer scanned 20 times per reading in reflectance mode, and spectra were averaged by SpectraWiz software (Stellarnet Inc., Tampa, FL). Each sample was scanned three times at different locations throughout the LM sample.

Spectra preprocessing, outliers and compression

Spectral data was imported to The Unscramble®X 10.3 software (CAMO Software AS, Oslo, Norway) and principal component analysis (PCA) was performed on data matrix in order to visualize any separation, detect grouping and samples outliers. Before model development, data preprocessing, outlier detection and data compression is normally need in order to create an effective and robust model. In this study, standard normal variate (SNV) spectra preprocessing was applied to remove slope variation and correct light scatter effects in beef samples [8]. The Martens' uncertainty test was conducted for selection of the most informative wavelengths (WL) [11].

Samples were categorized into two groups of interest: tender and though according with the WBSF (<50 N, tender and ≥50 N, tough). An ANN was trained using collected spectra and the two groups of interest. A multi-layer perceptron using back-propagation and a sigmoid activation function was applied. The ANN was built using the Weka (Waikato environment of knowledge analysis) data mining software [12].

III. RESULTS AND DISCUSSION

The WBSF of samples ranged from 21.71 to 101 N (62.42 ± 19.07 N) and 48 samples were classified as tough samples (WBSF≥55 N). The mean spectra for tender and tough samples from 400 to 1395nm are presented in Figure 1. Opposite to previously reported in the literature [4, 5], spectra of tender samples were more reflective along wavelengths when compared to tough samples. These differences were noticeable from 405nm to 460nm and from 490 to 590nm, but kept fairly far from each other from 670 to 1,395nm.

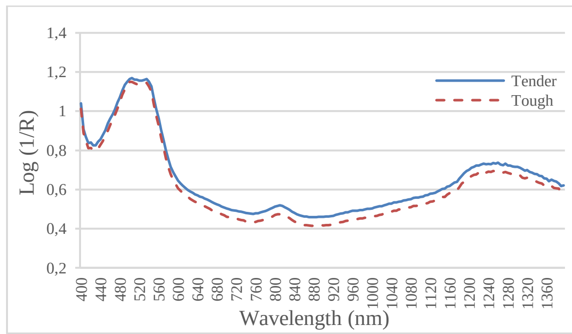

Figure 1: Vis/NIR spectra of intact beef *Longissimus* for two WBSF ranges: 'Tender' WBSF <50 N and 'Tough' WBSF ≥50 N.

In their study with lamb, Andrés et al. [13] also observed higher absorbance values for the most tender samples, but only in the visible range (400-950 nm). According to the authors, a possible explanation for this event may rely on the fact that variations on pH could affect the ability of the meat to scatter the light, because this variations on pH can alter the oxidation process of heme pigments, thus the ability of the pigment absorb light is altered. Nevertheless, this inversion in absorbance values for tender and tough classes found in this study should be investigated on a deeper level before stronger assumptions.

Figure 2 represents the score plot for PCA from non-preprocessed spectra and it shows that there is no particular grouping between tender and tough sample classes. The first and second principal components (PCs) explained 91% and 6% of the spectral variance, respectively.

The presence of outliers might have important adverse impact on model's performance [9], however, no evident outliers were found in this study data set (Figure 2).

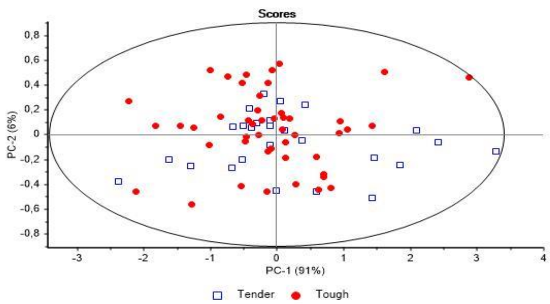

Figure 2: PCA score plot of first and second principal component of VIS/NIR spectra. The ellipse represents the Hotelling's T^2 statistics (p-value of 5%).

The ANN classification models were built using the full spectra data set (200 WL) and the reduced one, containing only the important WL selected in the Martens' uncertainty test (25 WL - 430, 435, 455, 480, 495, 510, 525, 530, 795, 960, 1010, 1175, 1180, 1190, 1200, 1215, 1225, 1235, 1250, 1275, 1285, 1310, 1325, 1365, and 1385). The Martens' uncertainty test was applied as a way to simplify the model and make it more reliable [10].

Some parameters of ANN such as the number of neurons in the hidden layer, learning hate, momentum factor and initial weigh are crucial on the performance of final model [8]. For both spectra set (200 WL and 25 WL), the number of hidden layers set was (a+c)/2, where 'a' is the number of input features and 'c' is the number of decision classes (2 groups); and the training time was set to 10,000 epochs. The learning rate was set to 0.4 and 0.1 for the 200 WL and the 25 WL spectra set, respectively. The generated models were evaluated using leave-one-out cross-validation.

Table 1 presents the results of the ANN classifier for both spectra data sets. Using the full spectra collection, the ANN classifier had an accuracy of 90% and 0.3169 of root mean square error (RMSE), and when selecting the most informative WL, the accuracy increased to 92% and RMSE decreased to 0.2784. The ANN algorithm benefits from a lower dimensional feature space, ie it generalizes better the given information to construct the classification models. This could explain why the slightly better result for the reduced model.

These results indicate that ANN might be a promising way to classify beef meat into tenderness groups, even with a reduced number of WL used in classification model. It is especially important when developing models to use online, because the scanning time can be decreased significantly, once fewer WL are used to build the classification model.

The high variation of equipment used for spectra acquisition and different treatments applied in developing classification models over the different studies makes difficult to establish a direct comparison between the results. Moreover, this becomes even more difficult because, to our knowledge, there is no published work attempting classify meat tenderness using ANN based on VIS/NIR spectra.

However, if considered in a general way with the results of tenderness classifier based on VIS/NIR data, the results observed in this work are in accordance with reported by the literature [4, 5].

Park et al. [4] classified beef from the results of PLS models and the observed overall accuracy of the classification was 79%. Liu et al. [5] also classified beef steaks from VIS/NIR spectroscopy based on predicted/measured WBSF values and the observed overall accuracy of the classification was 83% for PLS based model and 96% for SIMCA/PCA (Soft Independent Modeling of Class Analogy of Principal Component Analysis). It is important to point out that all these authors subjected the beef samples to different ageing times to increase the variability of structural properties of the muscle fibers.

IV. CONCLUSION

This study indicates that VIS/NIR spectra and ANN classification algorithm has high potential to classify beef longissimus tenderness at chilling room conditions.

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Table 1: Results of the VIS/NIR spectra and ANN tenderness classifier.

#	RMSE			Predicted Tender	Predicted Tough	Accuracy[1]	Precision[2]	Recall[3]	F-Measure[4]
25	0.2784	Reference	Tender	21	4	92%	91%	84%	87%
			Tough	2	46		92%	96%	94%
200	0.3169		Tender	19	6	90%	95%	76%	84%
			Tough	1	47		89%	98%	93%

Number of wavelengths used to build the model. RMSE means root mean square error. [1]Accuracy: is the percentage over the number of correctly classified samples. [2]Precision: is the fraction of retrieved instances inside a class, which were correctly classified. [3]Recall: fraction of instances belonging to the class that were retrieved inside this same class. [4]F-Mearure: harmonic mean of precision and recall.

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