Hyperspectral Imaging for Beef Tenderness Assessment

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Abstract: Tenderness is one of the principal properties of meat quality. The traditional way to measure tenderness the beef is time consuming and also destructive, and therefore not appropriate for rapidly identifying quality parameters on the processing line, with the minimum of human intervention. The objective of the present research was to measure the tenderness of cooked beef samples obtained from four types of muscles (*i.e. infraspinatus* (TB), *gluteus medius* (TS), *psoas major* (TL), and *longissimus thorasis* (RE)) at three different durations of dry aging (Fresh (0 days), 14 days, and 21 days), using near infrared hyperspectral imaging. Hyperspectral reflectance spectra (900 nm $<\lambda<$ 1700 nm) were acquired for a total of 260 beef steak samples with dry-ages of 0, 14 or 21 days. After imaging, samples were cooked and the Warner-Bratzler shear force (WBSF), a parameter inversely related to meat tenderness, was measured. After reflectance calibration, a region of interest (ROI) was selected from each acquired hyperspectral image and stepwise regression was applied to the ROI to select wavelengths that were strongly related to cooked meat tenderness. Multiple Linear Regression (MLR) calibration models were developed for quantitative evaluation of beef tenderness. The correlation coefficient (R) and the root mean square error ($RMSE$) were employed to evaluate the calibration model's predictive ability for each group. The calibration model developed predicted tenderness with R values of 0.89, 0.86, 0.81 and 0.83 for TS, RE, TB, and TL, respectively. The results revealed that the HSI could be used for non-destructive measurement of beef tenderness in beef having undergone three different durations of aging.

Keywords: Hyperspectral imaging, Tenderness, Beef, Meat quality, Warner-bratzlershear force, dry-aging, Multiple linear regression.

1. INTRODUCTION

Meat quality is determined by a combination of factors including intramuscular fat, marbling, water absorption, muscle fiber structure, pH, and the quality at the time of eating, as indicated by tenderness, juiciness and flavor [1]. The visual appearance, texture and color of raw meat are important decision factors for consumers in purchasing meat. These factors are linked to chemical parameters such as marbling, water and protein contents. One of the primary beef quality attributes determining consumers' acceptance of meat is tenderness, and it is therefore of utmost importance for the meat industry to produce meat of good quality which is safe to consume.

Existing meat quality assessment methods still rely largely on visual judgment, which is unfortunately subjective and time consuming. Therefore, there is a crucial need in the meat industry for a fast, accurate and non-destructive approach to determining beef quality [2]. Recently, many objective spectroscopic and imaging methods have been developed and successfully applied to assessing meat quality [3-6]; however, these do not provide detailed information about the samples [7, 8].

Hyperspectral imaging is an emerging technology now being used for real-time, robust and non-destructive inspection and quality evaluation of food and agricultural products [9-14]. Hyperspectral imaging combines the advantages of conventional imaging and spectroscopy, and simultaneously obtains spectral and spatial information from the object to determine its quality [13-15]. Therefore, it is possible to find out a number of important attributes, characteristics or diagnostic features through the surface reflectance spectra of food products.

Hyperspectral imaging has been reportedly used in determining the meat quality parameters of intramuscular fat, marbling, color, chemical composition, and especially tenderness [16-19]. Though some work has been done on meat quality assessment with hyperspectral imaging, few studies have reported on its use in predicting beef tenderness for meat having undergone different periods of aging. The non-destructive nature of hyperspectral imaging is an advantage when determining the quality of raw material and final product [20, 21].

2. MATERIALS AND METHODS

2.1. Sample Collection

A total of 10 carcasses (8 steer and 2 heifer) between the ages of 403 and 536 days were selected from a slaughterhouse (VG Meats, Simcoe, Ontario,

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Canada). For each month, a predefined numbers of bulls were slaughtered on the first Thursday. The carcasses were chilled and electrically stimulated after slaughter. At 24 h post-mortem, subprimals were removed from each carcass and separated into individual muscles: *infraspinatus* (Top blade, TB), *gluteus medius* (Top sirloin, TS), *psoas major* (Tenderloin, TL), and *longissimus thorasis* (Rib eye, RE). Using a mechanical slicer, fresh and dry-aged samples were sliced from each muscle on the first Friday (fresh samples), third Friday (14 days dry-aged samples), and fourth Friday (21 days dry-aged samples) of each month. Slices were vacuum-packed and kept frozen during shipping to the Hyperspectral Imaging Lab, Macdonald Campus of McGill University (Sainte-Anne-de-Bellevue, QC, Canada). A total of 260 raw beef samples were collected and images of each sample were captured before cooking and subsequent measurement of tenderness by the Warner-Bratzler shear force method.

2.2. Hyperspectral Imaging System (HSI)

A laboratory near-infrared (NIR) hyperspectral imaging (HSI) system was set up to collect the hyperspectral images of the beef samples. The NIR-HSI system consisted of an In Ga As camera mounted with a line-scan spectrograph (Headwall Photonics, Fitchburg, MA, USA, 900-1700 nm), two 50W tungsten-halogen lamps placed at a 45° angle to illuminate the camera's field of view, a moving conveyor driven by a stepping motor with a user-defined speed (MDIP22314, Intelligent Motion System Inc., Marlborough, CT, USA), a supporting frame, and a computer (Figure. **1**). The system consisted of a line-scan push broom with a 4.8 nm resolution, allowing one to scan the sample line by line and generate a data cube with one spectral and two spatial axes. Each raw beef sample was imaged on both surfaces using the NIR-HSI system.

2.3. Image Correction

Data analysis in this project involved spectral and image analysis for beef tenderness prediction. Each hypercube was corrected from the dark current of the camera prior to segmenting the region of interest (ROI) of each sample. To correct the spectral images, a dark image *B* with about 0% reflectance and a white image *W* with about 99% reflectance were obtained by covering the lens with a cap, and by taking an image from a standard white reference plate (Spectralon, Labsphere, North Sutton, NH, USA), respectively. The relative reflectance *I* of each image was calculated as:

$$I = \frac{I_0 - B}{W - B} \tag{1}$$

Where I_0 is the reflectance of the original image.

A single beef sample was placed on a dark panel to collect the hyperspectral data. Images of both surfaces of the beef sample were taken and saved for subsequent analysis. The images obtained were stored in a data *hypercube,* composed of one spectral and two spatial coordinates.

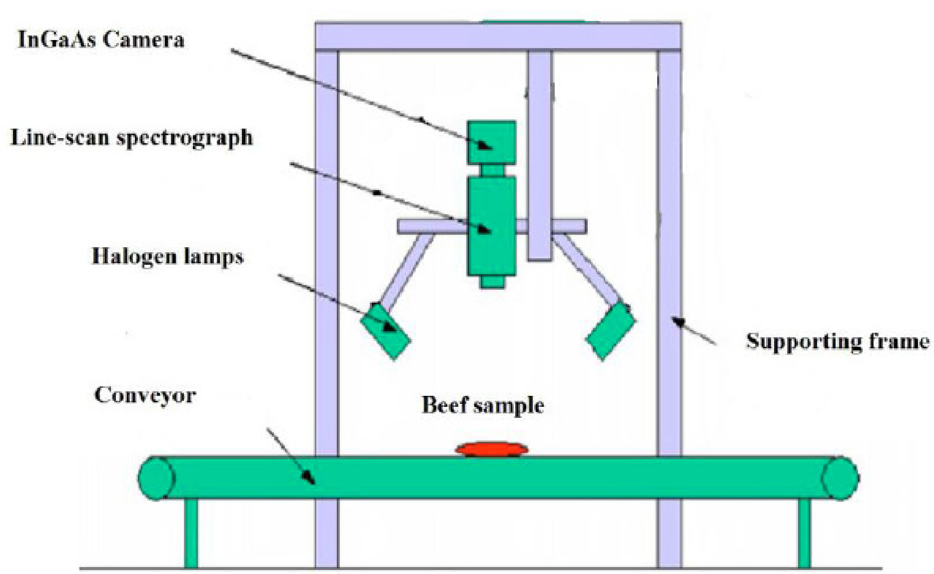

Figure 1: Illustration of the near-infrared hyperspectral imaging system.

2.4. Measuring of Beef Tenderness

There exist different methods in order to measure either the tenderness or the toughness of meat. One of the most popular techniques is the Warner-Bratzler shear force (WBSF) method [22-24], which measures the force required to shear through a sample of cooked beef using an Instron machine. A standard method[1] was used for WBSF measurements. Steaks used for WBSF measurements were cut into 2.54 cm (1.0 in) thicknesses. Since the internal temperature of the sample influences tenderness, it must be the same for all samples. Frozen samples were thawed until an internal temperature of between 2 to 5°C was reached. The steak was placed on a grill and cooked on one side to an internal temperature of 40ºC, turned and cooked to a final internal temperature of 71ºC. Six cores, each 1.27 cm (0.5 in) in diameter, were removed from each sample, parallel to the longitudinal orientation of the muscle fibers and then sheared perpendicular to the muscle fiber orientation. The individual peak shear force value was recorded for each core test. The Warner-Bratzler shear force was reported as the mean of all core values [1, 25-27].

2.5. Data Processing

Data analysis and image processing operations followed the procedure outlined in Figure **2**. All of the acquired data hypercubes were processed and analyzed using MATLAB 7.3.0 (The Math Works, Inc., MA., USA). Using a method developed by Liu *et al.* [28],each hypercube's region of interest (ROI) was automatically segmented. Due to the low signal-to-noise ratio at the two ends of the spectral range, only spectral images from 970-1630 nm were used for image analysis. After ROI selection, the mean reflectance spectrum of each side of the beef sample was calculated and the average spectrum of the two sides served as the final spectrum. Each mean spectrum was smoothed through the Standard Normal Variate (SNV) method in MATLAB 7.3.0 (The Math Works, Inc., MA., USA), and finally the second derivative of the mean spectrum was calculated.

2.6. Wavelength Optimization

The second derivative of the mean spectrum was used to select the optimal wavelengths, based on a high coefficient of determination (R^2) for the relationship between reflectance and tenderness. Wavelength selection was performed by GLMSELECT in SAS (SAS 9.3, Cary, NC, USA)

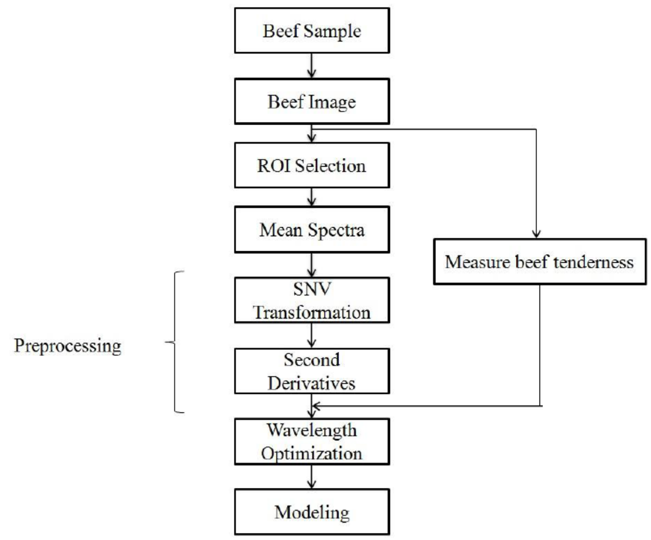

Figure 2: Flow chart for image analysis.

2.7. Multivariate Linear Regression

For each muscle type, samples were divided into calibration and validation sets at a ratio of three to one: all samples were arranged in an ascending order according to tenderness values, and then one sample, from four samples, was picked out for the validation set. A predictive model of beef tenderness was created with selected wavelengths of the calibration set based on the Multiple Linear Regressions (MLR) technique using Unscrambler multivariate software (v10.13, Camo, Norway). For the validation set of beef samples, the measured reflectance constituted the MLR model's input when assessing its prediction accuracy for beef tenderness. The correlation coefficient (*R*) and Root Mean Square Error (*RMSE*) between the predicted and measured tenderness score of the calibration (R_C , $RMSE_v$) and validation (R_V, $RMSE_v$) sets were used to evaluate the prediction models. A good model with high value of R_C and R_V, small values of RMSEv and $RMSE_v$ was obtained in calibration and maintained in validation.

3. Results and Discussions

Tenderness of all beef samples (n = 260) were measured by the Warner-Bratzler shear force (WBSF) method and the summary of statistics, *i.e.*, mean, standard deviation and range, is provided in Table **1**.An example of images collected from both sides of a beef sample is shown in Figure **3** and the corresponding segmented ROI in Figure **4**.

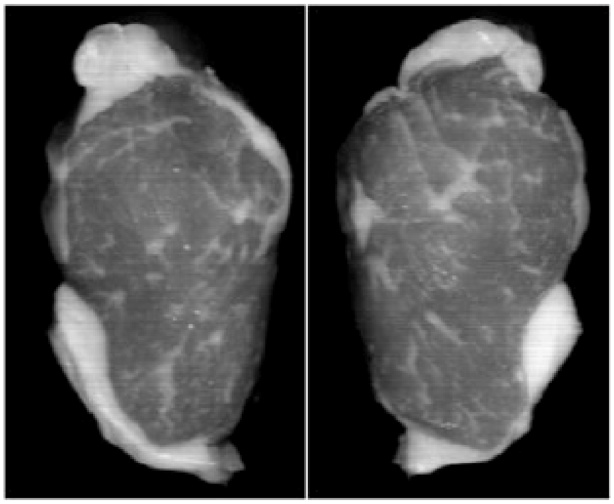

Figure 3: NIR (λ = 1086 nm) images of beef meat.

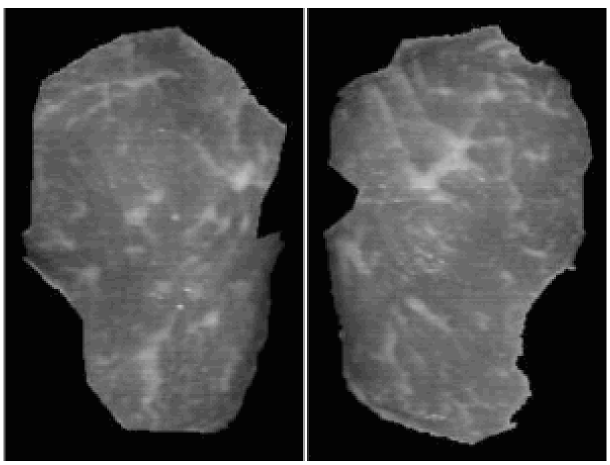

Figure 4: ROI of (λ = 1086 nm) NIR images of beef meat.

The mean spectrum of the ROI (*i.e.*, the average values of the ROI of image planes over the wavelength range) of each beef sample served as spectral features of the hypercube. The spectral feature of a beef sample was defined as the average profile of the mean spectra for both sides of the beef sample. Figure **5** shows typical spectral features for different muscles at different dry ages. Preprocessing by SNV transformation was applied to the means spectra (Figure **6**), followed by second derivatives for wavelength selection (Figure **7**).

For each muscle type, the wavelength selection was performed separately. Based on the results of the stepwise analysis, effective wavelengths were selected, as shown in Table **2.**

A comparison of the Warner-Bratzler shear force (inverse of tenderness) for the calibration and validation sets of different cuts (Table **3**) shows that for all cut types the range of WBSF in the validation set was covered by the range of the calibration set, indicating an appropriate distribution of samples for modeling.

The Multiple Linear Regressions (MLR) has been used to build determination models. The effective wavebands selected by the stepwise approach were respectively set as the independent variable X for development of tenderness determination models. The correlation coefficient (*R*) and Root Mean Square Error (RMSE) of each model and the corresponding prediction results are shown in the Table **4.**

Table 1: Statistics for Cooked Beef Meat Warner-Bratzler Shear Force (Inverse of Tenerness)

Muscle Type	Aging (days)	Mean± Standard Deviation (N)	Minimum (N)	Maximum (N)
RE	0	19.77±3.49	13.33	29.79
	14	16.53±3.53	11.48	25.28
	21	16.84±3.53	11.07	25.73
TB	0	19.60±4.62	13.97	33.70
	14	16.50±3.70	11.74	20.77
	21	16.15±4.19	12.25	22.70
TL	0	17.04±3.01	10.74	24.36
	14	15.35±3.33	9.51	21.19
	21	13.73±2.72	9.30	20.58
TS	0	23.69±4.71	16.37	33.73
	14	20.27±4.30	14.31	30.54
	21	17.92±3.99	13.89	28.76
RE: rib eye; TB: top blade; TL: tenderloin; TS: top sirloin				

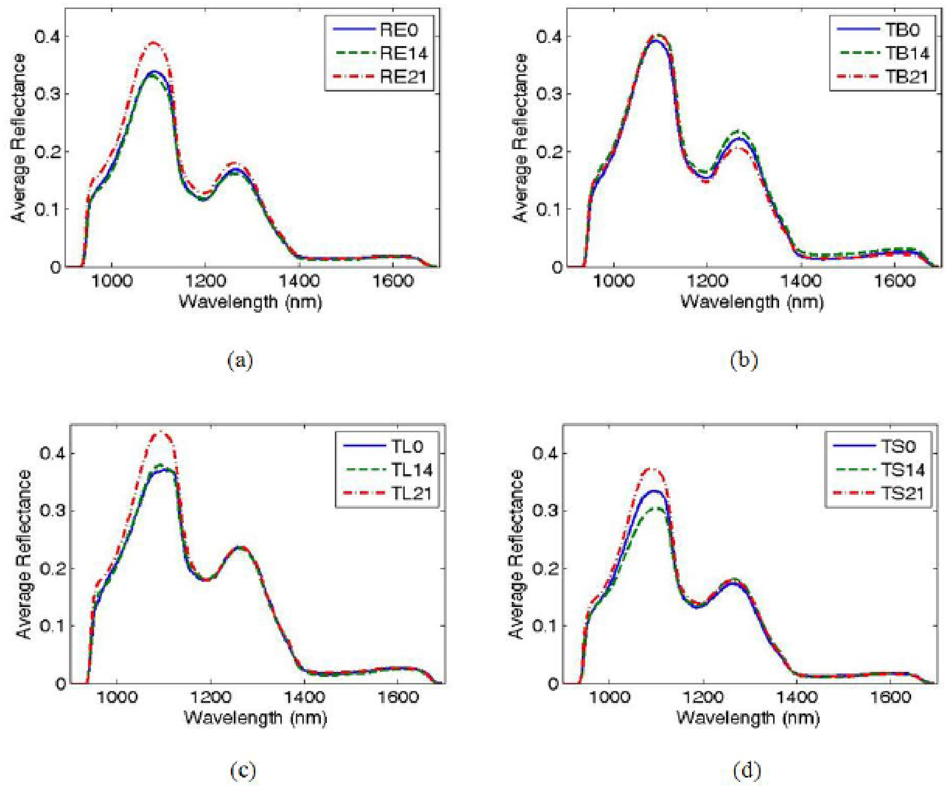

Figure 5: Spectral features for muscles (a) RE, (b) TB, (c) TL, (d) TS after different dry aging durations. RE: rib eye; TB: top blade; TL: tenderloin; TS: top sirloin.

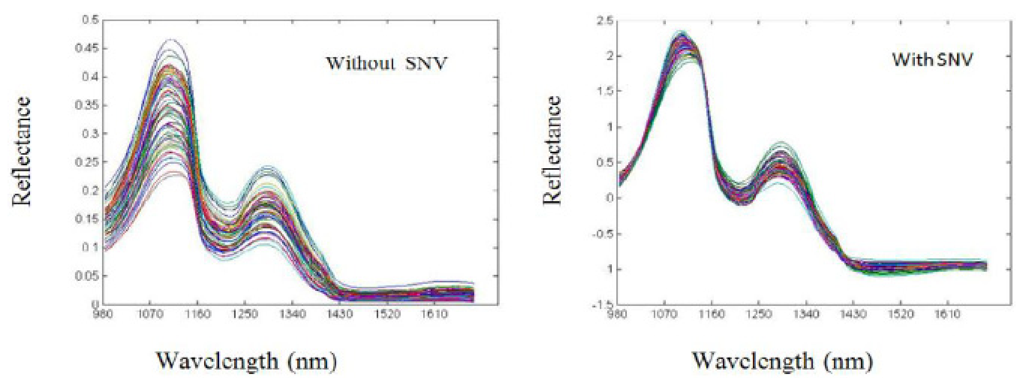

Figure 6: SNV transformation of mean NIR spectra for the samples used in this study.

Specifically, the correlation coefficient for calibration and validation sets lies in the range of 0.84-0.92 and 0.81-0.89, respectively. This indicated that our model significantly increased the accuracy of prediction compared to the results reported in the literature, *i.e.* 0.67 reported in Cluff *et al*. [16] and around 0.7 reported in Liu *et al*. [4]. The improved results for tenderness prediction of different beef muscles proved that the higher wavelengths in NIR (900-1700 nm) are more effective than the visible/NIR area (400-1000 nm) in sensing chemical constituents such as protein, water and fat, which are considered to have great effect on meat tenderness.

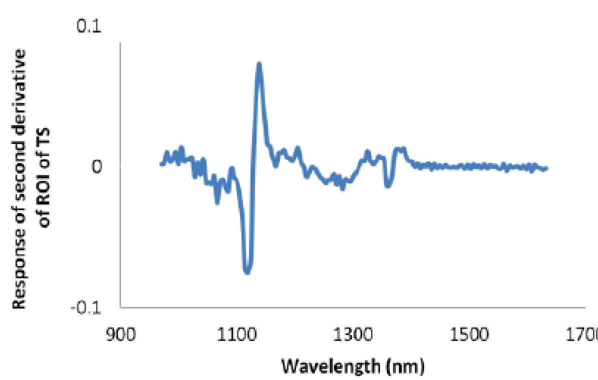

Figure 7: Typical second derivatives of mean reflectance spectra.

Table 2: Wavebands Selected by the Stepwise Regression Operation

Muscle Type	Waveband Selected (nm)	Number of Wavebands
RE	971,995,1014,1018,1042,1086,1124,1253,1263,1469,1517,1575	12
TB	1081,1100,1215,1320,1340,1359,1368,1392,1479,1541,1565,1632	12
TL	1172,1354,1421,1431,1483,1488,1522,1527,1551	9
TS	980,999,1023,1062,1071,1196,1220,1320,1460,1493	10
RE: rib eye; TB: top blade; TL: tenderloin; TS: top sirloin		

Table 3: Warner-Bratzler Shear Force Value of Calibration and Validation Sets for 4 cuts of Meat

Muscle Type	Sample Set	Number of Samples	Minimum	Maximum	Mean
RE	Calibration	54	11.07	25.73	17.11
	Validation	18	12.16	26.39	17.59
TB	Calibration	44	11.74	26.62	16.78
	Validation	15	12.25	25.70	17.09
TL	Calibration	52	9.30	24.36	15.49
	Validation	17	9.51	22.69	15.60
TS	Calibration	45	16.37	23.78	20.19
	Validation	15	17.77	20.20	20.11
RE: rib eye; TB: top blade; TL: tenderloin; TS: top sirloin					

Table 4: Results of the Tenderness Prediction Models

Muscle Type	R_c	$RMSE_c$	R_v	$RMSE_v$
RE	0.88	1.72	0.86	1.76
TB	0.84	1.62	0.81	1.72
TL	0.86	1.86	0.83	1.98
TS	0.92	1.85	0.89	2.2
RE: rib eye; TB: top blade; TL: tenderloin; TS: top sirloin *Note.* Indexes "c" and "v" indicate calibration and validation sets, respectively.				

The actual vs. predicted values of the tenderness of four types of muscles are plotted in Figure **8**. While beef tenderness prediction results for all four type muscles showed good accuracy, prediction accuracy for tenderness of Top Sirloin (TS) was greater than that for other muscles. This indicates that overall hyperspectral images in the NIR range had a good explanatory power for beef tenderness. The success of non-destructive detection of beef tenderness made it possible to develop a rapid and accurate on-line system to assess beef tenderness.

4. CONCLUSION

This study was conducted to assess the possibility of using NIR hyperspectral imaging of raw beef, coupled with proper image processing techniques, to predict cooked beef tenderness. To accomplish this purpose, multiple linear regression models at optimal wavelengths were constructed.

Prediction models for beef tenderness of four types of beef muscles after three different aging durations were developed from hyperspectral imaging data in the near infrared region. Prediction accuracies (*R*) were 0.89, 0.86, 0.81, 0.83 for TS, RE, TB, and TL respectively. These results confirmed the potential of hyperspectral imaging as an online, rapid and non-destructive technique for developing predictive models for beef tenderness at three different aging periods. Further work will focus on improving the predictive accuracy, building industrial instruments for objective

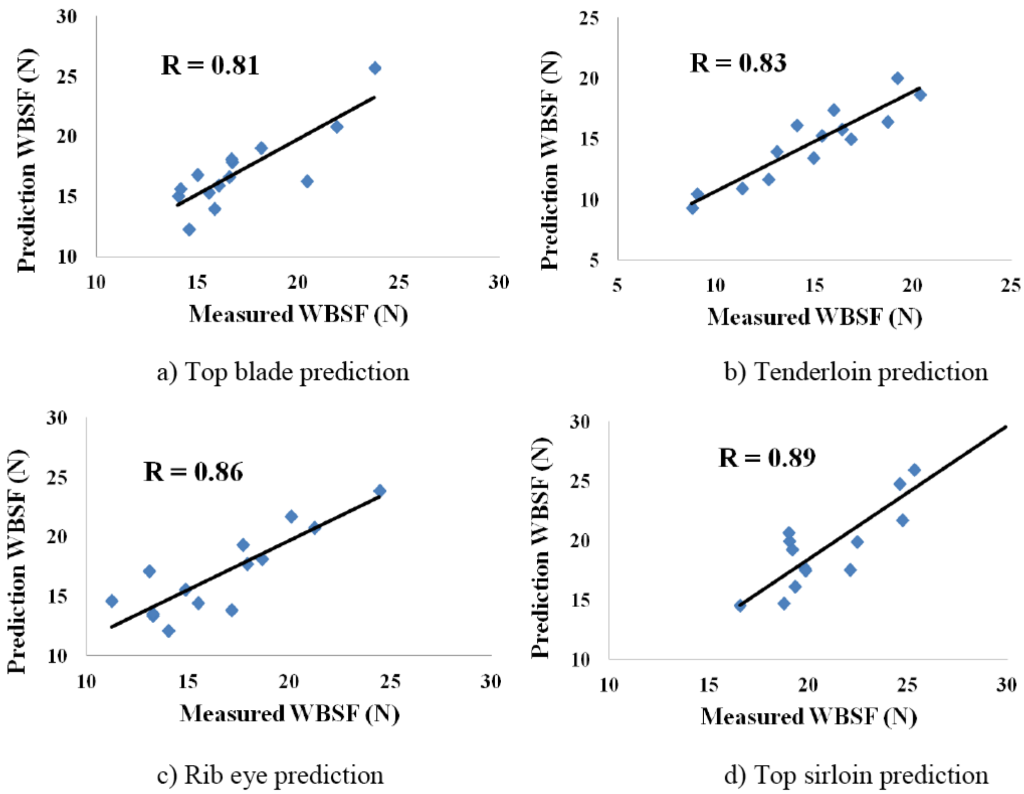

Figure 8: Measured vs. predicted value of the Warner-Bratzler shear force (WBSF).

tenderness evaluation and exploring the potential of other NIR hyperspectral imaging techniques for prediction of beef tenderness.

We believe that our study contributes to the existent literature in the field by providing a prediction method that indicates the tenderness of the beef with an acceptable accuracy. This approach provides more applicable tool to its users comparing to the other models in literature those provide only classification models in which beef can be categorized in small number of classes based on its tenderness.

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