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VISIBLE AND NEAR-INFRARED HYPERSPECTRAL IMAGING FOR PREDICTING TECHNOLOGICAL AND SENSORY TRAITS OF BEEF

Georgios Anagnostou [1,2], Ruth M. Hamill [1], Emily C. Crofton [1]. Jesus Maria Frias Celayeta [3], Alessandro Ferragina [4,1]

[1] Food Quality and Sensory Science Department, Teagasc Food Research Centre, Ashtown, D15 DY05 Dublin, Ireland ; School of Food Science and Environmental Health, Technological University Dublin, D07 H6K8 Dublin, Ireland ; [3] Sustainability and Health Research Hub, Technological University Dublin, D07 H6K8 Dublin, Ireland ; [4] Department of Veterinary Science, University of Parma, 43126 Parma, Italy
*Corresponding author email: ruth.hamill@teagasc.ie

I. INTRODUCTION

The quality of red meat, including its colour, texture, and flavor, significantly influences consumer satisfaction, thus necessitating the quantification of these attributes prior to consumption to meet consumers' expectations [1]. As consumers become more conscious of food quality due to higher living standards, aligning meat quality according to their preferences requires robust meat quality control strategies [2]. Conventional methods, including chemical, instrumental, and sensory techniques are destructive, time-consuming and inefficient for online application. In contrast, hyperspectral imaging (HSI) is a rapid, non-invasive technique that has proven to be a promising technology for meat quality evaluation [3], combining spatial and spectral information. The main aim of this study was to investigate the potential of using visible (Vis) and near-infrared (NIR) HSI to predict beef sensory and technological traits, alongside the development of robust PLS-R calibration models to relate spectral information and quality attributes.

II. MATERIALS AND METHODS

A total of 30 crossbred heifers (17-22 months old) were slaughtered in a commercial abattoir, and their carcasses subjected to three different suspension techniques (conventional achilles hung, hip tied, and hip hung [4] were applied to alternating carcass sides). Four steaks of 2.54 cm thickness (Figure 1), were removed from four muscles per side (*longissimus thoracis et lumborum*, *semimembranosus*, *semitendinosus* and *triceps brachii*) and blast-frozen (-19^{o}C) 13-14 days, post mortem. Meat image acquisition was performed on both cut surfaces of thawed steaks (n=240, Steak 3) using a custom designed Vis-NIR HSI line-scan system (DV Optics, Padova, Italy) in the range of 400-1700nm. Following meat image acquisition, technological meat quality analysis (pH, thawing loss, colour) was conducted on the same steaks (Steak 3) and sensory evaluation (7-9 highly trained panellists) was carried out on adjacent steaks (Steak 2 and Steak 4). The Vis-NIR HSI system used in this study, captures 121 spectral bands (λ) with the spatial size of 780×466 [X, Y] in the visible range (400-1000nm) and 161 bands with spatial size of 320 × 466 [X, Y] in the near-infrared range (900-1700nm). A white (~99%) and black reference were used for the image correction. The correction process was followed by the identification of region of interest (ROI) in the tested samples to ensure valid spectral data extraction. For the identification of ROI, a masking technique was applied, where the mask was obtained by subtracting a low-reflectance band from a high-reflectance band and then segmented at a threshold between 0.20 and 1. The ROI image (width × length × wavelengths) for each sample was unfolded to a 2D structure ((width × length) × (wavelengths)), and within each sample mean spectrum of each cutting surface was calculated, generating two spectra per sample (one per cutting surface). A final mean spectra was then computed by averaging the two cutting surfaces spectra, resulting to one spectrum per sample.

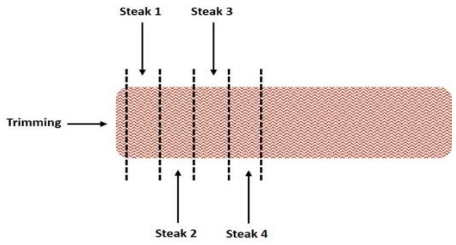


Figure 1 Four beef steaks obtained from each muscle for the study

For the prediction of beef sensory and technological traits, Partial Least Squares Regression (PLS-R), combined with various preprocessing methods, including Standard Normal Variate, Detrend, Savitzky-Golay 1st derivative and 2nd derivative, was used. The analysis was carried out using the "mdatools" package (R Studio Team, 2022). Samples were randomly split by muscle into Training and Testing sets. A Venetian blind algorithm with ten single folds was employed to calculate the mean square error of the cross-validation ($RMSE_{cv}$) and the cross-valiation determination coefficient (R^2_{cv}) was used to evaluate the PLS models, followed by external validation on the Testing set, using the cross validation determination of the external validation (R^2_{ext}) for evaluation.

III. RESULTS AND DISCUSSION

Table 1 summarizes the statistics of the best prediction models of technological and sensory traits for the tested beef samples. Table 1 illustrates that R^2 values for sensory traits were lower than those for pH, thawing loss, L*, a* and b*. The highest R^2_{ext} values, among the technological traits were achieved for thawing loss, L*, and b* value. In particular, the PLS-R models achieved reliable predictions for pH (R^2_{ext}= 0.74, $RMSE_{ext}$=0.08) thawing loss (R^2_{ext}= 0.84, $RMSE_{ext}$=0.01), L* (R^2_{ext}= 0.86, $RMSE_{ext}$= 1.30) and b* (R^2_{ext}= 0.80, $RMSE_{ext}$= 0.76), whereas predictions for a* were inadequate, likely due to the narrow variability of a* values. These results align with previous research findings on beef colour [5–7] and pH-related studies [7,8]. For sensory traits, although the PLS-R predictions showed lower performance values (R^2_{ext}= 0.47-0.51, $RMSE_{ext}$= 0.64-0.88), grouping samples through the developement of classification models according to their measured attributes, could improve their coefficients of determination [9].

Table 1. Best fitting statistics of prediction for technological and sensory traits on beef samples

Trait	Pre-treatment	nC	R^2_{cal}	$RMSE_{cal}$	R^2_{ext}	$RMSE_{ext}$
pH	S-G 1st derivative & SNV-D	10	0.78	0.07	0.74	0.08
Thawing loss (%)	S-G 1st derivative & SNV-D	12	0.86	0.01	0.84	0.01
Colour L*	None	8	0.85	1.33	0.86	1.30
Colour a*	S-G 1st derivative & SNV-D	5	0.51	1.16	0.48	0.93
Colour b*	None	4	0.83	0.80	0.80	0.76
Initial tenderness	S-G 2nd derivative	7	0.47	0.56	0.47	0.64
Chewiness	None	11	0.53	0.76	0.51	0.88
Overall tenderness	S-G 1st derivative	11	0.49	0.67	0.51	0.73

SNV-D: Standard Normal Variate – Detrend, S-G 1st derivative: Savitzky-Golay first derivative, S-G 2nd derivative: Savitzky-Golay second derivative, nC: number of components in the PLS-R model, R^2_{cal}= coefficient of determination for calibration, $RMSE_{cal}$= root mean square error for calibration, R^2_{ext}= coefficient of determination for external validation, $RMSE_{ext}$= root mean square error for external validation

IV. CONCLUSION

This study confirms the potential of Vis-NIR HSI to predict certain beef quality traits such as pH, thawing loss, and colour. The variations in muscle types and suspension methods have contributed to increase data variability, enhancing the model's' versatility. However, predicting beef sensory traits was less precise, suggesting that Vis-NIR HSI although promising, requires further improvements. Despite this, the study provides initial chemometric models for sensory traits assessed by trained panels, offering valuable insights for future strategies to improve beef sensory attributes.

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REFERENCES

1. Holman, B.W.B.; Hopkins, D.L. The Use of Conventional Laboratory-Based Methods to Predict Consumer Acceptance of Beef and Sheep Meat: A Review. *Meat Sci.* **2021**, *181*, 108586, doi:10.1016/j.meatsci.2021.108586.
2. Henchion, M.; McCarthy, M.; Resconi, V.C.; Troy, D. Meat Consumption: Trends and Quality Matters. *Meat Sci.* **2014**, *98*, 561–568, doi:10.1016/j.meatsci.2014.06.007.
3. Anagnostou, G.; Ferragina, A.; Crofton, E.C.; Maria, J.; Celayeta, F.; Hamill, R.M. The Development of Optical Sensing Techniques as Digital Tools to Predict the Sensory Quality of Red Meat: A Review. **2025**, *15*, 1719.
4. Hostetler, R.L.; Link, B.A.; Landmann, W.A.; Fitzhugh, H.A. Effect of Carcass Suspension on Sarcomere Length and Shear Force of Some Major Bovine Muscles. *J. Food Sci.* **1972**, *37*, 132–135, doi:10.1111/j.1365-2621.1972.tb03402.x.
5. Leroy, B.; Lambotte, S.; Dotreppe, O.; Lecocq, H.; Istasse, L.; Clinquart, A. Prediction of Technological and Organoleptic Properties of Beef Longissimus Thoracis from Near-Infrared Reflectance and Transmission Spectra. *Meat Sci.* **2004**, *66*, 45–54, doi:10.1016/S0309-1740(03)00002-0.
6. Prieto, N.; Andrés, S.; Giráldez, F.J.; Mantecón, A.R.; Lavín, P. Ability of near Infrared Reflectance Spectroscopy (NIRS) to Estimate Physical Parameters of Adult Steers (Oxen) and Young Cattle Meat Samples. *Meat Sci.* **2008**, *79*, 692–699, doi:10.1016/j.meatsci.2007.10.035.
7. Elmasry, G.; Sun, D.W.; Allen, P. Near-Infrared Hyperspectral Imaging for Predicting Colour, PH and Tenderness of Fresh Beef. *J. Food Eng.* **2012**, *110*, 127–140, doi:10.1016/j.jfoodeng.2011.11.028.
8. Dixit, Y.; Al-Sarayreh, M.; Craigie, C.; Reis, M.M. A Global Calibration Model for Prediction of Intramuscular Fat and PH in Red Meat Using Hyperspectral Imaging. *Meat Sci.* **2021**, *181*, 108405.
9. Barbin, D.F.; Elmasry, G.; Sun, D.W.; Allen, P. Predicting Quality and Sensory Attributes of Pork Using Near-Infrared Hyperspectral Imaging. *Anal. Chim. Acta* **2012**, *719*, 30–42, doi:10.1016/j.aca.2012.01.004.