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Multiblock PLS modelling of red meat quality parameters using a variety of sensors. (#411)

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Introduction

Objective, non-invasive and rapid evaluation meat quality is often described as the holy grail of meat science. However, no single sensing technology has been shown to effectively estimate meat quality parameters of interest to consumers, such as intramuscular fat percentage (IMF%), pH and tenderness. In this study we estimate these parameters in New Zealand beef shortloin using Multiblock partial least squares regression (MB-PLS) with data from a range of different spectroscopic sensing modalities. These modalities include Hyperspectral imaging, NIR spectroscopy, Raman spectroscopy and Nuclear Magnetic Resonance (NMR). Multiblock statistical methods for analysis of food are becoming increasingly popular as the number of reliable sensor data increases. Previous studies have shown improved predictive performance using multiblock analyses compared to traditional methods (E. Borr`as et al. 2015).

Methods

182 beef shortloin were cut into 364 cross section samples. The samples ranged in IMF% from 0.6-19.36%, pH from 5.2-6.95 and adjacent steaks were used to measure the tenderness at 7, 14 and 21 days ageing analysed according to MIRINZ tenderometer protocol (B. B. Chrystall, 2015). A portion of the steaks were cold-shortened in order to ensure the sample set had a wide range of tenderness values. Spectroscopic data was collected at 24 hours post-slaughter. A Xenics XEVA 1.7-320 hyperspectral camera offers the widest wavelength range (550-1700 nm) but longest imaging duration (C. Craigie et al. 2017). Two snapshot HSI cameras spanning the visible (470-630 nm) and near-infrared (670-950 nm) spectrum have lower resolution and fast imaging times. HSI images aresegmented using a Yen threshold technique to remove the background and subcutaneous fat. Each image is averaged pixel-wise and normalised using standard normal variate (SNV) normalisation to give a single spectrum per image. We use multiblock PLS to analyse the performance of the sensors and generate predictive models for pH, IMF% and tenderness. Data from each sensor are treated as independent blocks. PLS models are generated for each block, and features from those models are then used to build a final predictive model (E. Borr`as et al. 2015). Because of this, multiblock methods can be used to highlight which sensor data is most relevant to predicting certain quality parameters via their block scores.

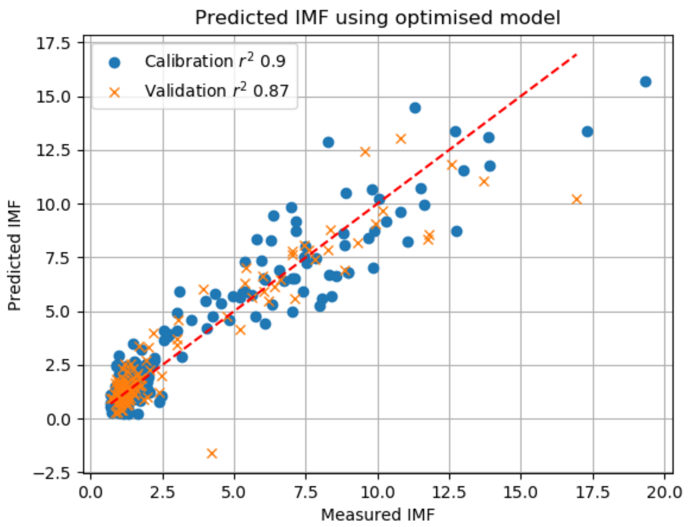
Results

Combinations of the available spectroscopic data have been used to build a models to predict meat quality parameters. Two thirds of the samples are used to generate the predictive models (calibration data set) and the remainder are used to check the performance of the model (validation data set). Figures 1 and 2 show the predicted IMF% and pH, respectively, compared to their independently measured result. For IMF and pH predictive models the r^2 of validation is 0:87 and 0.91 respectively, with mean square error of 1.416, and 0.021. Using only data from the two snapshot cameras to develop IMF and pH MB-PLS models results in r^2 of validation is 0.78 and 0.87 with mean square error of 2.4, and 0.029.

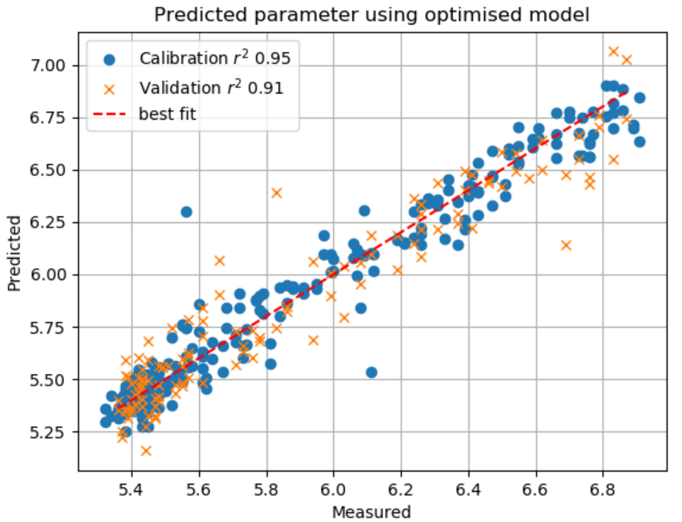
Conclusion

Multiblock PLS has been used to build models to predict pH and IMF% of beef short loin samples with data from various spectroscopic sensors. For both pH and IMF%, there is little improvement over modelling using only data from the Xenics XEVA 1.7-320 camera. However this device is least applicable in an industrial setting. Using only data from more appropriate sensors results in slightly depreciated predictive models. These models may improve when Raman spectrocopy and NMR data are included.

Notes



Predicted IMF percentage of beef shortloin using MBPLS
Figure 1. IMF% predicted using a MBPLS generated model compared to the independently measured result.



Predicted pH of beef shortloin using MBPLS
Figure 2. pH predicted using a MBPLS generated model compared to the independently measured result.

Notes