NON-INVASIVE METHODS TO MEASURE PHYSIOLOGICAL RESPONSES OF CATTLE IMMEDIATELY PRIOR TO SLAUGHTER AND THEIR RELATION TO SENSORY QUALITY OF BEEF

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I. INTRODUCTION

Animal welfare and sensory quality are increasingly becoming factors considered important by meat consumers [1]. Furthermore, sensory attributes, such as tenderness, juiciness and flavour play a critical role in consumer preference of beef products [2, 3]. Due to this, the Meat Standards Australia (MSA) quality assurance program utilizes tenderness, juiciness, flavour and overall liking to generate a single meat quality score (MQ4) to predict palatability [4]. Pre-slaughter stress has been suggested, by previous research, to have a detrimental impact on meat quality, which can lead to a decrease in sensory quality. Physiological stress can be assessed through indicators such as heart rate (HR), respiration rate (RR) and body temperature. However, common techniques to monitor stress indicators have been related to procedures that could be a stressor by itself, as well as, time consuming and labour intensive [5]. In that sense, remote sensing techniques such as thermal imagery processing [5] and biometric techniques using the Eulerian Video Magnification algorithm, have been proven techniques to non-invasively measure surface temperature, HR and RR in humans [6, 7]. These techniques may also be useful tools to measure these parameters in animals. The main objective of this research was to identify factors that could be influencing the final quality of meat. Non-invasive biometric technologies were implemented in order to measure physiological responses to stress, to identify whether physiological parameters are related to sensory quality of meat and its indicators, and whether they can be used to predict quality of beef.

II. MATERIALS AND METHODS

Sixty-eight grass-fed cattle from four beef farms located in Tasmania were transported by truck to the abattoir one day prior to slaughter. To obtain remote sensed information related to physiological parameters, thermal infrared [FLIR AX8 with a spectra range of 7.5 – 13 µm and an accuracy of ±2°C (FLIR® Systems)] and an RGB (Raspberry Pi Camera Module V2, with a resolution of 8-megapixel) cameras were placed in the stunning box to collect images and videos during the stunning process. Image and video processing was carried out using customized codes written in MATLAB 2016a (Mathworks Inc., Matick, MA, USA) to obtain HR (from the RGB videos), RR (from non-radiometric videos) and eye temperature (from the thermal images). From the carcasses of these animals, samples of oyster blade (OYS036; *infraspinatus*) and striploin (STR045; *longissimus lumborum*) where obtained and at a later date, after storage and freezing, grilled and served to consumers for sensory analysis. Consumer panelists scored the tenderness, juiciness, flavor and overall liking of the samples on a scale from 0 to 100 and MQ4 score was derived from these using the equation MQ4 score (1) = 0.3 (T) + 0.1 (J) + 0.1 (F) + 0.3 (OL) [4]. Statistical analysis was performed including correlation coefficients (r) between HR, RR and temperature, and the sensory quality scores given by the consumer panelists. Also, Artificial Neural Networks (ANN) using the Neural Networks Toolbox of MATLAB were built with the aim of predicting MQ4 as the target, using the physiological data, obtained from the cameras, as inputs. The ANN used was a Multilayer perceptron (MLP), which included five input nodes, three hidden nodes and one output node. The total data (n) for this modelling was 708, where 70% was used for the training process, 15% for the validation process and 15% for the testing process.

III. RESULTS AND DISCUSSION

Temperature, HR and RR showed moderate to high correlations with the sensory scores of tenderness, juiciness, flavor, overall liking and MQ4 for both the oyster blade and striploin (Figure 1.A). For the oyster blade, the correlation (r) between temperature and the sensory scores, including MQ4, ranged from r= 0.46 to 0.69. The r between HR or RR and sensory scores, including MQ4, ranged from 0.36-0.64 and 0.34-0.57. The highest correlation was obtained between HR and tenderness with r=0.67. In the case of striploin, the range of correlation between the physiological measures temperature, HR and RR with sensory scores, including MQ4, ranged between r=0.42-0.56, 0.36-0.53 and 0.59-0.77 respectively. Overall, tenderness appears to be the sensory quality indicator with the highest correlation when compared to the analyzed physiological parameters (r=0.52-0.77). The accuracy of the prediction obtained by the ANN model was R^2= 0.86 between observed and predicted MQ4 (Figure 1.B). The training process resulted in an R^2= 0.805 and the testing process resulted in R^2= 0.856.

A

Cut	Physiologic / Eating quality	Tenderness	Juiciness	Flavour	O/all Liking	MQ4
OYS036	Temperature	0.697	0.685	0.463	0.679	0.444
	HR	0.637	0.592	0.364	0.605	0.425
	RR	0.521	0.555	0.342	0.569	0.359
STR045	Temperature	0.556	0.430	0.416	0.456	0.025
	HR	0.531	0.425	0.362	0.441	0.048
	RR	0.768	0.601	0.585	0.684	0.111

B

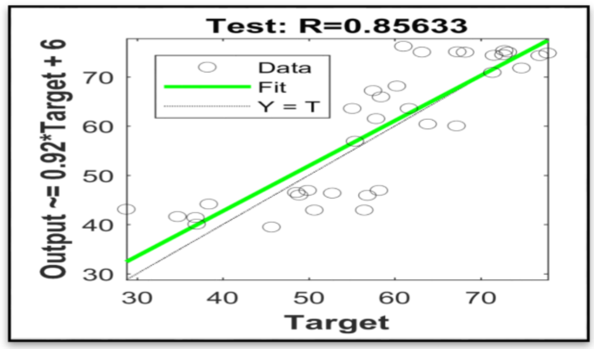

Figure 1, **A** Correlation between physiological parameters and eating quality **B** Output of ANN model.

IV. CONCLUSION

Based on these results, it can be concluded that non-invasive measurements of temperature, HR and RR of cattle at the abattoir had moderate to high correlation with consumer sensory scores for quality. In addition, the preliminary ANN, obtained using non-invasive physiological parameters, appears to be a useful tool in the prediction of the important trait for describing beef quality, namely MQ4. This indicates opportunity to use these non-invasive input parameters for machine learning modelling as a potential application of artificial intelligence in the abattoir, to predict and secure a desired meat quality by the industry.

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