Prediction of lamb tenderness using combined quality parameters and meat surface characteristics

Chandraratne, M. R.[1]; Samarasinghe, S.[2]; Kulasiri. D.[1,2]; Bekhit, A. E. D.[1] and Bickerstaffe, R.[1]

[1] Agriculture and Life Sciences Division, Lincoln University, New Zealand
[2] Centre for Advanced Computational Solutions (C-fACS), Lincoln University, New Zealand
[3] Christchurch School of Medicine and Health Sciences, University of Otago, Christchurch, New Zealand

Conclusions

- A total of 148 geometric and texture features were reduced to 22 features using Principal Component Analysis (PCA).
- Statistical non-linear regression and Neural network (NN) models were developed using the reduced set of variables and ultimate pH as inputs and tenderness as output.
- The greatest predictability of cooked lamb tenderness from images of lamb chops ($R^2 = 0.91$) was achieved with NN model using six geometric, eight co-occurrence matrix (GLCM), four grey level difference matrix (GLDM), four grey level run length matrix (GLRM) features and the ultimate pH.
- The cumulative effect of different texture analysis techniques togther with pH proved to be effective in predicting cooked lamb tenderness.

Background

- Tenderness is a major factor that ensures consumer satisfaction with meat quality. Current methods to determine meat tenderness are destructive, time consuming, costly and do not meet industry needs.
- Computer vision is a robust and consistant system with enormous potential for evaluating meat quality. This potential is supported by the ongoing advances in information technology and image analysis.
- Using a single statistical approach resulted in R^2 of 0.7 and 0.746 for beef[1] and lamb[2]. An improvement in the prediction level was achieved by using additional quality parameters (e.g. colour, marbling)[1].
- We hypothesised that utilizing a multi statistical approach in addition to other quality parameters could improve the prediction of lamb tenderness.

Objectives

The objectives of the present study were:

- to investigate the predictability of cooked lamb tenderness from textural parameters extracted from lamb chops images using GLRM and GLDM techniques.
- to study the combined effects of texture features, marbling and ultimate pH on the prediction models.

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Methods

Samples

- The data was from samples of mid loin chops taken at 13th rib from randomly selected sides of 160 lamb carcasses (17.37± 1.48 kg). Ultimate pH was measured at 24 hrs post-mortem (range 5.54- 6.49).

Imaging System and Image Capture

- The imaging system[3] consisted of a digital camera, lighting system, computer and image processing software.
- For imaging, meat samples were placed flat on a non-glare black surface and illuminated with standard lighting. The still images of lamb chops were later transferred to the PC for storage and analysis.

Shear force measurement:

- Samples were cooked in leak proof plastic bags, until they reached an internal temperature of 75⁰C. Tenderness was tested using MIRINZ tenderometer and the shear force (kgF) was determined[4].

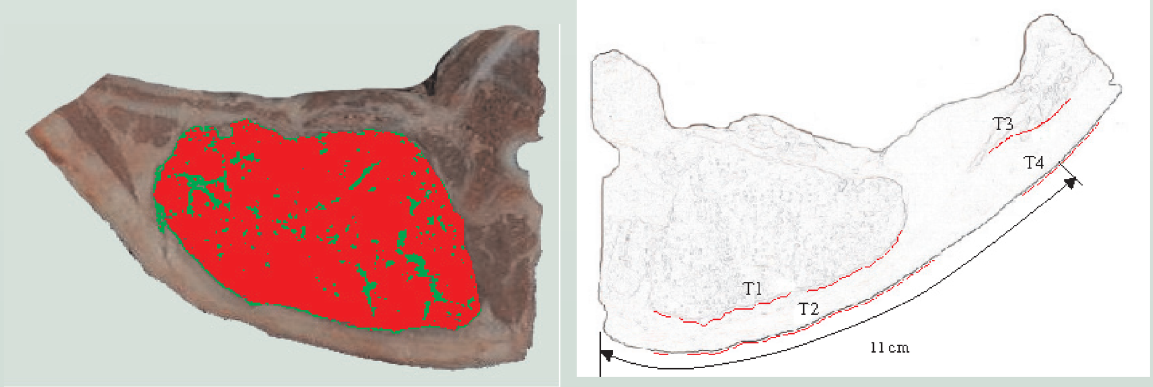

Figure 1. Lean, marbling area, and fat thichness measurements

Data Analysis

- Principal component analysis (PCA) and cluster analysis together with correlation coefficients and ANOVA were used to reduce the dimensionality of the data. The final set of texture variables included six geometric variables, eight GLCM, four GLDM, four GLRM texture variables.
- Classification was performed with the reduced set of variables and ultimate pH as input and the tenderness of cooked lamb as output using regression models (SPSS; release 10.05) and NN models (NeuroShell 2).
- Group Method of Data Handling (GMDH) network was used for NN models.

Table 1. Results of regression models

	Variables	R^2
1	6 geometric + 8 GLCM	0.44
2	6 geometric + 8 GLCM + pH	0.50
3	6 geometric + 8 GLCM + 4 GLDM	0.55
4	6 geometric + 8 GLCM + 4 GLRM	0.48
5	6 geometric + 8 GLCM + 4 GLDM + 4 GLRM	0.60
6	6 geometric + 8 GLCM + 4 GLDM + 4 GLRM + pH	0.65

Image processing and analysis

- Geometric variables were measured from the images after being segmented into lean (dark) and fat (light) areas. Fat thickness values were obtained as shown in Figure 1. A total of 12 image geometric variables were calculated as described earlier[2].

Texture analysis

- Grey level co-occurrence matrix (GLCM) method[4] was used to extract texture features. A total of 90 texture variables was obtained using GLCM.
- Five scalar meausrements were obtained from grey level difference histogram (GLDM)[5] and we defined four scalar measurements analogous to the GLCM features. The nine scalar measurements were calculated in 0°, 45°, 90°and 135° directions which resulted in a total of 36 texture features.
- Grey level run length matrix (GLRM) method[6] was used to calculate five functions in 0° and 90° directions. A total of 10 run length texture variables were obtained.

Results and Discussion

- Models that included textural varibles from different techniques improved the prediction of cooked lamb tenderness.
- Different techniques for analysing image texture may contain different information and an additive effect could result from adding variables from different techniques in the prediction model which improved the coefficient of determination (R^2, Tables 1 and 2).
- In all instances, NN models produced the best prediction.
- Computer vision and appropiate data handling can be an effective tool to predict lamb tenderness.

Table 2. Results of neural network models

	Variables	R^2
1	6 geometric + 8 GLCM	0.74
2	6 geometric + 8 GLCM + pH	0.75
3	6 geometric + 8 GLCM + 4 GLDM	0.79
4	6 geometric + 8 GLCM + 4 GLRM	0.86
5	6 geometric + 8 GLCM + 4 GLDM + 4 GLRM	0.87
6	6 geometric + 8 GLCM + 4 GLDM + 4 GLRM + pH	0.91

References

1. Li et al. (1999). *Meat Sci.,* 53, 17-22.
2. Chandraratne et al. (2003). *Proceedings of the 49th ICoMST,* pp ??.
3. Chandraratne et al. (2002). *Proceedings of the 48th ICoMST,* pp 756-757.
4. Haralick et al. (1973). *IEEE Trans. on System*, *Man and Cybern*etics, SMC - 3, 610-621.
5. Weszka et al. (1976). *IEEE Trans. on System*, *Man and Cybern*etics, SMC - 6, 269-285.
6. Galloway (1975). *Computer Graphics and Image Processing,* 4, 172-179.