

## PREDICTION OF LAMB TENDERNESS USING TEXTURE FEATURES

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## Background

Meat quality is a subject of growing interest. The meat industry, in response to consumer demand for products of consistent quality, is placing more and more emphasis on quality assurance issues. Tenderness is an important quality parameter and is rated as very important by the average customer (Lawrie, 1998). Meat tenderness is measured objectively by determining the force required to shear or penetrate a piece of meat. Equipment like the Warner-Bratzler shear device and MIRINZ tenderometer are available for objective measurement of meat tenderness. These methods are however destructive. Therefore an accurate, consistent, rapid and non-destructive method to evaluate meat tenderness is needed in the meat industry.

Recent advances in the area of computer vision have created new ways to monitor quality in the food industry. Computer vision has enormous potential for evaluating meat quality as image-processing techniques can quantitatively and consistently characterize complex geometric, colour and textural properties. This technique consists of associating a camera for image acquisition, with a computer for image analysis.

Marbling and colour scores have been used as indicators of beef tenderness. But colour and marbling scores have limited power to predict cooked beef tenderness. The possible reason for this poor prediction is that colour and marbling scores do not contain reliable information about tenderness. This has motivated researchers to find alternative indicators for tenderness. Image texture features have shown to be a useful indicator of beef tenderness. Colour, marbling and image texture features have been used to develop tenderness prediction models for beef (Li et al., 1999). They performed statistical as well as neural network analyses to relate image features to tenderness score. In the work of Li et al. (2001), multi-scale texture analysis based on wavelets was used to classify beef samples into tender and tough categories in terms of cooked beef tenderness.

Artificial neural networks (ANNs) are information processing systems which implement simplified models of their biological counterparts, biological neural networks. An ANN contains many simple processing elements (neurons) and are capable of learning from the environment in which they operate and adapting their responses according to the feedback that they receive.

## Objectives

The objectives of the present study were: a) to determine the usefulness of raw meat surface characteristics in cooked meat tenderness prediction; and b) to use neural network models to relate lamb tenderness with geometric and textural data extracted from lamb chop images

## Methods

**Sample collection:** Lamb mid loin chops were taken from 160 lamb carcasses. After 24 hrs of aging, two sets of mid loin chops at 13<sup>th</sup> rib were removed from both sides of the carcass. One set of samples was used for 24 hrs tenderness evaluation and imaging. The other set was aged at 1°C until 21 days post-mortem and then used for tenderness evaluation.

**Image capture:** The imaging system consisted of a digital camera, lighting system, personal computer and image processing and analysis software (Chandraratne et al., 2002). The samples were all bloomed for 30 min. and surface moisture removed with a paper towel prior to image capture. For imaging, lamb chops 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. The images included lean area, marbling, subcutaneous fat, intermuscular fat and bone.

**Shear force measurement:** Samples were cooked in leak proof plastic bags, containing weights, immersed in a water bath set at 80°C until they reached an internal temperature of 75°C. After cooling on ice between 8 and 10 pieces of meat (10 x 10 x 30 mm) were removed with muscle fibres running parallel to the longitudinal direction of the piece of meat. The pieces of meat were tested using MIRINZ tenderometer and the shear force (kgF) was determined. The detailed tenderness testing procedure is given in Bickerstaffe et al., 2001.

**Image and texture analyses:** Image processing and analysis was accomplished using Image-Pro Plus (Media Cybernetics, USA). Thresholding was done through trial and error by observing and selecting the best value. Initial values for thresholding were selected from the plot of pixel intensities. A total of 12 image geometric variables were measured. These included 4 area measurements (*lean area, marbling area, subcutaneous fat area, lean ratio* (ratio between lean and lean + marbling)), *number of marbling specks*, 3 measurements of subcutaneous fat thickness (*sub fat average, sub fat maximum, sub fat minimum*), fat thickness at 11 cm from the midline of the carcass (*fat 11*) and 3 measurements of fat thickness between 10 and 12 cm from the midline of the carcass (*fat 11 average, fat 11 maximum, fat 11 minimum*). Grey level co-occurrence matrix was used to extract texture features. The number of texture parameters calculated from the co-occurrence matrix was 18 (Haralick et al., 1973). The texture parameters were calculated from five co-occurrence matrices: four directional matrices (0°, 45°, 90°, 135°) and summation matrix. There were a total of 90 texture variables.

**Data analysis:** Statistical analysis was performed with Minitab (release 13.1, Minitab Inc.) and SPSS (release 10.0.5, SPSS Inc.). Neural network analysis was performed with NeuroShell 2 (Ward Systems Group Inc., Frederick, MD).

## Results and Discussion

Statistical modelling methods have been used in the past for prediction tasks. However ANN, a non-linear approach, could be a promising alternative method for prediction when prediction models are non-linear. ANNs are capable of performing complex prediction and classification tasks. ANNs are trained to do these tasks by repeatedly presenting it with known input vectors and corresponding outputs. After training, the network can perform the task for new inputs that it has never seen before. In classification and non-linear function approximation, multi-layer perceptron (MLP) networks have become very popular in recent years.

For each image, 102 features were calculated: 12 image variables and 90 co-occurrence texture variables. With 102 inputs and one output, the number of weights in the MLP network was much larger than the number of samples. As a result, some of the weights cannot be uniquely determined from observed data. Therefore, an effective method for reduction of dimensionality of the input feature space was desired. On the

other hand, the dimensionality reduction is justified as some of the variables measured are highly correlated with others and carry no additional information, making them redundant. Principal component analysis (PCA), a method of data compression developed to identify the directions of main variability in a multivariate data space, was used to reduce the dimensionality of input variables.

According to the results of PCA, 96% of the total variance of image geometric variables can be condensed into six variables. The results were confirmed by cluster analysis. The final set of six variables included *lean area*, *marbling area*, *fat area*, *lean ratio*, *sub fat average* and *fat II*. In a similar way, 90 variables calculated from co-occurrence matrix were condensed to eight (*mean*, *entropy*, *homogeneity*, *contrast*, *cluster prominence*, *cluster shade*, *difference entropy* and *information measures of correlation 2*) whilst retaining 99% of the total variance.

An MLP with back propagation algorithm was performed to train the network with one-, two- and three-layers of hidden nodes. To prevent overtraining of developed models, the original dataset was randomly divided into training (80%), testing (10%) and validation (10%) sets. Testing dataset was applied to prevent over-fitting and validation dataset was used to validate the developed model. Several different neural networks and learning schedules were tested to select the best neural network. The default number of hidden neurons specified by the program for the three-layer network was 15. Neural networks with number of hidden nodes (12 to 22) were trained. Different combinations of learning rates (0.1 to 0.9), momentums (0.1 to 0.9) and initial weights (0.1 to 0.9) were tested. Different activation functions (logistic, symmetric logistic, tanh, sine, Gaussian and Gaussian complement), weight updates (vanilla, momentum and turboprop) and pattern selections (rotation or random) were also examined. In all cases, linear scale functions [-1,1] were used for input nodes.

The results from neural network models are shown in Table 1. In the ANN analysis, the 14 variables in the reduced feature space (six-image geometric and eight texture variables) were used as inputs and the tenderness (21 days) was used as the output. Neural network analysis was also performed using six geometric variables as inputs to assess the suitability of geometrical variables alone for tenderness prediction. In all cases, networks reached the stopping criterion of 6000 learning epochs in less than 30 seconds. The best coefficient of determination ( $R^2$ ) achieved with six geometric variables and 14 (geometric + texture) variables was 0.621 and 0.746, respectively. The  $R^2$  of 0.72 and 0.70 have been reported using statistical and neural networks, respectively (Li et al., 1999).

ANNs have the power to approximate any non-linear input output relationship, provided that certain steps are carefully followed in designing and training the network. Number of factors need to be considered for an ANN to produce the best results by detecting the patterns contained in a data set. The network performance should be optimised with respect to the network architecture and the size of the training data set. The other variables that affect the ANN model development and performance are the type of learning rule (momentum and learning rate) and transfer function. The network selection has a significant effect on the results obtained. The network architecture also needs to match with the objectives of the study as measured by the generalisation ability of the network. The complexity of the network that mainly depends on its architecture must be matched to the complexity of the problem and the number of training samples. A very complex network can perfectly learn the training set but generalise poorly (Smith, 1996; Tarassenko, 1998).

## Conclusion

The PCA was used to reduce 12 geometric variables to six and 90 texture variables to 8. ANN models were developed using the reduced set of data as inputs and tenderness as output. The results indicate that the data extracted from images of lamb chops can be effectively used to predict lamb tenderness. The  $R^2$  of prediction using the geometrical features alone was 0.621. The use of texture variables improved the  $R^2$  to 0.746, indicating that the textural features can be used as indicators of quality characteristics of lamb samples in conjunction with geometric variables. ANNs can provide good results in a relatively short time, if a great deal of care is taken over the collection and pre-processing of the data and the design of the network architecture.

## Pertinent Literature

- Bickerstaffe, R., Bekhit, A. E. D., Robertson, L. J., Roberts, N. and Geesink, G. H. (2001). *Meat Science*, 59 (3), 303-315.
- Chandraratne, M. R., Kulasiri, D., Samarasinghe, S., Frampton, C. and Bickerstaffe, R. (2002). 48<sup>th</sup> ICoMST, Rome, Italy, 25-30 August 2002, pp 756 - 757.
- Haralick, R. M., Shanmugan, K. and Dinstein, I. (1973). *IEEE transactions on Systems, Man and Cybernetics*, SMC-3 (1), 610 - 621.
- Lawrie, R. A. (1998). *Meat science*. Cambridge: Woodhead Publishing.
- Li, J., Tan, J., Martz, F. A., & Heymann, H. (1999). *Meat Science*, 53, 17 - 22.
- Li, J., Tan, J., & Shatadal, P. (2001). *Meat Science*, 57, 341 - 346.
- Smith, M. (1996). *Neural networks for statistical modelling*. London; Boston: International Thomson Computer Press.
- Tarassenko, L. (1998). *A guide to neural computing applications*. London: Arnold.

Hidden layers	Input nodes	Hidden nodes	Hidden nodes activation functions	Weight update	Pattern selection	Learning rate	Momentum	Initial weight	$R^2$
1	6	15	tanh	momentum	random	0.1	0.6	0.3	0.435
2	6	5+5	tanh / Gaussian	momentum	random	0.5	0.1	0.3	0.525
3	6	5+5+5	tanh15 / sine / symmetric logistic	vanilla	random	0.1	0.1	0.6	0.621
1	14	23	logistic	turboprop	rotation	0.1	0.1	0.2	0.746
2	14	8+8	tanh / logistic	momentum	random	0.9	0.1	0.3	0.615
3	14	6+6+6	tanh15 / symmetric logistic / logistic	vanilla	random	0.3	0.1	0.3	0.677

Table 1. Results of neural network models