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LAMB CARCASS CLASSIFICATION SYSTEM BASED ON COMPUTER VISION PART 2: TEXTURE FEATURES AND NEURAL NETWORKS

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Abstract

In this study, the ability of neural network models for lamb carcass classification was compared with a multivariate statistical technique with respect to the classification accuracy. The lamb carcass classification system is based on image and texture analyses. Digital images of lamb chops were used to calculate twelve image geometric variables. In addition, a set of ninety textural features was used to extract the textural information from the acquired images. Texture analysis is based on the grey level co-occurrence matrix method.

Principal component analysis (PCA) was used to reduce the dimensionality of feature spaces. Two feature sets were generated. These feature sets comprised of 14 principal component (PC) scores calculated from the original variables and 14 variables selected from the original set of variables. Both feature spaces were used for neural network and discriminant analysis.

Several network configurations were tested and the classification accuracy of 93% was achieved from three-layer multilayer perceptron (MLP) network. Its performance was 14% better than that from the Discriminant function analysis (DFA). The study shows the predictive potential of combining neural networks with texture analysis for lamb grading.

Key words: Image analysis, Texture features, Lamb grading, Computer vision, Discriminant analysis, Artificial neural networks, Co-occurrence matrix

1. Introduction

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. Visual assessment has become the principal component of several meat classification and grading systems. Instrument grading of animal carcasses has been studied to meet the demand for increased accuracy and uniformity of meat grading. The development of an accurate, reliable and robust inspection system is needed to improve the current visual grading approach.

Computer vision has enormous potential for evaluating meat quality as image processing and analysis 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. A digital image is represented as a two dimensional matrix of numbers. Its fundamental elements are pixels. The process of displaying an image creates a graphical representation of this matrix, where the pixel values are assigned to a particular colour or grey value. In New Zealand, the assignment of lamb carcasses to specific quality grades (Figure 1) has been an integral part of a lamb carcass classification system. The current classification is based solely on carcass weight and fatness measurements (Chandraratne et al., 2003; New Zealand Meat Board, 1992).

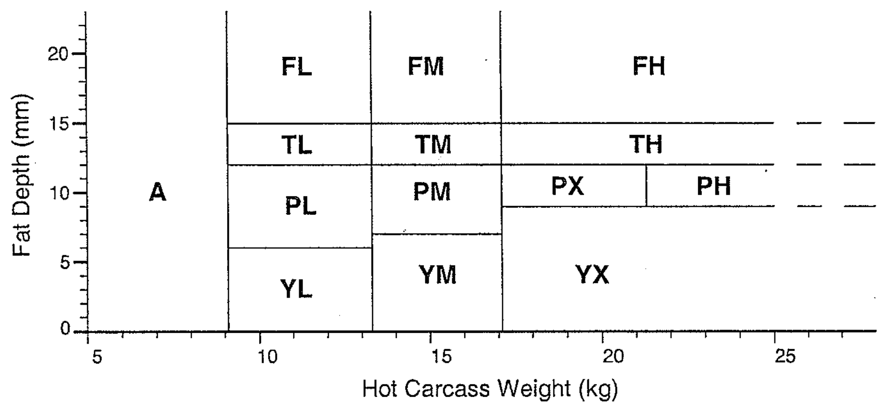

Figure 1. New Zealand lamb carcass classification system

Image texture has been used in image analysis for segmentation and analysis. Texture is the term used to characterize the surface of a given object or phenomenon and is one of the main features used in image processing. Since the textural properties of images appear to carry useful information, it is important to extract textural features from images. One way to bring this type of information into analysis is to consider not only the distribution of intensities but also the position of pixels. The process of texture analysis requires the calculation of various feature measures that provide a quantitative measure of a certain texture characteristic. These features contain not only information representative of visual characteristics but also characteristics that cannot be visually differentiated.

A variety of techniques for analysing image texture have been proposed over the past 3 decades. Feature extraction techniques used for image texture description have been classified into two categories (statistical and structural) by Ahuja and Rosenfeld (1981), Haralick (1979), Van Gool et al. (1985) and Wechsler (1980). More recently, Gonzalez and Woods (2002) classified texture analysis methods into three categories: statistical, structural and spectral. Tuceryan and Jain (1999) classified texture analysis methods into four categories as statistical, structural (geometrical), model-based and signal processing.

In this study, we selected grey level co-occurrence matrix (GLCM) method to estimate texture features. The selection was based on reported performance, popularity in the literature, ease of implementation and use. Texture analysis is an important and useful area of study in machine vision. Most natural surfaces exhibit texture and a successful vision system must be able to deal with the textured world surrounding it.

Early studies have shown that image analysis technology has great potential to improve the current human grader based meat quality operation (Cross et al., 1983; Wassenberg et al., 1986). Texture features extracted using GLCM (Li et al., 1999; Shiranita et al., 1998), grey level run length matrix (GLRM) method (Li et al., 1999; 2001), fractal approach (Ballerini and Bocchi, 2001) and wavelets (Li et al., 2001) have been used in meat quality evaluation exercises.

Statistical modelling methods have been used in the past for image classification. However artificial neural networks (ANNs) could be a promising alternative method for classification when classification boundaries are non-linear and the interactions of input variables are complex. ANNs are capable of performing complex prediction and classification tasks.

Neural networks have been widely used in meat evaluation purposes. In the study of Li et al. (1999), a neural network model has been used to predict beef tenderness. A feed forward back propagation (BP) neural networks model has been developed for prediction and classification of beef quality attributes (Park et al., 1994). MLP network with BP algorithm has been used for pork colour classification (Lu et al., 1997). In the study of Tian et al. (1997), a three-layer feed forward neural network with BP algorithm have been used for the prediction of tenderness. Shiranita et al. (2000), used a three-layer neural network to study the implementation of a meat quality grading system.

The aim of the present study was to investigate the use of image processing and texture analysis techniques in the classification of lamb chop images. The specific objective was to develop a method based on ANN approach to evaluate lamb carcass grade using image and texture features extracted from lamb chop images. Furthermore, the classification performance of neural networks was compared with results from the DFA approach.

2. Materials - Source of Lamb Chops and Image Acquisition

The data was collected from 160 digital images of lamb mid loin chops. The imaging system consisted of a Digital Camera, Lighting system, Personal Computer and Image processing and analysis software. Images were captured as described in Chandraratne et al. (2003).

3. Methods

3.1. Image Processing and Analysis

Image processing and analysis were accomplished in the Windows 98 environment using Image-Pro Plus imaging software. A total of 12 image geometric (thickness and area) variables were measured (Chandraratne et al., 2003).

3.2. Texture Features Extraction - Grey Level Co-occurrence matrix (GLCM)

In this research, we used GLCM to extract texture features from lamb chop images. This algorithm has proven useful on a variety of real world problems (Conners and Harlow, 1980; Conners et al., 1984; Haralick et al., 1973; Ohanian and Dubas, 1992; Weszka et al., 1976). The GLCM is based on the estimation of second order joint conditional probability density functions $P(i, j: d, \theta)$. Each $P(i, j: d, \theta)$ is the probability that two neighbouring pixels with grey levels i and j occur for a given distance d and direction θ. This yields a matrix of dimensions equal to the grey levels in the image, for each distance and orientation (d, θ) (Chandraratne et al., 2003).

The co-occurrence matrices were calculated in the four principal directions $\theta = 0^0$, 45^0, 90^0 and 135^0 with $d = 1$. To implement the rotation invariance we combined co-occurrence matrices in four principal directions and obtained summation matrix $P\,(i, j\,)$. The five matrices are then normalized by dividing each entry of the co-occurrence matrix by the total number of paired occurrences in the image. Eighteen texture parameters were calculated from each of the five normalized co-occurrence matrices making a set of 90 variables (Chandraratne et al., 2003).

3.3. 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, Frederick, MD). Image data was analysed using ANN and DFA procedure was used for comparison.

3.3.1. Dimensionality Reduction

Total number of inputs to the neural network was 102 (12 image geometric variables and 90 texture variables). With 6 outputs specifying the grades, 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. This situation is over-parameterisation and is a serious problem in meat quality prediction.

This problem can be solved by either providing a large number of training samples to satisfy the requirement of the network or reducing the number of weights (i.e. reducing the number of hidden neurons) to match with the number of training samples. The former approach usually create following disadvantages: 1) large number of inputs result in complex networks with excessively long training time; 2) the back-propagation (BP) algorithm usually suffers from a slow convergence property due to interacting effects of synaptic weights on the error signal; with large number of inputs this can create a severe problem, which in turn can make it computationally expensive. If the inputs to the MLP network are uncorrelated then the use of simple local accelerating procedures permit a considerable speedup in the convergence process (Haykin, 1999). Therefore, an effective method for reduction of dimensionality of the input feature space was desired. PCA was used to reduce the dimensionality of data. Reducing the number of inputs (i.e. reducing number of weights) to the network allows us to collect less data while maintaining an appropriately reduced level of network complexity.

Principal component analysis (PCA)

PCA is a method of data compression, developed to identify the directions of main variability in a multivariate data space. It linearly transforms the original set of variables into new axes or principal components (PCs), while retaining as much variation as possible in the original data set. The PCs are uncorrelated and ordered so that the first PC displays the largest amount of variation and each successively defined PC expresses successively decreasing amount of variation. The first few PCs contain most of the variation in the original data set (Manly, 1994).

Table 1. Results from PCA for image variables and texture variables

	Principal components	Eigen value	% Variance	Cumulative variance
Image geometric variables	PC1	5.24	43.7	43.7
	PC2	2.46	20.5	64.2
	PC3	1.79	14.9	79.1
	PC4	1.05	8.7	87.8
	PC5	0.62	5.1	93.0
	PC6	0.38	3.1	96.1
Co-occurrence texture variables	PC1	47.03	52.3	52.3
	PC2	17.67	19.6	71.9
	PC3	11.20	12.4	84.3
	PC4	5.89	6.5	90.9
	PC5	4.89	5.4	96.3
	PC6	1.20	1.3	97.6
	PC7	0.78	0.9	98.5
	PC8	0.59	0.7	99.2

According to the results of PCA, 96.1% of the total variance of image geometric variables can be condensed into six variables (Table 1). In a similar way, 90 variables calculated from co-occurrence matrix were condensed to eight, whilst retaining 99.2% of the total variance. Two feature sets were generated based on the results of PCA. The first set (feature set 1) comprised of 14 PC scores. Six PC scores were calculated from geometric variables and eight from texture variables. The second set (feature set 2) comprised of 14 variables, which were selected from the original set of variables, one variable for each principal component. This set includes six geometric variables (*fat* 11, *lean ratio, sub fat average, lean area, fat area* and *marbling area*) and eight texture variables (*mean*, *homogeneity*, *entropy*, *contrast*, *cluster prominence*, *cluster shade*, *difference entropy* and *IMC* 2) (Chandraratne et al., 2003).

3.3.2. Discriminant function analysis

DFA is concerned with the problem of assigning objects into certain groups that are already identified in the sample. DFA finds a set of linear combinations of the variables, whose values are as close as possible within groups and as far apart as possible between groups. A discriminant function is a linear combination of the discriminating (independent) variables. Both feature sets (feature set 1 and 2) were used for DFA analysis. The same sets were used for neural network analysis described in the next section. The Discriminant analysis procedure and the results have been discussed in detail in Chandraratne et al., 2003.

4. Neural networks analysis

In classification and non-linear function approximation, MLP networks have become very popular in recent years. An MLP with back-propagation algorithm was performed to train the network with hidden layers. Figure 2 shows the structure of an MLP network used for the classification of lamb images. The input-output relationships in the hidden and output layers are respectively defined as

$$y_j = g(u_j) = g\left(\sum_{i=1}^{I} a_{ij}x_i + a_{0j}\right) \qquad j = 1, 2, \ldots, J$$

$$z_k = f(v_k) = f\left(\sum_{j=1}^{J} b_{jk}y_j + b_{0k}\right) \qquad k = 1, 2, \ldots, K$$

I, J and K are the number of inputs x_i, the number of hidden nodes (neurons) with outputs y_j and the number of output nodes with outputs z_k, respectively. The a_{ij} is the weight that connects the input node i to the hidden node j and b_{jk} is the weight that connects the hidden node j to the output node k. The bias weight of the hidden node j is a_{0j}, while that of the output node k is b_{0k}. The inputs to the hidden node j and the output node k are u_j and v_k respectively. The activation functions of the hidden and the output neurons are $g(\cdot)$ and $f(\cdot)$ respectively. It is usually a non-linear function. The activation functions examined in the study are logistic, symmetric logistic, tanh, Gaussian, Gaussian complement.

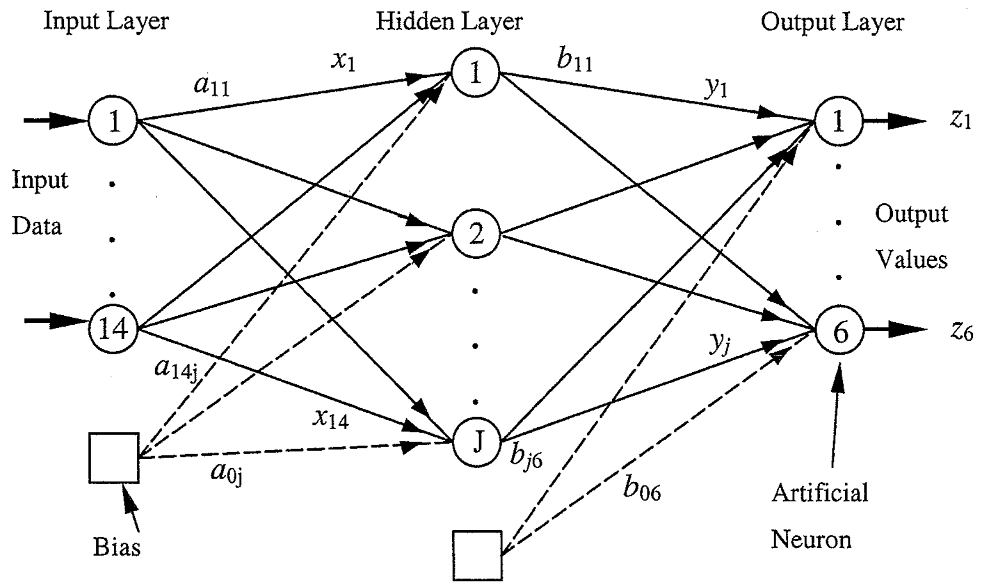

Figure 2. Three layer fully connected MLP network

Once a network has been structured for a particular application, training of the network is done through adjustment of connection weights to achieve a desired overall behaviour, via a learning rule. The error correction learning rule and the back-propagation learning algorithm was used to train the network. In learning, the overall error function is defined as the mean squared error: the average of the square of the differences between the network output and the target output over the training data set, as follows:

$$E = \frac{\frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{K}\left(z_{kn} - t_{kn}\right)^2}{NK}$$

where t_{kn} and z_{kn} are the target output and the actual output respectively, of node k for the n^{th} input signal, N is the number of examples in the training data set. The error minimization is carried out with respect to the weights by means of the back-propagation algorithm.

ANN analysis was performed with feature sets 1 and 2. The 14 variables in the feature sets were used as inputs and the grades were used as outputs. To avoid any hierarchy among grades, the symbols representing six grades were translated into six variables, one for each grade, that is coded 1 for belonging to the grade and 0 for not belonging. In processing the data through the trained neural network the highest output was set to 1 and the others to 0. To prevent overtraining of developed models, the original dataset was divided into training, testing and validation sets. Testing data were applied to prevent over-fitting of the model during the training stages and validation data were used to validate the developed model. The network that produced best results (minimum average error) on the test set, the "best test set", was saved as the best network. The average error for the test set was computed after 200 test set patterns propagated through the network.

5. Results and Discussion

Several different network architectures and learning parameters were examined to select the best neural network. ANN with number of hidden layers (1 to 3) and hidden nodes (12 to 30) were trained. The default number of hidden neurons specified by the program for the three-layer network was 21. Different combinations of learning rates (0.1 to 0.9), momentums (0.1 to 0.9), initial weights (0.1 to 0.9) and activation functions (logistic, symmetric logistic, tanh, Gaussian, Gaussian complement) were tested. Different weight updates (vanilla[1], momentum and turboprop[2]) and pattern selections (rotation or random) were also examined. In all cases, linear scale functions [-1,1] were used for input nodes and the logistic activation function was found to be the best for output nodes.

Table 2. Results of classification of meat grades using feature set 1

Analysis method	No of grades correctly classified (%)						
	FH	PM	PX	TH	YM	YX	Total
DFA*	100	66.7	48.1	100	54.8	72.0	66.3
DFA	100	66.7	59.3	80.0	77.4	82.7	76.9
3-layer MLP	71.4	53.3	85.2	80.0	77.4	97.3	85.6
4-layer MLP	100	73.3	74.1	80.0	71.0	93.3	83.8
5-layer MLP	100	60.0	77.8	80.0	77.4	94.7	85.0

* using 6 geometric variables as inputs

[1] In vanilla, only learning rate is applied to weight updates but not momentum.

[2] In turboprop, weights are updated every epoch. The turboprop uses an independent weight update sizes for each different weight, rather than the same learning rate and momentum for all weights. The step sizes are adaptively adjusted as learning progresses.

The results from neural network models and DFA for feature set 1 are shown in Table 2. For MLP networks, the overall classification accuracy varies between 83.8% and 85.6%. There is a considerable variation in the classification rate of individual grades; 53.3% in 3-layer network for grade PM to 100% in 4- and 5-layer networks for grade FH. The results from neural network models and DFA for feature set 2 are shown in Table 3. For MLP networks with 14 inputs, the overall classification accuracy is higher than feature set 1 and varies between 90% and 93.1%. But there is a considerable variation in the classification rate of individual grades; 40% in 5-layer network to 100% in 3- and 4-layer networks for grade TH.

In both cases, highest classification accuracy was achieved with 3-layer network. The advantages of feature set 2 over feature set 1 are: the classification accuracy using feature set 2 (93.1%) was 7.5% better than that using feature set 1; the classification rate of individual grades using feature set 2 varies between 71.4% and 100% while that of feature set 1 varies between 53.3% and 97.3%. The computational time required to calculate feature set 2 is much less than that of feature set 1. The feature set 1 is calculated from the original set of variables, which required calculation of 102 variables from images and then calculation of 12 PC scores. The feature set 2 doesn't require all 102 variables; only 14 selected variables are calculated. Therefore we selected only the results of feature set 2 for further discussion.

Table 3. Results of classification of meat grades using feature set 2

Analysis method	No of grades correctly classified (%)						
	FH	PM	PX	TH	YM	YX	Total
DFA*	100	73.3	44.4	100	58.1	66.7	64.4
4 layer MLP*	71.4	46.7	92.6	100	90.3	93.3	87.5
DFA	100	73.3	63.0	100	74.2	85.3	79.4
3 layer MLP	71.4	93.3	96.3	100	87.1	96.0	93.1
4 layer MLP	71.4	93.3	92.6	100	87.1	96.0	92.5
5 layer MLP	85.7	93.3	77.8	40.0	93.4	96.0	90.0

* using 6 geometric variables as inputs

A network with two hidden layers (12 and 10 hidden nodes in the first and second layer, respectively), turboprop weight update, and rotation pattern selection produced a classification accuracy of 92.5%. The learning rate, momentum and initial weight used were 0.1, 0.1 and ± 0.3, respectively. Logistic activation function was used for both hidden layers. A network with three hidden layers (each having 7 hidden nodes), momentum weight update, and rotation pattern selection produced classification accuracy of 90%. The activation functions used were tanh, Gaussian and logistic for first, second and third hidden layers, respectively. The learning rate, momentum and initial weight used were 0.1, 0.1 and ± 0.3, respectively.

The highest classification rate of 93.1% was achieved using a network with single hidden layer (23 hidden nodes), turboprop weight update and rotation pattern selection. Logistic activation function was used for hidden nodes. The learning rate, momentum and initial weight used were 0.1, 0.1 and ± 0.2, respectively. In all cases, the network reached the stopping criterion of 6000 learning epochs in less than 50 seconds.

Table 4. Details of misclassified images - 3 layer MLP

	FH	PM	PX	TH	YM	YX	Total
FH	71.4	0.0	0.0	14.3	0.0	14.3	100.0
PM	0.0	93.3	0.0	0.0	6.7	0.0	100.0
PX	0.0	0.0	96.3	0.0	0.0	3.7	100.0
TH	0.0	0.0	0.0	100.0	0.0	0.0	100.0
YM	0.0	0.0	0.0	0.0	87.1	12.9	100.0
YX	0.0	0.0	4.0	0.0	0.0	96.0	100.0

Considering the highly variable nature of the input data, the results from neural network models show remarkable accuracy that varies somewhat with the grade (Table 3). The behaviour of the FH grade is somewhat different in terms of classification. It produced 71.4% classification with three- and four-layer networks and 85.7% with five-layer network, which is much lower than the 100% classification accuracy obtained from DFA. The grade TH produced low classification rate with five-layer network. In all the other cases neural networks produced higher classification rates than DFA. Classification rate for the grades PM and YX remains unchanged for all three types of neural networks. Five-layer MLP had a better classification rate for grades FH and YM, but the overall classification rate was lower than the other two types of MLPs.

More than 35% of the New Zealand lambs produced for the export market belong to the YM grade (Meat New Zealand, 2001). The YX, PM and PX grades together account for nearly 50% of the export lamb production. The TH and FH grades comprise about 5%, the grades YL and PH account for about 6% and the other grades (PL, TL, TM, FL and FM) contribute 1%. The majority of carcasses fall, therefore, into YM, YX, PM and PX grades. Thus higher classification accuracy is required for these grades.

Table 5. Details of misclassified images - 4 layer MLP

	FH	PM	PX	TH	YM	YX	Total
FH	71.4	0.0	14.3	14.3	0.0	0.0	100.0
PM	0.0	93.3	0.0	0.0	6.7	0.0	100.0
PX	0.0	3.7	92.6	0.0	0.0	3.7	100.0
TH	0.0	0.0	0.0	100.0	0.0	0.0	100.0
YM	0.0	9.7	0.0	0.0	87.1	3.2	100.0
YX	0.0	0.0	4.0	0.0	0.0	96.0	100.0

The details of misclassified images are shown in Tables 4, 5 and 6 for three-, four- and five-layer networks, respectively. All the misclassified images of the grade PM were classified as grade YM. These two grades lie between the same weight ranges. A fat depth of 7 mm separates the grades. A fat depth higher than 7 mm is graded as PM and fat depth with 7 mm or less is graded as YM. On the other hand, in 4- and 5-layer networks, the misclassified images of the grade YM fell into the grades PM and YX, the two grades adjacent to YM. In 3-layer network, all the misclassified images of the grade YM fell into YX.

Table 6. Details of misclassified images - 5 layer MLP

	FH	PM	PX	TH	YM	YX	Total
FH	85.7	0.0	0.0	0.0	0.0	14.3	100.0
PM	0.0	93.3	0.0	0.0	6.7	0.0	100.0
PX	0.0	0.0	77.8	0.0	0.0	22.2	100.0
TH	60.0	0.0	0.0	40.0	0.0	0.0	100.0
YM	0.0	3.3	0.0	0.0	93.4	3.3	100.0
YX	0.0	1.3	2.7	0.0	0.0	96.0	100.0

Similar observations were made between the grades YX and PX. The two grades are separated by 9 mm fat depth. In 3- and 5-layer networks, all the misclassified images of the grade PX fell into the grade YX, while in 4-layer network, the misclassified images of the grade PX fell into grades YX and PM. In 3- and 4-layer networks, all the misclassified images of the grade YX fell into the grade PX, while in 5-layer network, the misclassified images of the grade YX fell into the grades PX and PM.

Figure 3 depict the effect of hidden neurons and hidden layers on classification rate using feature set 2. The network performance was highest around 23 hidden nodes. Single and two hidden layer models had a fairly high classification rate (> 70%) throughout the range examined with the number of hidden nodes between 12 and 30. The network with single hidden layer produced the highest classification rate of 93.1% with 23 hidden nodes. Assigning the appropriate number of hidden neurons and layers are mostly a trial and error method.

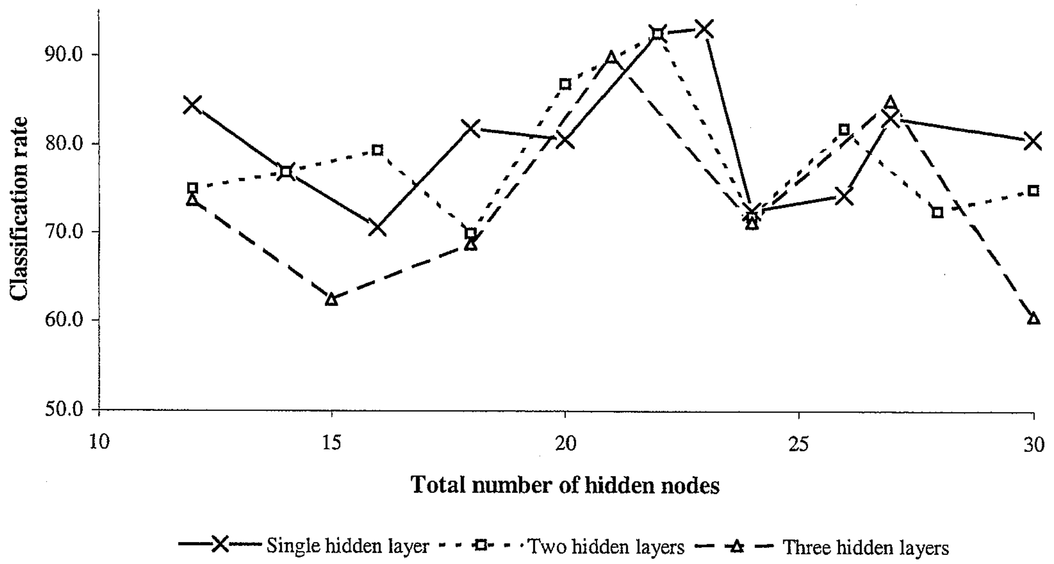

Figure 3. Effect of hidden neurons and hidden layers on classification using feature set 2

Neural network analysis was also performed using six geometric variables as inputs, to assess the suitability of geometrical variables alone for meat classification. The six grades were used as outputs. A network with two hidden layers (each having 8 hidden nodes), momentum weight update, and random pattern selection produced classification accuracy of 87.5% (Table 3). The learning rate, momentum and initial weight used were 0.1, 0.1 and $\pm$ 0.3, respectively. The activation functions used were Gaussian and tanh for first and second hidden layers, respectively. Even though the overall classification rate was high, the weakness was its low classification rate (46.7%) in grade PM. The addition of texture variables (feature set 2) improved the overall classification accuracy to 93.1%, while maintaining high (>71%) classification rates for individual grades.

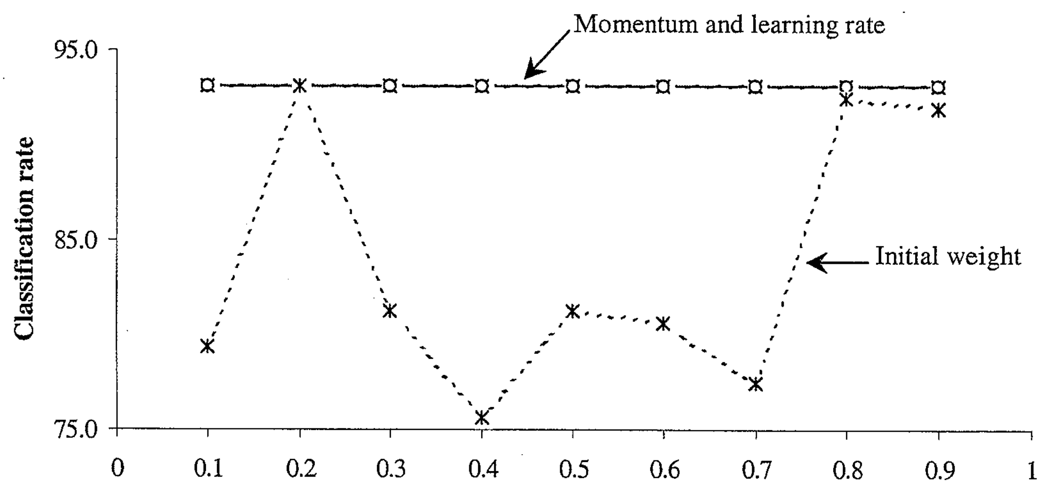

Figure 4. Effect of initial weight, momentum and learning rate on classification

The learning rate, momentum and initial weight were varied between the limits of 0.1 and 0.9 and their effect on classification rate was evaluated. The results for single hidden layer network are shown in Figure 4. Changing the initial weight between 0.3 and 0.7 had no major effect on classification rate. But higher initial weights (0.8 and 0.9) produced fairly high classification rates. The classification rate was independent of momentum and learning rate.

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. If training is poor, even a well-designed network can produce inadequate results. Number of factors need to be considered for an ANN to produce 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 and transfer function. The network selection has a significant effect on the results obtained. The network architecture needs to match with the objectives of the study, measured by the generalisation ability of the network. The complexity of the network that mainly depends on its architecture (i.e. number of layers, hidden neurons, weights etc.) 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).

In addition, there are number of other important aspects need to be considered in designing and training the network including: 1) number of epochs - should be large enough for the network to learn the patterns in the training data set but should not be too large to risk over-fitting, 2) quantity and quality of data - should have sufficient number of data points, relative to the noise, to make generalisation and the training set should carry sufficient information to describe the input-output relationship; ultimate performance of the network depend on the quantity and quality of the data set used to train the network, 3) selecting input variables - the correctly selected variables will allow the network to obtain sufficient information about the patterns in the training data set, 4) data pre-processing - the treatment of data before using it for training is also important (sometimes essential) to improve the model efficiency and 5) format of the data - the correct format of variables could increase the networks learning ability (Smith, 1996).

DFA was performed using the reduced sets of variables (six geometric variables and 14 geometric and texture variables). The analysis was carried out using linear and quadratic discriminant functions, with and without cross validation. In both cases, linear discriminant functions produced better classification than quadratic discriminant functions. The accuracy of classification using six geometric variables and 14 geometric and texture variables were 64.4% and 79%, respectively. The details of misclassified images of DFA are shown in Table 7. Misclassification in grades PM and YM are similar to 4- and 5-layer networks. But the grades YX and PX had quite different results. The grade YX had misclassified images as PM, PX and YM, while the grade PX had misclassified images as YM and YX.

Table 7. Details of misclassified images - DFA analysis

	FH	PM	PX	TH	YM	YX	Total
FH	100.0	0.0	0.0	0.0	0.0	0.0	100.0
PM	0.0	73.3	0.0	0.0	26.7	0.0	100.0
PX	0.0	0.0	63.0	0.0	3.7	33.3	100.0
TH	0.0	0.0	0.0	100.0	0.0	0.0	100.0
YM	0.0	9.7	0.0	0.0	74.2	16.1	100.0
YX	0.0	1.3	6.7	0.0	6.7	85.3	100.0

6. Conclusions

The suitability of ANN models for classification of lamb carcasses, using image and texture features, was studied. The classification performance of the neural network approach was compared with the statistical approach.

The classification showed encouraging results indicating that the data extracted from images of lamb chops can be effectively used to predict the lamb carcass grades. The accuracy of classification using feature set 1 with three-, four- and five- layer MLP network was 85.6%, 83.8% and 85.0%, respectively. Higher accuracy of classification was achieved using feature set 2. The classification accuracy with three-, four- and five- layer MLP network was 93.1%, 92.5% and 90.0%, respectively. The classification accuracy varies with the grade ranging from 71% to 100%. ANN models demonstrate a good potential for application in lamb classification with advantages of accuracy and compatibility with the existing visual grading system.

The classification accuracy using ANN with six geometric inputs alone was 87.5%, indicating that the textural features improve the classification accuracy and can be used as indicators of quality characteristics of lamb samples in conjunction with geometric variables. NN 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. Statistical approach (DFA) produced 79% classification. The neural network approach in this case performed better than the DFA method with 14% improvement of the overall classification accuracy.

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