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Learning techniques used in computer vision for food quality evaluation: a review

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Abstract

Learning techniques have been applied increasingly for food quality evaluation using computer vision in recent years. This paper reviews recent advances in learning techniques for food quality evaluation using computer vision, which include artificial neural network, statistical learning, fuzzy logic, genetic algorithm, and decision tree. Artificial neural network (ANN) and statistical learning (SL) remain the primary learning methods in the field of computer vision for food quality evaluation. Among the applications of learning algorithms in computer vision for food quality evaluation, most of them are for classification and prediction, however, there are also some for image segmentation and feature selection. In this paper, the promise of learning techniques for food quality evaluation using computer vision is demonstrated, and some issues which need to be resolved or investigated further to expedite the application of learning algorithms are also discussed.

Keywords: ANN; Classification; Computer vision; Decision tree; Feature selection; Food; Fuzzy logic; Genetic algorithm; Image segmentation; Learning; Prediction; Quality evaluation; SL

1. Introduction

Quality is a key factor for modern food industry because the high-quality of product is the basis for success in today's highly competitive market. In the food industry, the quality evaluation still heavily depends on manual inspection, which is tedious, laborious, and costly, and is easily influenced by physiological factors, inducing subjective and inconsistent evaluation results. To satisfy the increased awareness, sophistication and greater expectation of consumers, it is necessary to improve quality evaluation of food products (Brosnan & Sun, 2004). If quality evaluation is achieved automatically, production speed and efficiency can be improved in addition to the increased evaluation accuracy, with an accompanying reduction in production costs (Sun & Brosnan, 2003a).

As a rapid, economic, consistent and even more accurate and objective inspection tool, computer vision systems have been used increasingly in the food industry for quality evaluation purposes (Sun, 2000). The application potential of computer vision to the food industry has long been recognised (Tillett, 1990). The food industry ranks among the top 10 industries using computer vision technology (Gunasekaran, 1996), which has been proven successful for the objective and non-destructive quality evaluation of several food products (Timmermans, 1998). Being an objective, rapid and non-contact quality evaluation tool, computer vision has been attracting much R&D attention from the food industry, and rapid development has been increasingly taking place on quality inspection of a wide range of food products (Sun, 2004).

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Combined with an illumination system, a computer vision system is typically based on a personal computer (PC) in connection with electrical and mechanical devices to replace human manipulative effort in the performance of a given process. Illumination is an important prerequisite of image acquisition for food quality evaluation. The quality of captured image can be greatly affected by the lighting condition. A high quality image can help to reduce the time and complexity of the subsequent image processing steps, which can decrease the cost of an image processing system. Different application may require different illumination strategy. Novini (1990) reported that most lighting arrangement could be grouped as one of the followings: front lighting, back lighting, and structured lighting. For image processing algorithms, software implementation on a PC allows for rapid development, debug, and test. However, as image sizes grow larger and algorithms become more complex, the speed will be slower and cannot satisfy the requirement of high speed in real-time systems. Conversely, hardware implementation offers much greater speed than software one. There are several viable options for hardware implementation of image processing algorithms, such as application specific integrated circuits (ASICs), digital signal processors (DSPs), and field programmable gate arrays (FPGAs). Although the speed can be improved by hardware implementation, one must consider the increase in development cost for creating a custom hardware design. Therefore, hardware designers usually use some sorts of PC programming environment to implement a design to verify functionality prior to a lengthy hardware design. This paper will focus on the software part of learning techniques used in computer vision for food quality evaluation. The illumination system and hardware implementation of image processing algorithms required for a computer vision system will not be discussed in details here. Interested readers can refer to papers and books on the topic for details (Gunasekaran, 1996; Jóźwiak, Ślusarczyk, & Chojnacki, 2003; Moore, 1995; Perkowski, Jóźwiak, Foote, Chen, & Al-Rabadi, 2002; Russ, 2002).

During the last decade, considerable research effort has been directed at developing learning techniques for food quality evaluation. Goyache et al. (2001) advocate the application of artificial intelligence techniques to quality assessment of food products, which can help to extract operative human knowledge from a set of examples, to conclude interpretable rules for classifying samples, and to ascertain the degree of influence of each objective attribute of the assessed food on the final decision of an expert. Corney (2002) introduced intelligent systems and highlighted their use in all aspects of the food industry.

Learning technique is one of the essential features for food quality evaluation using computer vision, as the aim of computer vision is to ultimately replace the human visual decision-making process with automatic procedures. Computer vision tries to clone human behaviour of performance in colour, content, shape, and texture inspection (Domenico & Gary, 1994). Backed by the powerful learning systems, computer vision provides a mechanism in which human thinking process is simulated artificially and can help human in making complicated judgments accurately, quickly and very consistently over a long period (Abdullah, Guan, Lim, & Karim, 2004). Learning techniques can be employed to learn meaningful or nontrivial relationships automatically in a set of training data and produce a generalisation of these relationships that can be used to interpret new, unseen test data (Mitchell, Sherlock, & Smith, 1996). Therefore, using sample data, a learning system can generate an updated basis for improved classification of subsequent data from the same source, and express the new basis in intelligible symbolic form (Michie, 1991). Nevertheless, there is a definite need for research dealing with the combination of computer vision and learning techniques for food quality inspection (Vízhányó & Felföldi, 2000).

The aim of this paper is to investigate the recent applications of learning techniques in computer vision for food quality evaluation, and to illustrate their role and discuss the remaining challenges. Fig. 1 shows the general learning system configuration used in computer vision for food quality evaluation. As indicated in Fig. 1, using the image processing techniques, the images of food products are quantitatively characterised by a set of features, such as size, shape, colour, and texture. In literature, a variety of different methods have been developed to measure size, shape, colour, and texture features, which have been reviewed elaborately by Du and Sun (2004). These features are objective data used to represent the food products, which can be used to form the training set. Once the training set has been obtained, learning algorithm extracts the knowledge base necessary to make decision of unknown case. Based on the knowledge, intelligent decision is made as output and fed back to the knowledge base at the same time, which generalises the way that inspectors use to accomplish their tasks. Among the applications where learning techniques have been employed for building knowledge base, artificial neural network (ANN) and statistical learning (SL) are the two main methods. In the mean

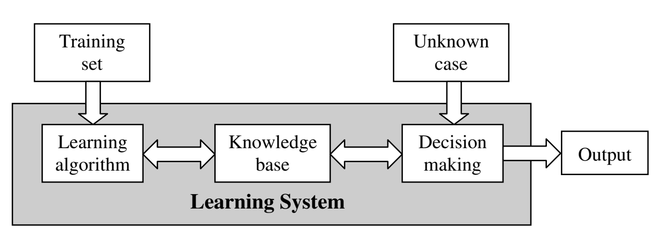

Fig. 1. The general configuration of machine learning system.

time, fuzzy logic, decision tree, and genetic algorithm have also been used for learning.

2. Artificial neural network (ANN)

Initially inspired by biological nervous systems, ANN approaches combine the complexity of some of the statistical techniques with the objective of machine learning of imitating human intelligence, which are characterised by their self-learning capability. Fig. 2 illustrates a general topology structure of ANN. The complete network represents a very complex set of interdependencies, and may incorporate any degree of non-linearity in theory. For food quality evaluation, very general functions can be modelled to transform physical properties into quality factors. ANN technology allows the extension of computer vision technology into the areas of colour, content, shape, and texture inspection at near-human levels of performance, and can provide the decision making and classification capabilities to succeed in these inspection tasks (Domenico & Gary, 1994). Recently, ANNs have been applied for classification, predication and segmentation in quality evaluation of food products using computer vision.

2.1. Classification

2.1.1. Cereal grains

In several applications, ANN has been trained to grade cereal grains. In the work of Luo, Jayas, and Symons (1999), a multi-layer ANN classifier was applied for the classification of cereal grain kernels, including Canadian Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, rye, and oats, and for the classification of healthy and six types of damaged CWRS wheat kernels. The average classification accuracies were 98.4%, 96.2%, 98.4%, 97.4%, and 98.5% for CWRS wheat, CWAD wheat, barley, rye, and oats, respectively, and were 91.4% (healthy), 91.6% (broken), 97.1% (mildewed), 97.8% (grass-green/green-frosted), 98.2% (black-point/smudged), 96.3% (heated), and 99.9% (bin/fire-burnt), respectively (Luo et al., 1999). To evaluate the classification accuracy of nine different neural network architectures, Paliwal, Visen, and Jayas (2001) used five different kinds of cereal grains, i.e. Hard Red Spring (HRS) wheat, CWAD wheat, barley, oats, and rye, and found that the best results were obtained using a four-layer back-propagation network with each layer connected to the immediately previous layer, while a general regression neural network architecture was the least suitable for grain classification. The classification accuracies were in excess of 97% for HRS wheat, CWAD wheat and oats, while about 88% for barley and rye.

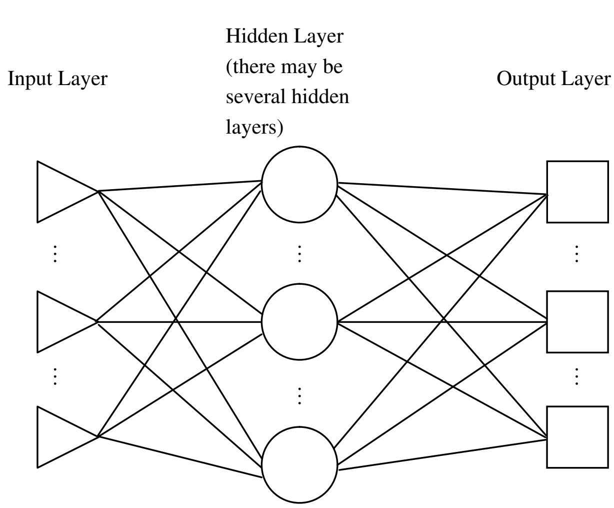

Fig. 2. The general topology structure of artificial neural network.

2.1.2. Fruits

2.1.2.1. Apples. The majority of applications of ANNs in fruit classification using computer vision can be found for apple grading. Nakano, Kurata, and Kaneko (1992) developed a method for colour grading of apple using a three-layer ANN. The experimental results proved that the classifier had the ability to classify quality into three grades of external appearance of apples. However, the problem of unequal colour gradient on a spherical apple caused by lighting characteristics still need to be overcome, therefore, Nakano (1997) developed another ANN model for grading the whole surface colour of an apple into 'superior', 'excellent', 'good', 'poor colour', and 'injured'. Fig. 3 shows the structure of the ANN used by Nakano (1997). Although the ratios for 'excellent' and 'good' are not very high with only 33.3% and 65.8% respectively, the grade judgement ratios for 'superior', 'poor colour', and 'injured' were very high with 92.5%, 87.2%, and 75.0% respectively.

Technical advancements in the area of spectral reflectance imaging have helped the applications of ANN for apple grading. Kavdir and Guyer (2002) sorted Empire and Golden Delicious apples using back-propagation (BP) ANNs and spectral imaging. A 2-class and a 5-class classification were performed and the classification success rates in the 2-class classification were between 89.2% and 100%. In the 5-class classification, classification success rates for Empire apples were between 93.8% and 100%, while classification success rates for Golden Delicious apples were between 89.7% and 94.9%. To find the right ANN structure for spectral reflectance evaluation of apple blemishes, Miller, Throop, and Upchurch (1998) compared different multi-layer back propagation ANN models with different number of hidden nodes or neural net architecture. The correct classification rates range from 83% to 85% for the 1996 data and from

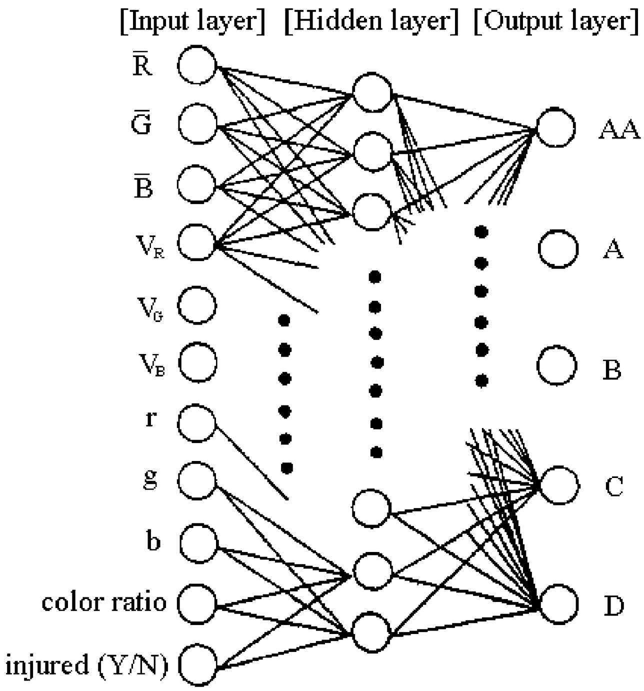

Fig. 3. Structure of artificial neural network: AA = superior; A = excellent; B = good; C = poor colour; D = injured (Nakano, 1997).

94% to 96% for the 1995 data. However, the increased complex ANN models of jump connections and multiple transfer functions in the hidden layer used in their study (Miller et al., 1998) did not provide higher success rates.

For blemish detection, BP ANNs could be applied. Since the input feature data possessed some unknown, probably quite complex properties, a single-layer perceptron without hidden layers did not converge for the training samples (Yang, 1993). Instead, a BP ANN algorithm with one hidden layer could be used as applied by Li, Wang, and Gu (2002) to classify stem-calyx from true defect areas of apples, where the test results showed that the accuracy of the network classifier was over 93%. In order to accelerate the learning rate, Yang (1993) applied an improved BP learning algorithm to train the multi-layer ANN. When three major apple surface features were considered, namely non-defective area, patch-like blemish, and elongated blemish, an average classification accuracy of 96.6% was achieved.

Based on X-ray imaging technique, ANN has also been employed for classification of apples into different watercore levels. For example, an ANN classifier, multiplayer perceptron (MLP) with BP algorithm, was used to categorise apples into three different watercore levels, i.e. clean, mild, and severe, using eight features extracted from an X-ray scanned apple image (Kim & Schatzki, 2000). Provided the apples all had the same orientation, the system was able to correctly recognise apples into clean and severe categories with false positive and negative ratios in the range of 5–8%.

2.1.2.2. Other fruits. Various types of ANN have been designed to classify pistachio nuts. Ghazanfari, Irudayaraj, and Kusalik (1996) proposed a multi-structure neural network (MSNN) classifier, which consisted of four parallel discriminators, to classify four classes of pistachio nuts using physical attributes of the nuts extracted from their images as input. Compared with the performance of a multi-layer feed-forward neural network (MLNN) classifier, the average classification accuracy of MSNN classifier was 95.9%, an increase of over 8.9% of the performance of MLNN. Another type of ANN has also been used to grade pistachio nut. Relying on X-ray imaging technique, Casasent, Sipe, Schatzki, Keagy, and Lee (1998) developed an improved version of the piecewise quadratic ANN. The classification accuracies were 89.3% and 88.0% for the training and test sets, respectively, using eight statistical features for both raw and edge-enhanced images. However, the preliminary results indicated the potential to reduce to only 2% of the major defect nuts and 1% of good nuts rejected.

It is also feasible for ANN to sort other fruits such as pears, strawberries, and table olives. Ying, Jing, Tao, and Zhang (2003) used Fourier transformation and an ANN to detect stem and shape of Huanghua pears. The first 16 harmonic components of the Fourier descriptor were used as the inputs to an ANN to classify pears with accuracy of 90%. Based on the shape features extracted, a grading system using ANN technology was developed to classify four kinds of strawberry varieties (Nagata & Cao, 1998). The classification accuracies were 95%, 97%, 98%, and 94% for 'Reiko', 'Toyonoka', 'Nyoho' and 'Akihime' strawberry, respectively. In order to discriminate four classes of table olives depending on the defects on the surface of the fruits, Diaz et al. (2004) developed a neural network classification system based on resilient BP, which was able to adapt its structure in a fast and, at the same time, a safe way. The olives of the first and the third grades are classified perfectly, while the second and the fourth ones have a failure rate of 8.9% and 6.7%, respectively.

2.1.3. Fish and meat

Besides agricultural products, ANN can be used for classification of food products. One application is to employ for fish species recognition. Using the widths and heights at various locations along fish samples as inputs, an ANN can be trained to recognise the fish species. In the work of Storbeck and Daan (2001), a learning rate, a momentum factor and the elimination of non-contributing connections and nodes were introduced to decrease the time for training the network, and the testing of the network showed that more than 95% of the fish could be classified correctly.

Using the measurement of image features as inputs, ANN is also practical for beef grading. Borggaard, Madsen, and Thodberg (1996) applied a complete framework with ANN, i.e. the second generation of beef carcass classification centre (BCC-2), to classify beef carcass in the slaughter industry. The BCC-2 used was adaptive and robust, which classified all carcasses except the ones most damaged in the slaughter process. In a separate application, Li, Tan, and Shatadal (2001) used ANNs to classify tough and tender beef by image texture analysis. The overall correct classification rate of 82.3% and 74.4% were obtained based on texture features of primitive fractions and run lengths, respectively.

Combined with spectral imaging techniques, the applications of ANNs can been extended for poultry classification. Park, Chen, Nguyen, and Hwang (1996) used the spectral images scanned at both 542 and 700 nm wavelengths combined with an ANN classifier to separate tumorous poultry carcasses from normals with 91.4% accuracy. For on-line poultry carcass inspection, Park and Chen (2000) examined ANN models with different learning rules (delta and hyperbolic tangent) and transfer functions (sigmoid and norm-cum-sigmoid) using features extracted from spectral images. The optimum neural classifier utilising a delta learning rule and a hyperbolic tangent transfer function obtained the classification accuracies of 91.1% and 83.3% for wholesome and unwholesome carcasses, respectively, while the accuracies of 94% and 87% were achieved by Chao, Chen, Hruschka, and Gwozdz (2002) when tested the performance of ANN classification models with combination of the filter information.

2.1.4. Vegetables

Several kinds of vegetable can be graded by different kinds of ANN, such as carrots, green peppers and onions. Brandon, Howarth, Searcy, and Kehtarnavaz (1990) designed an ANN to classify carrot tips into five classes using shape features. Trained with 80 simulated carrot tips and tested with 250 fresh market carrots, the average misclassification rate was 11.5%. In another application, a grading system of green pepper was developed using ANN technology with classification accuracy of 89% (Nagata & Cao, 1998). ANN was also combined with X-ray imaging technique for sweet onion classification. Shahin, Tollner, Gitaitis, Sumner, and Maw (2002) reported that with spatial edge features combined with selected discrete cosine transform coefficients as indicators for internal defects, a neural classifier performed better than the Bayesian classifier for sorting onions into two classes (good or defective) by achieving an overall accuracy of 90%.

Table 1 summarises the ANN applications for classification of various food products. To avoid or reduce bias, the classification accuracy shown in Table 1 is the average rate reported in all the related references. The classification of oat kernels achieved the best results using morphological and colour features with 97.8%, which is the average result reported by Luo et al. (1999) and Paliwal et al. (2001). It is a fundamental problem in the ANN applications to make a choice of input features, i.e. to construct an ANN with an optimised architecture by choosing proper descriptive features (e.g. size, shape, colour, and texture) as the input layer. Therefore, the characterisations of various food products are also listed in Table 1. As indicated in Table 1, shape and colour features are most frequently applied to classify food products using ANN in computer vision.

Table 1
Summary of artificial neural network applications for classification of food products

Category	Products	Characterisation	Accuracy (%)
Fishery	Fish	Widths and heights at various locations of different species	95.0
Fruit	Apple	Surface quality conditions	93.3
		Spectral reflectance of blemishes	89.5
		Fractal features	93.0
	Pear	Fourier descriptor of shape	90.0
	Pistachio nuts	Physical attributes	95.9
		X-ray data	88.7
	Strawberry	Shape features	96.0
	Table olive	Defects in the surface	96.1
Grain	Barley	Morphological and colour features	93.2
	Oat	Morphological and colour features	97.8
	Rye	Morphological and colour features	92.7
	Wheat	Morphological and colour features of healthy and damaged kernels	96.0
		Morphological and colour features	97.2
Meat	Beef	Texture features of primitive fractions and run lengths	78.8
	Poultry carcasses	Spectral reflectance of unwholesome and wholesome carcasses	89.1
Vegetable	Carrot	Shape features	88.5
	Green peppers	Shape features	89.0
	Sweet onions	Internal defects	90.0

2.2. Prediction

2.2.1. Meat

ANNs have shown to be a viable means for beef quality prediction, such as tenderness and maturity prediction. An ANN model was performed to relate image features of beef to sensory tenderness scores (Li, Tan, Martz, & Heymann, 1999), and the image textural features were found to be useful indicators of beef tenderness. The ANN model developed (Li et al., 1999) was able to predict beef tenderness based on colour, marbling and image texture features with R^2-values up to 0.70. In order to predict USDA beef maturity grades, Hatem, Tan, and Gerrard (2003) used a trained ANN with colour image features of ossification as input. The accuracy of prediction was 75% for the first set of samples and 65.9% for the second set of samples, indicating the potential of using computer vision techniques for beef maturity assessment. The lean yield is an important quality factor because consumers prefer lean meat. For predicting the lean yield of beef, an ANN model of three-layer was developed by Lu and Tan (2004) based on the image-based measurements. However, the results suggested that the ANN model developed did not generalise as well as the linear regression model did, therefore, the inclusion of nonlinearity in the predictive models was not beneficial.

Besides for beef quality prediction, ANN has been trained to perform colour score prediction of pork. An ANN model used a BP learning algorithm were employed to predict the colour scores of pork by using the image features as inputs (Lu, Tan, Shatadal, & Gerrard, 2000). Prediction error was lower than 0.6 for 93.2% of the 44 pork loin samples, which showed that an image processing system in conjunction with an ANN was an effective tool for evaluating fresh pork colour.

2.2.2. Other products

For the quality prediction of other products such as orange and snack, Kondo, Ahmad, Monta, and Murase (2000) investigated the feasibility of quality evaluation of Iyokan orange fruit using computer vision and ANN techniques. Several ANNs were found to be able to predict the sugar content or pH from the fruit appearance with a reasonable accuracy. Sayeed, Whittaker, and Kehtarnavaz (1995) developed an ANN approach via image texture and shape features for the evaluation of the quality of typical snack products. The network was shown to predict the sensory attributes of the snack quality with a reasonable degree of accuracy and could be used in the food industry to evaluate the snack quality in a non-destructive sense.

Several ANN architectures have been developed for wheat quality predication. Ruan, Xu, and Jones (1995) employed ANNs to estimate the deoxynivalenol (DON) levels (ppm) and the weight percentage of scabby wheat kernels (WPSK) using different combinations of colour and colour-texture features as input. When all features were used for network training, the global average difference (GAD) between predicted and measured DON value was 1.97 ppm. However, when only colour features, intensity texture features, saturation texture features, or hue texture features were used as the input features of ANN, the GAD was 2.38, 2.94, 5.16, or 3.01 ppm, respectively. When all features except saturation texture features were used, the GAD was 2.11, which was very close to 1.97 ppm. This demonstrated that the performance of ANN could be improved by constructing optimised architecture with careful selection of input feature set. Furthermore, an automatic system based on computer vision and ANN was developed to rapidly determine WPSK (Ruan et al., 2001). The correlation coefficient between estimated WPSK using an ANN and actual WPSK was 0.96, with a mean absolute error of 1.32% and maximum absolute error of 5.22%.

2.3. Segmentation

Segmentation of food images is very important for many image analysis and computer tasks, since its performance directly affects the result of the subsequent image processing steps (Sun & Du, 2004). Various types of ANNs have been employed for segmentation of different food products. Hamey and Yeh (1996) presented a technique for segmentation of images of bakery products based on baking curves. A one-dimensional self-organising map (SOM) was used to identify the characteristic baking curve for each product, and the images of product samples were then segmented on the basis of the colour information contained in baking curves. The segmentation was derived without the requirement of negative examples during the training process, which is a significant benefit in industrial applications. For apple segmentation, an ANN model was used to classify pixels at any part of an apple surface into five classes, i.e. 'normal red', 'injured colour red', 'poor colour red', 'vine', and 'upper or lower background colour' with the judgement ratio more than 95% (Nakano, 1997).

ANN also showed the feasibility of the object segmentation and contour generation for complex, fuzzy and irregular beef images. A system composed of pre-network, network, and post-network processing stages was developed to automatically distinguish lean tissues in the image of a complex beef cut surface and generate the lean tissue contour (Hwang, Park, Nguyen, & Chen, 1997). The system developed successfully separated the portion of the lean tissue from the beef cut surface in a robust manner without human intervention. Fig. 4 illustrates some typical results of processing a beef sample.

Fig. 4. Results of processing for a sample: (a) enhanced input image; (b) network output; (c) resized image; (d) image after morphology opening; (e) contour of the lean tissue; (f) input image merged with contour (Hwang et al., 1997).

3. Statistical learning (SL)

SL utilises the statistical properties of the observations from training set. It is generally characterised by having an explicit underlying probability model, for example, Bayesian theory, which is mathematically rigorous and provides a probabilistic approach to inference. Fig. 5 illustrated the structure of a Bayesian classifier for classification of table olives (Diaz, Faus, Blasco, Blasco, & Moltó, 2000). Based on a well-established field of mathematics, SL has been proven successful for classification, feature selection, and segmentation in computer vision for quality evaluation of food products.

3.1. Classification

3.1.1. Grains

SL is a plausible method for corn and edible bean classification. Zayas, Converse, and Steele (1990) applied image analysis techniques for discrimination of whole from broken corn kernels. Multivariate discriminant analysis was used to develop classification rules to identify whole kernels and/or broken kernels, and all of the broken and 98% of the whole corn kernels in an independent set of unknown kernels were correctly identified. A statistical classification method based on discriminant analysis was used to compare the classification results of the quality of edible beans (Chtioui, Panigrahi, & Backer, 1999). The discriminant analysis provided 95.19% and 84.70% correct recognition of the training and test sets, respectively.

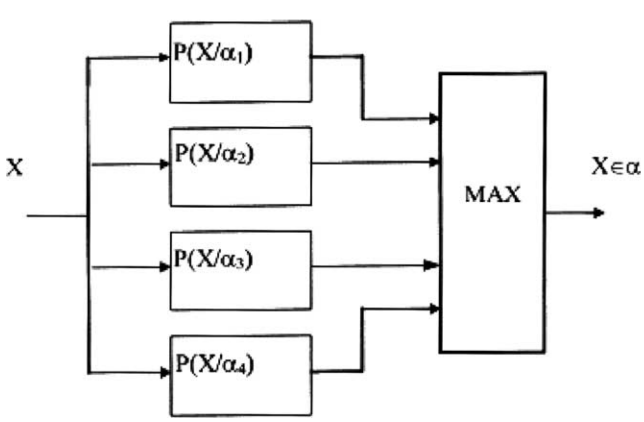

Fig. 5. Structure of the Bayesian classifier (Diaz et al., 2000).

Using various image features extracted, SL has shown practical for wheat, barley, oat, and rye classification. Several studies have been conducted to use discriminant analysis for classification of individual kernels of CWRS wheat, CWAD wheat, barley, oats, and rye based on morphological features (Majumdar & Jayas, 2000a), colour features (Majumdar & Jayas, 2000b), and textural features (Majumdar & Jayas, 2000c). In these studies, SL was tested on an independent data set, and the results showed that using the 10 most significant features in the morphology model, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 98.9%, 93.7%, 96.8%, 99.9%, and 81.6%, respectively, as compared with accuracies of 94.1%, 92.3%, 93.1%, 95.2%, and 92.5% for using the first 10 most significant colour features, and with accuracies of 85.2%, 98.2%, 100.0%, 100.0%, and 76.3% if the 15 most significant features in the texture model were used. The highest classification accuracies were achieved when combining morphological, colour and textural feature sets (Majumdar & Jayas, 2000d), as mean accuracies of 99.7% and 99.8% were obtained on independent and training data sets when the 20 most significant features in the morphology-texture-colour model was employed.

3.1.2. Fruits

In order to improve the objectivity of the inspection, various SL methods have been implemented for the automated grading of fruits, including discriminant analysis and Bayesian classifier. Most of the reviewed applications are for the grading of apples. Multivariate discriminant techniques have been performed to distinguish between yellow and green 'Golden Delicious' apples (Tao, Heinemann, Varghese, Morrow, & Sommer, 1995). Representing features with hue histograms, over 90% accuracy in inspection of apples was achieved by the vision system. Based on features extracted from defects, Leemans and Destain (2004) developed a hierarchical grading method of apples. Using quadratic discriminant analysis, the fruits were correctly graded with a rate of 73%. In another study, Shahin, Tollner, Evans, and Arabnia (1999) used a Bayesian classifier to sort red delicious apples. With three input features, i.e. fruit area in the segmented image, mean intensity of fruit in the original image, and the 10th harmonic of the discrete cosine transform, the linear Bayesian classifier achieved classification accuracy of 79%.

Besides apples, SL is also feasible for classification of citrus, lemons, and mandarins. The mean fruit colour, a measure of the dispersion of the colour and a shape parameter were used to grade citrus fruits according to their external quality (Miller, 1995). The Bayesian Gaussian techniques had the best classification results with between 69% and 86% of the fruit correctly graded into accepted or rejected classes. In the work of Aleixos, Blasco, Navarrón, and Moltó (2002), Bayesian discriminant model was generated to classify mandarins and lemons using the RGB (red, green, and blue) bands. The results obtained showed that in both the cases, i.e. mandarins and lemons, the classification rates were higher than 94% in all of the categories.

Other fruits, such as raisins, table olives, and tomatoes, have also been graded using SL technique. A Bayesian classifier was used to separate the raisins into three grades: B or better, C, and substandard based on the features measured by computer vision (Okamura, Delwiche, & Thompson, 1993). The computer vision system graded raisins with accuracy and precision comparable to current grading methods and could be a viable alternative to the present grading methods with improvement in processing speed. For classification of table olives by computer vision, Diaz et al. (2000) presented a fast algorithm based on the Bayesian discriminant analysis. The classification accuracies obtained using the Mahalanobis distance method with normalisation in images were 92.88%, 62.67%, 70.52%, and 99.26% for the four olive classes, respectively. In other application, Fisher's linear discriminant analysis was used to classify spectral images of tomatoes (Polder, Van der Heijden, & Young, 2002). Experimental results showed that the classification error rate increased from 19% to 35% when using different light sources.

3.1.3. Fishery and meat

Applications of SL have also been extended for classification of fishery and meat products. Li and Wheaton (1992) used three minimum-Mahalanobis-distance classifiers based on the Bayesian theory to classify each oyster within the various groups into either the hinge or non-hinge class. The classification error rate was 2.5% of the 1733 hinge line images by the computer vision system.

In several other applications, SLs have been used to identify wholesome carcasses and unwholesome poultry carcasses. Tao, Shao, Skeeles, and Chen (2000) explored the possibility of detecting splenomegaly of turkey carcasses with a computer imaging system. Statistical classification was developed to detect abnormalities. Based on a total of 57 turkey sample images, correct classification rates of 92% and 95% in detection of spleen abnormality were obtained using a self-test set and an independent test set, respectively. In another application, linear and nonlinear discriminant models with linear and quadratic covariance matrix analysis methods were developed for classifying poultry carcasses (Park, Lawrence, Windham, Chen, & Chao, 2002). Linear discriminant models were able to identify unwholesome carcasses with a classification accuracy of 91.4%, however, the average accuracy for identifying wholesome carcasses was low (less than 51.5%). The quadratic model had an average accuracy of about 75% and 62% for identifying wholesome and unwholesome carcasses, respectively.

3.1.4. Vegetables

Among the SL techniques that have been applied to perform vegetable classification, discriminant analysis has been employed in most of the reviewed applications. To classify bell peppers, Shearer and Payne (1990) used discriminant analysis according to colour and damage. The accuracies of up to 96% and 63% were achieved for grading bell peppers by colour and damage, respectively. In the work of Rigney, Brusewitz, and Kranzler (1992), discriminant analysis was applied to inspect asparagus defects, where spreading tips, broken tips and scarred or cracked spears were detected with 8%, 25% and 42% error rate, respectively. Fisher's linear classifier is a well-known linear classification method. A discriminant analysis based on Fisher's linear discriminant functions was applied to classify mushroom samples with the brown blotch or ginger blotch diseases (Vízhányó & Felföldi, 2000). The overall correct classification ratio was 85% on the test materials with the two diseases. Since the relationships between the image-based measurements and the classes might be complex and nonlinear, multivariate discriminant techniques were applied to distinguish between good and greened potatoes (Tao et al., 1995). Representing features with hue histograms, over 90% accuracy in inspection of potatoes was achieved by the vision system.

Other vegetables rely on Bayesian classifier, such as carrots and sweet onions. Combined with a computer vision system, Howarth and Searcy (1992) used Bayesian classifiers to classify fresh market carrots for forking, surface defects, curvature, and brokenness, which performed well for all features with the overall misclassification rate of approximate 7.6%. Using X-ray imaging, Shahin, Tollner, Gitaitis, et al. (2002) employed a Bayesian classifier for sorting sweet onions into good or defective classes based on internal defects with accuracy of 80%.

3.1.5. Other product

It is practical to extend SL techniques for classification of other food products. For visual inspection of muffins, Abdullah, Aziz, and Mohamed (2000) developed an automated system incorporating multivariate discriminant algorithms to statistically classify muffins based on surface colour. The automated system was able to correctly classify 96% of pregraded and 79% of ungraded muffins.

Table 2 summarises the applications of statistical learning for classification of food products, where the classification accuracy is the average rate reported in all the related references. The classification of barley kernels and oat kernels achieved the best accuracy of 100.0% using textural features or morphological, colour and textural features. Again the characterisations of various food products are listed in Table 2 to show which features are more suitable for different food products. Colour features are most frequently applied to classify food products using SL in computer vision.

3.2. Feature selection

Feature selection is to identify a subset of features that are most responsible for splitting a set of observations into two or more groups. This is often a necessary step for object recognition or classification to be successful in computer vision because of the huge data of images. Stepwise discriminant analysis (SDA) is one of the most popular methods to perform this process. Lu and Lee (1995) conducted SDA to select the best set of shoal descriptors for species identification of fish shoals from echograms by an echo-signal image processing system. Using the selected external and internal descriptors, the accuracy of species identified by the system was 98% for round scad, 97% for anchovy, 94% for skipjack, 91% for larval fish, and 67% for horse mackerel, respectively. In the work of Shahin, Tollner, McClendon, and

Table 2
Summary of statistical learning applications for classification of food products

Category	Products	Characterisation	Accuracy (%)
Fishery	Oyster	Hinge	97.5
Fruit	Apple	Area, mean intensity, and harmonic of the discrete cosine transform	79.0
		Colour, shape, texture, and position	73.0
		Hue histograms	90.0
	Citrus	Colour and shape	77.5
	Lemon	Colour	94.0
	Mandarin	Colour	94.0
	Raisin	Wrinkle edge density, average gradient magnitude, angularity, and elongation	–
	Table olive	Defects in the surface	81.3
	Tomato	Spectral images	73.0
Grain	Barley	Morphological features	96.8
		Colour features	93.1
		Textural features	100.0
		Morphological, colour and textural features	99.7
	Corn	Shape and size of kernels	99.0
	Edible bean	Size, shape and texture features	89.9
	Oat	Morphological features	99.9
		Colour features	95.2
		Textural features	100.0
		Morphological, colour and textural features	100.0
	Rye	Morphological features	81.6
		Colour features	92.5
		Textural features	76.3
		Morphological, colour and textural features	99.3
	Wheat	Morphological features	96.3
		Colour features	93.2
		Textural features	91.7
		Morphological, colour and textural features	99.9
Meat	Poultry carcass	Spectral images of wholesome and unwholesome carcasses	77.8
Vegetable	Asparagus	Dark regions, significant edges, local grey-level variation	75.0
	Bell pepper	Colour	96.0
		Damage	63.0
	Carrot	Forking, surface defects, curvature, and brokenness	92.4
	Mushroom	Brown blotch or ginger blotch diseases	85.0
	Potato	Hue histograms	90.0
	Sweet onion	Internal defects using X-ray imaging	80.0
Others	Muffin	Surface colour	87.5

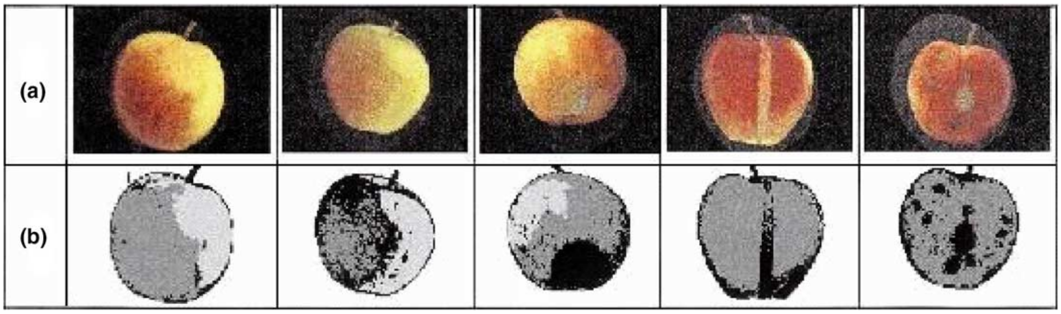

Fig. 6. Results of the algorithms. Row a: original images including healthy fruit with neat transition area, healthy fruit with a chaotic transition area, poorly contrasted defect, well contrasted linear russet, and result of a scab attack; row b: result of the segmentation (Leemans et al., 1999).

Arabnia (2002), SDA was used for selecting the salient features to classify apples based on surface bruises. Spatial edge features combined with the selected discrete cosine transform coefficients proved to be good indicators correlating with the fruit quality.

Another frequently used approach for feature selection is principal component analysis (PCA). PCA is one of the powerful techniques for dimensionality reduction, which transforms original feature vectors from large space to a small subspace with lower dimensions. The first principal component accounts for the most significant characteristic of the original data with the maximum variance. Each succeeding component accounts for less significant characteristic with as much of the remaining variability as possible. Practically, the last few principal components can be truncated and ignored as these last few principal components correspond to useless characteristics that are essentially noise. To reduce the dimensionality, PCA have been applied for quality evaluation for a wide variety of food products using computer vision, such as beef carcass (Borggaard et al., 1996), oil palm (Abdullah, Guan, & Mohd Azemi, 2001), pizza (Du & Sun, 2005a, 2005b), and salted cod fillets (Kohler, Skaga, Hjelme, & Skarpeid, 2002).

Besides the above methods, in order to evaluate the quality of food products using computer vision, some other methods have also been tried for feature selection in literature. A feature selection method called orthonormal transformation was employed to reduce the number of features, thereby eliminating the correlation among the reduced features (Uthu, 2000). Based on the selected features, the recognition of unknown samples was nearly 82% and 81% for durum and bread wheat cultivars, respectively. To classify chocolate using computer vision, Briones and Aguilera (2005) employed sequential forward selection (SFS) method for feature selection. The SFS strategy allowed correct classification of 97.8% of samples into four classes with only five features.

3.3. Segmentation

Image segmentation is a challenging task in the food quality evaluation for the richness of visual information in the image of food. In image segmentation of food products using SL techniques, most of the segmentation processes are for fruits. Moltó, Blasco, and Benlloch (1998) used computer vision for automatic inspection of fruits (oranges, peaches, apricots, apples or tomatoes). The segmentation was based on Bayesian theorem and multi-normal frequency distributions. In another application, a Bayesian classification process was used successfully to segment apple defects (Leemans, Magein, & Destain, 1999). The colour frequency distributions of the healthy tissue and of the defects were used to estimate the probability distribution of each class. Fig. 6 shows five representative original apple images and the results obtained from this method. The results showed that most defects could be segmented by this method, although russet was sometimes confused with the transition area between ground and blush colour. Lately, for the on-line estimation of the quality of oranges, peaches and apples, Blasco, Aleixos, and Moltó (2003) used a segmentation procedure based on a Bayesian discriminant analysis. Using the three basic colour components of the pixels, i.e. red, green and blue as independent variables, the segmentation method was fast and appropriate for on-line processes. However, for depending much on the colour of the objects to be inspected, the system needs to be trained frequently.

Besides fruits, SL has also been utilised for potato segmentation by assigning each pixel to different colour classes. Linear discriminant analysis (LDA) in combination with a Mahalanobis distance classifier was applied to segment potato images for grading and quality inspection based on a colour vision system (Noordam, Otten, Timmermans, & Zwol, 2000). The RGB pixels were classified into six different colour classes with classification rates being above 90% for five potato cultivars.

4. Other techniques

4.1. Fuzzy logic

Compared with traditional learning techniques, fuzzy logic simulates the human experience of generating complex decisions using approximate and uncertain information. Based on the membership functions, knowledge base can be built in a more natural way. Many practical classification problems have been found to be suitable in using fuzzy logic for food quality evaluation with computer vision.

The application of fuzzy logic in computer vision includes grading of fruits, such as apples and tomatoes. A fuzzy classifier was developed for sorting apples based on watercore severity using selected features (Shahin, Tollner, & McClendon, 2001). The classifier was tested on the validation data set and the results showed that it was able to separate apples into three watercore classes with an overall accuracy of 80%. The classification accuracies for 'good' (nil/mild watercore) and 'bad' (severe watercore) fruits were reasonably high with 86% and 89%, respectively. However, the classification accuracy for the intermediate class (moderate watercore) was very low with only 43%. To achieve an automatic grading of tomato, Jahns, Nielsen, and Paul (2001) proposed a tomato quality rating method based on a fuzzy model. Starting with visual appearance quality attributes like size, colour, shape, defects and abnormalities obtained by image analysis, a fuzzy method is proposed by mapping various fuzzy consumer aspects to overall quality classes. The objective of such a mapping is to achieve an automatic rating of fruit quality, modelling consumer aspects and producer needs.

For automated grading of fish products, fuzzy classification technique could be employed. Hu, Gosine, Cao, and de Silva (1998) presented the application of a fuzzy classifier with a four-level hierarchy based on the 'generalised *K*-nearest neighbour rules'. Both conventional and fuzzy classifiers were examined using a realistic set of herring roe data to compare the classification performance in terms of accuracy and computational cost. The classification results show that the generalised fuzzy classifier provides the best accuracy at 89%.

Fuzzy techniques also showed viable for other food products, such as crusting sausage and pizza. An approach based on the theory of fuzzy sets to reproduce the human evaluation of sensory properties of crusting sausage was proposed (Ioannou, Perrot, Hossenlopp, Mauris, & Trystram, 2002). By means of a camera and an adapted image processing, a percentage of compatibility of 88% was obtained between the model evaluation and the expert evaluations. In other applications, Sun and Brosnan (2003a, 2003b) developed a fuzzy logic system to classify the sauce spread samples and the pizza topping quality into classes of acceptable and defective quality. Fig. 7 illustrated a series of fuzzy sets of sauce area percentage. The experimental results for the sauce spread analysis and the pizza topping quality show that by using computer vision in conjunction with fuzzy logic a classification accuracy of 92% and an accuracy of 100% were achieved, respectively.

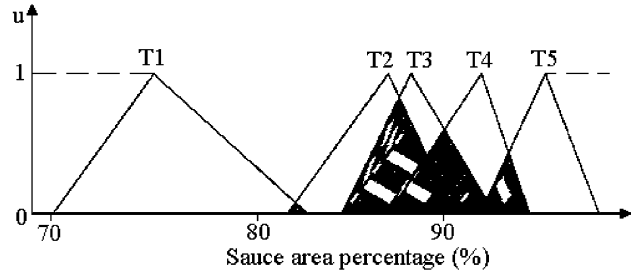

Fig. 7. The fuzzy sets representing membership of sauce area percentage (%) for the five linguistic levels. Set T1: reject underwipe; Set T2: acceptable underwipe; Set T3: even spread; Set T4: acceptable overwipe; Set T5: reject underwipe. The shadow areas are overlapping boundaries (Sun and Brosnan, 2003a).

4.2. Decision tree

Decision tree acquires knowledge in the form of tree, which can also be re-written as a set of discrete rules to make it easy to understand. For food quality evaluation using computer vision, decision tree has been applied to problems such as predicting meat yield and meat quality grade (Song, Kim, & Lee, 2002), and segmenting the colour images of chicory (Zhang, De Baerdemaeker, & Schrevens, 2003). Based on ultrasonic images, decision tree was used to predict carcass meat yield and meat quality grade of Korean native cattle with 81.4% and 63.1% accuracy, respectively (Song et al., 2002). To evaluate the colour change during the shelf storage of different varieties of chicory, Zhang et al. (2003) applied the HI-CUPP (hierarchical classification using projection pursuit) decision tree for image segmentation. The segmentation tree was shown in Fig. 8, where the thresholding values in three projections were determined by the segmentation curves. The colour images of chicory were separated into four coloured areas, i.e. white, red, yellow and brown.

4.3. Genetic algorithm

Genetic algorithm is an adaptive heuristic algorithm, which is based on the theory of natural selection and

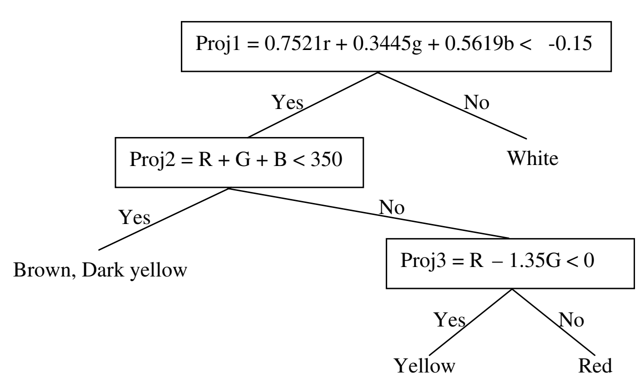

Fig. 8. The segmentation tree for the colour of chicory during storage (Zhang et al., 2003).

Table 3
Summary of applications of other machine learning techniques for food quality evaluation using computer vision

Techniques	Products	Applications	References
Fuzzy logic	Apple	Sorting apples based on watercore severity	Shahin et al. (2001)
	Tomato	Mapping various fuzzy consumer aspects to overall quality classes	Jahns et al. (2001)
	Crusting sausage	Evaluating sensory properties	Ioannou et al. (2002)
	Fish products	Automated grading	Hu et al. (1998)
	Pizza	Classification	Sun and Brosnan (2003a, 2003b)
Decision tree	Beef	Predicting meat yield and meat quality grade	Song et al. (2002)
	Chicory	Image segmentation	Zhang et al. (2003)
Genetic algorithm	Seed species	Feature selection	Chtioui et al. (1998)

evolution. Genetic algorithm could be used for feature selection to find a subset of informative variables. A genetic algorithm was applied for feature selection to discriminate four seed species by artificial vision (Chtioui, Bertrand, & Barba, 1998). Five features were selected from a set of 73 features when the probability of initialisation of the population at the first generation was fixed to 0.1. The classification errors were 6.25% and 3% of the seeds at generation of 140 and 400, respectively. Table 3 summarises the applications of other learning techniques for food quality evaluation using computer vision.

5. Discussion and future perspectives

Although learning algorithms such as ANN and SL remain central in the field of computer vision for food quality evaluation, many techniques have been developed for learning knowledge from empirical data during the last decade. Given the proliferation of learning techniques, it is not an easy task to select a proper method applied to different food products. The reason is that it is impossible to offer one technique as a general solution because each learning technique has its own strengths and weaknesses and is suitable for particular kinds of problem.

5.1. Artificial neural network

Since ANN learns knowledge directly from the training data, it entails less stringent assumptions regarding the statistical characteristics of the input data. Thus, ANNs are flexible enough to model most of systems more accurately, and relatively easier to use. Compared with statistical classifiers, ANN approaches have been cited for the advantages of knowledge plasticity to changing inputs and outputs, fault tolerance, noise immunity and interpolation/extrapolation capabilities (Miller et al., 1998). A neural network classifier and a Bayesian classifier were compared to address which classifier should be used for optimal classification of sweet onions (Shahin, Tollner, Gitaitis, et al., 2002). For sorting onions into two classes, i.e. good and defective, the neural network classifier performed better than the Bayesian classifier by achieving an overall accuracy of 90%. Losses and false positives were limited to 6% and 10%, respectively. For the Bayesian classifier, accuracy, losses and false positives were 80%, 16%, and 17%, respectively. Using the image features as inputs, both statistical and neural network models were employed to predict the colour scores of pork (Lu et al., 2000). For neural network and statistical models, correlation coefficients between predicted and original sensory scores were 0.75 and 0.52, respectively. For 93.2% of the 44 pork loin samples, prediction error was lower than 0.6 in neural network modelling, while only 84.1% of the samples gave an error lower than 0.6 in the statistical predictions. The results showed that an image processing system in conjunction with a neural network was an effective tool for evaluating fresh pork colour.

After training, the ANN is represented by a collection of interconnected identical nodes (processing elements) with certain weights and architecture. Therefore, the training data need not to be retained and only a little amount of computer memory is needed. Two statistical and one ANN classifiers were empirically compared for the classification cereal grain kernels and for the classification of healthy and six types of damaged using selected morphological and colour features extracted from the grain sample images (Luo et al., 1999). The k-nearest-neighbour and ANN classifiers gave the best and similar classification results. However, all of the training data usually have to be retained to keep the class probability information for k-nearest-neighbour classifier. It will take so large amount of computer memory that the classification process will be very slowly when a large training data is used. Furthermore, ANN is potential for parallel processing implementations instead of sequentially performing a programme. This means that no extensive computation is needed and the processing time can be decreased using massive parallelism. A symbolic, semantic network knowledge representation system named PARKA (PARallel Knowledge and Association), which takes advantage of the massive parallelism of connection machine, was developed by Evett, Hendler, and Spector (1994). The performance of PARKA was excellent in comparison to existing serial systems, and the timing of the system on random networks showed that PARKA was capable of effecting top-down inheritance inferences on 16,000-node networks in well less than a second.

However, there still exist some possible drawbacks need to be solved in the field of ANNs. Despite all the information about ANNs, there is not a general model to use (Timmermans & Hulzebosch, 1995). It lacks a profound theoretical basis for designing an ANN to choose the best topological structure, such as the number of hidden layers, and the number of nodes in each hidden layer. Therefore, to find the right ANN structure for a specific problem, one should try different settings such as neurons in hidden layer(s), the number of hidden layers, and the type of transfer function in the neurons of hidden and output layers (Kavdir & Guyer, 2002). Furthermore, ANNs are essentially black boxed: given any input a corresponding output is produced, but it is represented as just a matrix of parameters, and the relationship between the inputs and outputs is not well understood or is difficult to translate into a mathematical function. Therefore, it is often unclear why a decision is made and how reliable it will be. To classify light and standard bovine carcasses, Diez et al. (2003) were concerned with the use of learning algorithms able to make accurate predictors with only the input of the training sets instead of using learning algorithms based on ANNs. The reason was that ANNs need a previous definition of the layout and other parameters prior to performing the learning process, thus, it cannot always be known with certainty whether a possible failure in the learning process is a consequence of deficiencies in the customisation process or in the learning ability of training sets.

5.2. Statistical learning

Generally, there are three kinds of SL techniques among the applications, i.e. Bayesian learning, discriminant analysis, and nearest-neighbour. Bayesian learning can produce the probability distributions of the quantities of interest, and make the optimal decisions by reasoning about these probabilities together with observed data (Mitchell, 1997). Discriminant analysis is a very useful parametric statistical technique, which takes into account the different variables of an object and works by creating a new variable by combining the original variables in such a way that the differences between the predefined groups are maximised. Nearest-neighbour method is a non-parametric classification technique by assigning the unknown case as the class most frequently represented among the nearest samples.

Although the nearest-neighbour method avoids the subjective assumption of the probability distribution, the derived knowledge cannot be expressed analytically. Therefore, most of the applications are based on other two methods, which can provide optimal classification. However, their performance depends heavily on the assumption of normality of the input data. For normally distributed features, the SL can perform equally well or better as an ANN does. Bayesian and neural networks classifiers were compared for grading carrots using curvature and brokenness features (Howarth & Searcy, 1991). The neural networks approach performed better for classifying both features. The increased performance observed for curvature was not great, from 97.1% for the Bayesian to 98.5% for the neural network classifier. For brokenness feature, more improvement was observed, an increase of 82.4% for the Bayesian to 90.1% for the neural network. Statistical regression and ANN models were used to classify poultry carcasses using textural features of multi-spectral images (Park & Chen, 1996). When the statistical regression model was used, the accuracy for the separation of normal carcasses was 94.4%. For separating condemned carcasses between septicemic and cadaver, the accuracy was 96% for septicemic and 82.7% for cadaver cases. However, when neural network models were employed to classify poultry carcasses into three classes, the accuracy of classification were 88.9% for normal, 92% for septicemic, and 82.6% for cadaver cases.

On the other hand, ANN could perform much better for non-Gaussian features extracted from the images of food products. Three learning algorithms were applied to extract quality information of table olives from batches previously classified by expert workers (Diaz et al., 2004). Combined with an image analysis system, the olives were classified into four quality categories. The results showed that a neural network with a hidden layer outperformed the other two statistical methods with an accuracy of over 90%, while partial least squares discriminant and Mahalanobis distance were only over 70%.

5.3. Other techniques

Based on fuzzy set theory, fuzzy logic is a valuable tool in dealing with vague, ambiguous, or incomplete information. The rules generalised by fuzzy logic are very close to the nature of human's mind in some sense and can embody complex relationships. However, the performance of the fuzzy system depends on how well it was tuned. It becomes difficult in tuning a fuzzy classifier in multi-dimensional problems. A fuzzy classifier was developed and compared with a neural classifier to sort apples based on watercore features extracted from X-ray images of each fruit (Shahin et al., 2001). The classification accuracy was 80% for fuzzy classifier when sorting apples into three watercore classes, while the neural classifier performed better at 88% accuracy with fewer losses and false positive samples.

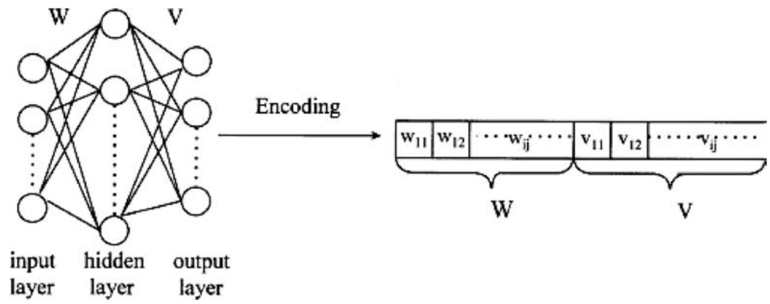

Fig. 9. Encoding of the weight values into a string, where W is the weight matrix from input layer to hidden layer, and V is the weight matrix from hidden layer to output layer (Guyer and Yang, 2000).

Genetic algorithms operate a population-based search to identify the best hypothesis, which can represent complex, multivariate condition straightforwardly (Corney, 2002). However, like ANNs, the implicit internal models generated are not easily understood by human beings. On the contrary, decision tree is an explicit model expressed in the form of tree, which are easily to be understood, but it is a method for approximating discrete-valued target functions. Ghazanfari, Wulfsohn, and Irudayaraj (1998) used a computer vision system to classify 'in the shell' pistachio nuts using grey-level histogram. Three classification schemes were compared, i.e. a Gaussian, a decision tree, and a multi-layer neural network (MLNN). It was found that they had similar recognition rates and the MLNN classifier resulted in slightly higher performance with more uniform classification accuracy than the other two classifiers.

5.4. Future perspectives

Because of the various strengths and weaknesses of different learning techniques, one of the most interesting fields for further application will be focused on combining several techniques for the food quality evaluation using computer vision. An enhanced genetic algorithm neural network (EGANN) was developed for defect detection on cherries, where a genetic algorithm was applied to design the topology and evolve the weights for multi-layer feed forward ANN (Guyer & Yang, 2000). Fig. 9 showed the structure of EGANN, which is to map connection weights of the ANN into a chromosome (a string of genes representing elements of the weight matrices). An average of 73% classification accuracy was achieved for correct identification as well as quantification of all types of cherry defects. Errors resulted only from misclassification of defect type or quantification of defect and no false positives or false negatives occurred. To partition colour images of edible beans, Chtioui, Panigrahi, and Backer (2003) developed a novel segmentation approach based on a self-organizing map neural network and fuzzy c-means clustering (SOM_FCM). The average percentage of correctly matched pixels was 99.31% for the SOM_FCM, which illustrated the potential to improve computer vision applications using combined learning techniques.

Another trend for further application is to adopt relatively novel learning techniques, such as support vector machine (SVM). SVM is a state-of-the-art learning algorithm, which has a good theoretical foundation in statistical learning theory (Vapnik, 1995). SVM fixes the decision function based on structural risk minimisation instead of the minimisation of the misclassification on the training set to avoid overfitting problem. It performs binary classification problem by finding maximal margin hyperplanes in terms of a subset of the input data (support vectors) between different classes. If the input data are not linearly separable, SVM firstly maps the data into a high dimensional feature space, and then classifies the data by the maximal margin hyperplanes. Furthermore, SVM is capable of learning in high-dimensional feature space with fewer training data.

6. Conclusions

The applications of learning techniques in computer vision to the different types of food product are reviewed in this paper. A variety of learning algorithms are used to perform the food quality evaluation with various successes:

- ANNs are flexible enough to model most of systems accurately, and relatively easy to use, which can be employed widely for classification, prediction and segmentation in quality evaluation of various food products using computer vision. However, ANNs lack a profound theoretical basis for designing their topological structure and are essentially black boxed.
- SL algorithms have a well-established underlying probability model, which is mathematically rigorous. For normally distributed features, SL can perform equally as well as other learning techniques or better, which has been proven successful for classification, feature selection, and segmentation in computer

vision for quality evaluation of food products. On the other hand, SL might perform worse for non-Gaussian features extracted from the images of food products.
- Fuzzy logic simulates the human experience of generating complex decisions using approximate and uncertain information, which have been found suitable for many practical classification problems in food quality evaluation using computer vision. However, the performance of the fuzzy system depends on how well it was tuned, which becomes difficult in multi-dimensional problems.
- Genetic algorithm can represent complex, multivariate condition straightforwardly, but the implicit internal models generated are not easily understood by human beings. On the contrary, decision tree is an explicit model and easily to be understood, but it is a method for approximating discrete-valued target functions. Only a few applications of genetic algorithm and decision tree have been found in computer vision for food quality evaluation.

To satisfy the demand of learning system in computer vision for food quality evaluation, one of the most interesting fields for further application will be focused on combining several techniques into one system. Another trend for further application is to adopt relatively novel learning techniques, such as SVM. As our understanding of learning algorithms continues to mature, it seems inevitable that machine learning will play an increasingly important role in computer vision for food quality evaluation.

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