11

Application of Artificial Neural Networks in Meat Production and Technology

Maja Prevolnik[1,2], Dejan Škorjanc[2], Marjeta Čandek-Potokar[1,2] and Marjana Novič[3]
[1]Agricultural Institute of Slovenia, Hacquetova ulica 17, 1000 Ljubljana,
[2]University of Maribor, Faculty of Agriculture and Life Sciences, Pivola 10, 2311 Hoče,
[3]National Institute of Chemistry, Hajdrihova 19, 1001 Ljubljana,
Slovenia

1. Introduction

The market of meat and meat products is growing continuously. In the sector of meat, there are many problems and challenges associated with the evaluation of meat quality at industrial level. The methods with the potential of industrial application should be accurate but also rapid, non-destructive, with no health or environment hazards, with benefits of automation and lower risk of human error. The lack of such methods represents a drawback for meat industry and the research focusing on the possible application of rapid methods is emerging. Many new promising techniques are being tested in meat science such as NIR (near infrared) and FT-IR (Fourier transformed infrared) spectroscopy, mass spectrometry, hyper- and multispectral imaging techniques, machine/computer vision, biosensors, electronic noses (array of sensors), ultrasound techniques, *etc*. However, the enormous amount of information provided by these instruments demands an advanced data treatment approach. The artificial intelligent methods can be used for such purposes since their primary target is to distinguish objects or groups or populations. Artificial neural networks (ANN) are a well-known mathematical tool widely used and tested lately for the problems in meat production and technology. Its advantages are in the ability to handle with non-linear data, highly correlated variables and the potential for identification of problems or classification. In particular promising applications of ANN in relation to meat sector is in carcass classification, quality control of raw material, meat processing, meat spoilage or freshness and shelf-life evaluation, detecting off-flavours, authenticity assessment, *etc*. In this chapter an overview of published studies dealing with the application of ANN in meat science is given. In the first part of the chapter basic concepts of artificial neural networks (ANN) are presented and described. The next part of the chapter summarizes the relevant publications on the use of ANN in case of meat production and technology issues and is divided in several paragraphs presenting the relevant research work with the most interesting applications of ANN.

2. Basic concepts of ANN

The ANN is a machine learning method evolved from the idea of simulating the human brain (Rosenblatt, 1961; Zou et al., 2008). Once regarded as an eccentric and unpromising algorithm for the analysis of scientific data, ANN has been developed into a powerful computational tool in the past decades (Cartwright, 2008) used in many fields of chemistry and biology. The key characteristic of ANN is its ability to learn. Important assets of ANN are related to its ability to handle large data sets, to find out interesting relationships or behaviour among complex data. It is highly adaptable and has an excellent fault tolerance. When a data set is well explained by an appropriate mathematical model (e.g. linear regression), a neural network is unlikely to be needed. It becomes useful in the cases where the rules that underlie the data are not known, or are only partially known. In this case a mechanistic model cannot be derived; instead, a data-driven model may be developed and for this purpose the ANN method is well suited. The functional relationship between input and output is formed during the learning process. This chapter will give only a brief and elementary description of the ANN used in various studies related to meat production and technology. For more detailed information a reader is advised to address the literature specialized in description and mathematical concepts of ANN. Different types of ANN are known, Kohonen, counter-propagation (CP), back-propagation ANN, the latter being the most often applied in studies on meat. Like in the biological neural network, the artificial ANN has an interconnection of neurons with three vital components: i) node character which controls signals *i.e.* the number of inputs and outputs, the weights and activation function associated with the node, ii) network topology defining how nodes are organized and connected and iii) learning rules for the initialization and adjustment of weights. There are two groups of ANN, supervised and unsupervised, which differ in the strategy of learning. In unsupervised learning, the input data is organised and processed without reference to the target, whereas in supervised learning, both the input and target (output) are used. Kohonen ANN is an example of unsupervised learning, where no referential (output) data are used in training of the network, and the algorithms used are excellent for establishing the relationship among complex sets of data. Counter-propagation ANN represents an up-grade of Kohonen ANN and is based on two-step learning procedure, unsupervised in the first step, and supervised in the second. CP-ANN is the most suitable method for classification of data, but can be used also as a method for developing predictive models for new objects of unknown properties. Back-propagation ANN is another example of supervised learning, where one or more target values are predicted from input data, meaning that both inputs and outputs should be known for the training dataset. A special type of ANN is radial basis function network which ordinarily does not involve the training of network, but is determined using a certain transformed function. However, the majority of algorithms work according to an iterative principle, which is similar to training of the network.

2.1 Feed-forward neural network

Feed-forward neural network was the first type of ANN developed. In this network, the information moves only in one direction, forward from the input neurons through the hidden neurons (if any) to the output nodes. There are no cycles or loops in the network. Perceptron (a linear classifier) is the simplest kind of feed-forward ANN. The most popular form is back-propagation (BP) ANN, a multilayer feed-forward network based on back-propagation learning algorithm. The BP-ANN consists of supervised learning algorithm that corrects the weights within each layer of neurons in proportion to the error of the preceding layer level *i.e.* backwards, from the last (output) layer towards the first (input) layer of neurons (Zupan, 1994). Giving the input vectors and targets, this network can approximate a function or classify input vectors in a way defined by the user. Typical BP-ANN has three layers (Fig. 1): the input neurons that receive the information from a data file, the output neurons that provide a response to the input data, in between are the hidden neurons which communicate with other neurons, they are a part of the internal pattern which provides a solution. In BP-ANN the information flows from one processing element to another within a set of weights. During the training, the interconnections can strengthen or weaken, so that a neural network produces a more correct answer. The number of neurons in the hidden layer influences the number of connections, which affect significantly the network performance and should be optimised. If the number of hidden neurons is too low the learning process can be obstructed, if the number of hidden neurons is too big the network can be over-trained. When developing BP-ANN, besides the mentioned number of neurons in hidden layer, the following parameters of network should be optimized: learning rate (0.1-0.9), momentum term (0.0-1.0), and number of epochs (starting with sample size, optimized on test-set error). When ANN is trained to a satisfactory level, the weighted links among the units are saved and later used as an analytical tool to predict results for a new set of input data.

2.2 Self-organizing maps (SOM) or Kohonen neural networks

Kohonen ANN was initially developed with the aim to mimic human brain functioning. In human brains similar information is stored in certain regions (neighbouring neurons) of cortex. This is related to the mapping of inputs in the Kohonen map which represents a type of unsupervised learning strategy and can be rationalised by the way how young children learn to recognize objects. They do not have to know the words of objects, they just look at the images and they automatically relay *e.g.* the houses in the same group of objects, no matter how many windows or chimneys they have. For the unsupervised learning strategy, only the description of objects are needed, *i.e.* the independent variables for the input vectors. The properties are not given, so the map obtained shows only the relationship between the independent variables of the objects, regardless of their property that may be known, but is not represented in object vectors. The main goal of Kohonen ANN is to project or map objects from m-dimensional into two-dimensional space on the basis of input data (similarity among objects). Thus Kohonen ANN is most frequently applied for visualization and clustering purposes.

The Kohonen ANN (Fig. 1) has only one (active) layer of N neurons represented as weights $W_j=(w_{j1}, w_{j2}, w_{ji}, \dots w_{jm})$. Each neuron ($j=1...N$) has several weight levels ($i=1...m$). There are as many weight levels as there are input variables. The learning in the Kohonen network is based on unsupervised competitive learning, where only one neuron from the layer is selected for each input. Input is a vector of variables *i.e.* descriptors ($X_s=x_{s1}, x_{s2}, x_{si}, \dots x_{sm}$). The winning neuron W_c is the neuron with weights closest to the input Xs according to the Euclidean distance. The weights of the winning neuron and its neighbouring neurons are corrected so that their weights become more similar to the input variable. A trained Kohonen network consists of m-dimensional neurons organised in $N_x \times N_y$ matrix with weights accommodated to the training set objects. Presenting the entire set of objects to the trained network we obtain the locations of the winning neurons in the $N_x \times N_y$ map, excited by individual objects. If we mark the excited neurons in the map by labels corresponding to individual objects, we obtain so-called top-map. The labels can be chosen according to known properties of the objects (e.g. feeding regime, breed, quality class, geographical location). In the top-map one can find clusters of objects, empty spaces (neuron that were not excited by any of the training objects), or conflicts (neurons, excited by two or more objects from different classes or having different properties). Clusters and empty spaces can be inspected without prior knowledge of property (dependent variables) of the studied objects, while the conflicts can only be determined knowing the properties as well. When developing Kohonen ANN the following parameters of network should be optimised: net size (number of neurons in x and y direction), boundary condition, neighbourhood correction, learning rate (minimal, maximal), number of epochs (starting with sample size, optimized on test-set error), the latest being the most influential parameter.

2.3 Counter-propagation artificial neural networks (CP-ANN)

The CP-ANN (Fig. 1) is based on a two-steps learning procedure, which is unsupervised in the first step. The first step corresponds to the mapping of objects in the input layer (also called Kohonen layer). This part is identical to the Kohonen learning procedure described above. The second step of the learning is supervised, which means that for the learning procedure the response or target value is required for each input. The network is thus trained with a set of input-target pairs $\{X_s, T_s\}$, where T_s is the vector representing dependent variables.
The training of the CP-ANN means adjusting the weights of the neurons in such a way that for each input sample X_s from the training set the network would respond with the output Out_s identical to the target T_s. The training is an iterative procedure similar to the procedure described for the Kohonen neural network, only that dependent variables or target vectors are considered as well. It involves the feeding of all input-output pairs $\{X_s, T_s\}$ to the network, finding the central neuron in the input layer for each X_s, and correction of weights of the neurons, not only in the input but also in the output layer, according to the differences between the targets and current outputs (T_s - Out_s). As already stressed, the targets are needed only in the last part of each iterative learning step. The unsupervised element in the CP-ANN learning procedure is the mapping of the objects vectors into the Kohonen layer, which is based solely on the independent variables, *i.e.* X-part of the $\{X_s, T_s\}$ pairs of the objects from the training set. For this step no knowledge about the target vector (property) is needed. Once the position (central neuron c) of the input vector is defined, the weights of the input and output layer of the CP-ANN are corrected accordingly.
When developing CP-ANN the same network parameters should be optimised as previously explained for Kohonen ANN. Properly trained CP-ANN can be used as predictive models for new objects of unknown properties. First the object is located in the Kohonen layer (on the most similar neuron) regarding the independent variables, which describe the unknown object. Then the position of the neuron is projected to output layer, which gives us the prediction of the sought properties. CP-ANN is also a suitable device for clustering, classification and determination of outliers.

2.4 Differences between CP-ANN and BP-ANN

There are two main differences between CP-ANN and BP-ANN which relate to the learning strategy and the connection between layers (Novič, 2008). Firstly, in contrast to BP-ANN, the learning strategy of CP-ANN is not supervised in all subsequent stages of the training process. The two steps are iteratively repeated for all objects of the training data: (i) finding the position of the object in the two-dimensional map (the most similar neuron in the input or Kohonen layer), which is unsupervised routine based solely on the object representation or independent variables, and (ii) correction of the weights, which also encompasses the output neurons and consequently the property or target values are needed for this purpose.

In this stage, the supervised part is introduced into the training process. Secondly, there is no hidden layer in the CP-ANN. The output (Grossberg) layer is positioned directly below input (Kohonen) layer, with a one-to-one correspondence of neurons. This means that each neuron from the input layer at a position (N_x, N_y) has an ascribed property stored in the output layer at the same position (N_x, N_y). In fact, the output layer, when properly trained, serves as a lookup table for all neurons from the input layer. It has to be stressed here that, in the process of training, all the neurons are affected, not only the central neurons fired by the object. The neighbouring neurons around the central one may remain "unoccupied" at the end of the training; consequently, the output layer contains also values different from the properties of the training objects (interpolated values between those from two occupied neurons). However, there is no chance to obtain predictions out of the range of properties of the training data, which means that extrapolations are not feasible with the CP-ANN. This can be regarded as an advantage, because it prevents unreliable extrapolated predictions, not viable in the experience-based ANN.

2.5 Radial basis function networks

Radial basis function networks (RBF networks) represent a special type of ANN, which are closely related to density estimation methods. A thorough mathematical description of RBF

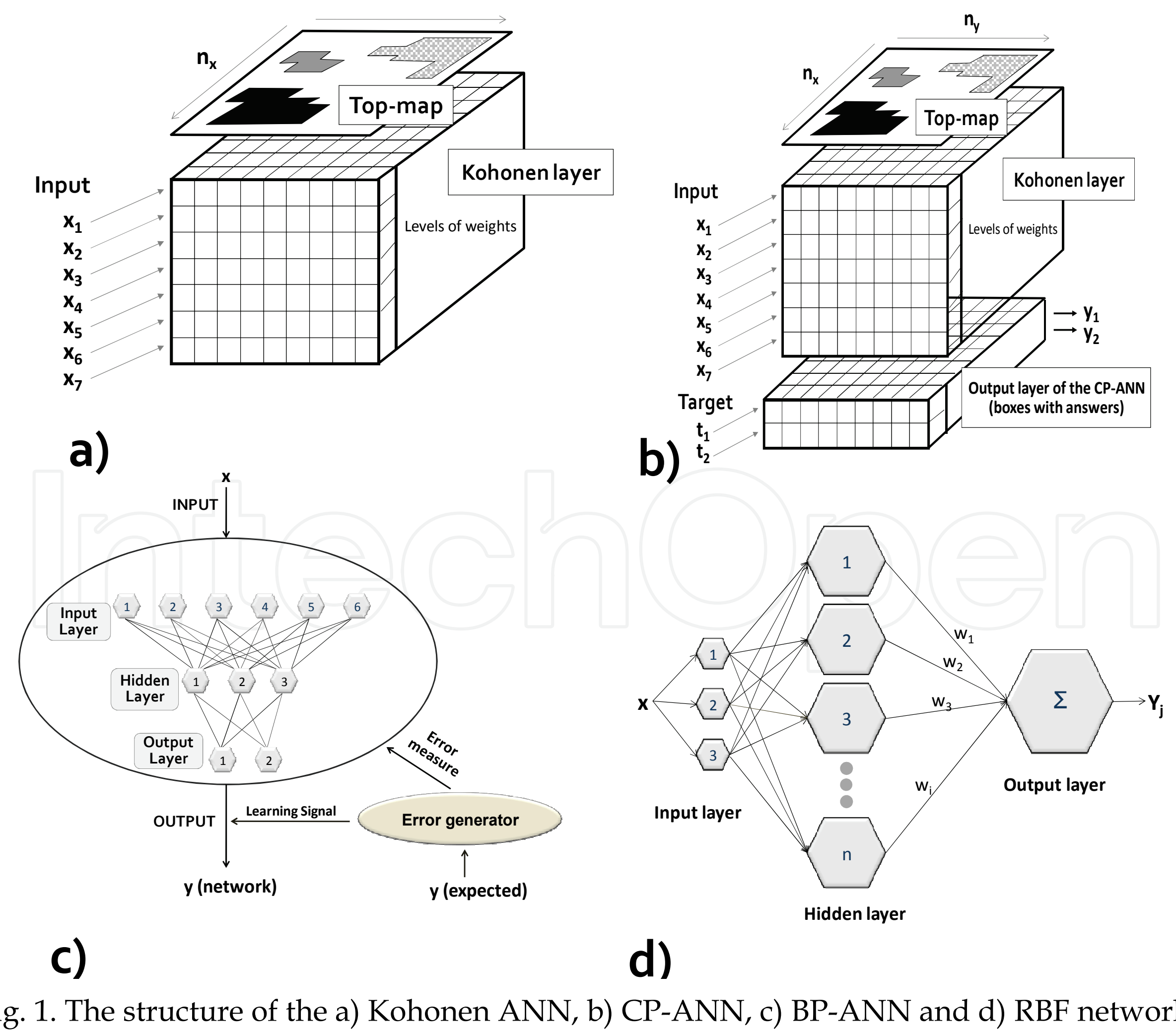


Fig. 1. The structure of the a) Kohonen ANN, b) CP-ANN, c) BP-ANN and d) RBF network

networks is given by Broomhead & Lowe (1988), a short introduction can be found in Lohninger (1993). RBF networks are considered as intermediate between regression models and nearest neighbour classification schemes, which can be looked upon as content-addressable memories (some workers in the field do not regard it as neural networks at all). The behaviour of a RBF network can be controlled by a single parameter which determines if the network behaves more like a multiple linear regression or a content-addressable memory. RBF networks (Fig. 1) have a special architecture, they have only three layers (input, hidden, output) and there is only one layer where the neurons show a nonlinear response (Lohninger, 1999). Some authors have suggested including some extra neurons which serve to calculate the reliability of the output signals (extrapolation flag). The input layer has, as in many other network models, no calculating power and serves only to distribute the input data among the hidden neurons. The hidden neurons show a non-linear transfer function which is derived from Gaussian bell curves. The output neurons in turn have a linear transfer function which makes it possible to simply calculate the optimum weights associated with these neurons.

3. Novel technologies using ANN in meat quality evaluation and control

Meat quality is a very complex term and it comprises various aspects which can differ according to the user’s standpoint *i.e.* different factors or properties are important for animal producer, meat processor or consumer. From the animal production perspective the quality mainly refers to lean meat content on which the payment to the farmer is based. Processing industry on the other hand is interested in meat technological quality (suitability for further processing) and factors affecting consumer’s choice. The consumer is sensitive about meat appearance (colour, lean to fat ratio), its sensory quality, nutritional value (macro and micro nutrients) and safety (presence/absence of toxic compounds, drugs, and pathogen or spoilage micro flora). Other factors like the way meat is produced (animal welfare, ecology) can also affect consumer’s choice. In meat production and technology, different properties can play an important role in quality classification of meat for different purposes or can be critically appraised by consumers (often their basis for meat selection or rejection). In pork for example, water-holding capacity of meat has big significance, whereas in beef, tenderness is an important attribute. Spoilage detection or meat shelf-life is also an important issue in meat sector. In the last decades, the methods used in meat evaluation, meat quality control, or inspection have undergone important developments with the application of novel technologies like computer (machine) vision, spectral imaging, spectroscopy, electronic nose or bio-sensing technologies. Since the application of ANN in meat science and technology is mainly associated with novel technologies, a brief presentation of technologies encountered is given.

Electronic nose (also electronic sensing or e-sensing) is an array of electronic chemical sensors with partial specificity and an appropriate pattern-recognition system, capable of detecting specific or complex odours (Craven et al., 1996). These instruments contain an array of sensors that utilize various technologies like organic polymers, metal oxides (Harper, 2001). The recognition process is similar to human olfaction and is performed for identification, comparison, quantification and other applications. These instruments show potential but are presently still in developmental phase due to many weaknesses (sensitivity to humid conditions, high alcohol concentration, instrumental drift, sensor span life) that should be overcome (Harper, 2001).

Computer vision is concerned with the theory behind artificial systems that extract information from images. The image data can take many forms, such as video sequences, views from multiple cameras, or multi-dimensional data from a medical scanner. The application of computer vision in the industry, where information is extracted for the purpose of supporting a manufacturing process, is called machine vision. Ultrasonography is a kind of imaging technique which uses ultrasound for diagnostic purposes. The reflection signature can reveal details about the inner structure of the medium. Spectral imaging or spectral analysis comprises different techniques such as hyper-, multi- and ultraspectral imaging. In contrast to the human eye, which can see only visible light, hyperspectral imaging collects and processes information from across the electromagnetic spectrum. Certain objects leave unique 'fingerprints' across electromagnetic spectrum. The differences among hyper-, multi- and ultraspectral imaging are based mainly on the type of measurements *i.e.* discrete or continuous bands, broad or narrow bands.

Near infrared (NIR) spectroscopy is a spectroscopic method which extracts the information about chemical and physical properties of organic substances on the basis of vibrations of bounds caused by NIR light (800 nm to 2500 nm). The characteristics of NIR spectra are molecular overtones and combination vibrations which are typically very broad in this part of the electromagnetic spectrum. It can be very useful in probing bulk material with little or no sample preparation.

Bio-sensing technology combines a sensitive biological element (e.g. enzymes, microorganisms, antibodies, *etc.*) with a physicochemical detector of an analyte (optical, piezoelectric, electrochemical). The physicochemical detector transforms the interaction of the analyte with the biological element into a signal which can be measured and quantified. The results are displayed in a user-friendly way.

The mentioned techniques generally produce enormous amounts of very complex information (spectra, images, *etc.*) which require sophisticated data treatment *i.e.* multivariate calibration methods. Due to its dynamic self-adapting system using a learning strategy ANN is able of pattern recognition, dealing with complexity of data and non-linear relationships, performing complex prediction and classification tasks. ANN has thus been applied also for solving the problems in meat science and technology. New methods were developed to either complete or replace subjective sensory testing (e.g. analysis of odour or flavour), to handle complex properties (e.g. meat tenderness), to speed up the process or replace human operator in on-line inspection. Literature review (Tables 1-4) demonstrates examples of successful or promising applications of ANN in meat technology in association with novel technologies.

4. Application of ANN in meat quality evaluation and meat chemical composition analysis

Artificial intelligence methods (ANN) were mainly investigated for the evaluation of meat sensory quality *i.e.* the properties that are subjectively evaluated or classified such as tenderness (Li et al., 1999; Li et al., 2001; Tian et al., 2005; Chandraratne et al., 2006), colour (Santé et al., 1996; Lu et al. 2000; Tan et al., 2000; Sheridan et al., 2007) or marbling score/level (Brethour, 1994; Qiao et al., 2007a). There were also studies dealing with water-holding capacity of pork (Prevolnik et al., 2009; Qiao et al., 2007b), quality of meat products (Dong, 2009; Valous et al., 2010) and categorization to different pork (Qiao et al., 2007a) or beef quality classes (Shiranita et al, 2000). The majority of studies were carried out on beef and pork (Table 1), and only a few of them to other *species* such as poultry (Santé et al., 1996) and lamb (Sebastian et al., 2004; Chandraratne et al., 2006). Contrary to the frequent use of ANN for meat quality assessment, this approach was seldom used for the prediction of meat chemical properties (Mittal & Zhang, 2000; Sebastian et al., 2004; Prevolnik et al., 2009). In the studies of meat quality assessment, variants of computer (machine) vision were often applied. The overview of the studies (Table 1) shows that ANN was used for the assessment of meat properties based on digital images of meat surface (Li et al., 1999; Lu et al., 2000; Shiranita et al., 2000; Tan et al., 2000), or based on near infrared spectra (Prevolnik et al., 2009), mass spectroscopy (Sebastian et al., 2004), hyperspectral imaging (Qiao et al., 2007a,b), ultrasonography (Brethour, 1994; Huang et al., 1998). Only few studies based application of ANN for meat quality assessment using just several simple physical measurements of meat (Santé et al., 1996; Prevolnik et al., 2009) or carcass traits (Hill et al., 2000). In the vast majority of the reported studies a supervised learning strategy of ANN (multi-layer perceptron neural networks with back-propagation learning, back-propagation ANN, feed-forward ANN, multi-layer perceptron) was used for addressing the issues of meat quality and composition, denoting an interest for prediction ability. There was only one study (Prevolnik et al., 2009) where a combination of unsupervised (Kohonen ANN) and supervised learning (CP-ANN and BP-ANN) and was used. Generally the presented studies (an overview is given in Table 1) demonstrate good results, and an improvement when compared to other multivariate techniques of data the analysis. The accuracy of classification

OBJECTIVE	SAMPLE	INPUT DATA	RESULTS	REFERENCE
^{C}Marbling	Bovine LD n=161	Ultrasonography, pattern recognition	84% correctness	Brethour, 1994
^{C}Meat colour	Turkey breast, n=68+40	pH, L^*, a^*, b^*, T, haem pigment, dielectric loss factor	70% correctness	Santé et al., 1996
^{P}WBSF, fat, moisture, collagen, sacromere length, calpastatine	Bovine LD	Wavelet textural features from ultrasonic elastograms	R^2=0.91-0.99	Huang et al., 1998
^{P}Cooked meat tenderness	Bovine loin n=97	Computer vision (digital colour image of meat)	R^2=0.70	Li et al., 1999
^{C,P}WBSF	Bovine LTL n=1452	Carcass traits	$^{P}R^2$=0.37-0.45 ^{C}51-53%	Hill et al., 2000
^{P}Meat colour	Pork LD n=44	Computer vision, image analysis	R^2=0.56	Lu et al., 2000
^{P}Temperature and moisture during cooking	Frankfurters	ratio fat/protein, initial & ambient T, radius, initial moisture, relative humidity	System is convenient and accurate	Mittal & Zhang, 2000
^{C}Meat grade	Bovine loin n=36	Image processing	Effective system, difference in grades < 1	Shiranita et al., 2000
^{C}Meat colour	Pork LD n>200	Colour machine vision	86% correctness	Tan et al., 2000
^{C}Meat tenderness (tough or tender)	Bovine loin n=59	Image texture analysis	83% correctness	Li et al., 2001
^{P}WBSF, collagen and lipid content	Lamb LD n=120	Curie point pyrolysis-mass spectrometry	r=0.85-0.90, 10-12% error	Sebastian et al., 2004

Table 1. The application of ANN in meat chemical composition and quality analysis

OBJECTIVE	SAMPLE	INPUT DATA	RESULTS	REFERENCE
^{P}Cooked meat tenderness	Bovine LD n=50	Computer vision technology	R^2=0.62	Tian et al., 2005
^{P}WBSF	Lamb loin n=160	Image surface texture analysis	R^2=0.62-0.75	Chandraratne et al., 2006
^{P}Moisture content	Cooked bovine joints	Computer vision (colour features)	r=0.75	Zheng et al., 2007
^{C}Pork quality class, marbling	Pork loin n=40	Hyperspectral imaging	>70 % correctness	Qiao et al., 2007a
^{P}Drip loss, L*, pH ^{C}WHC classes	Pork loin n=80	Hyperspectral imaging	^{P}r=0.77, 0.55 and 0.86 for drip loss, pH and L*, respectively ^{C}successful	Qiao et al., 2007b
^{C}Discoloration (fading)	Cured ham	L*, a*, b or spectral reflectance	Successful discriminating different stages of fading	Sheridan et al., 2007
^{P}WHC (drip loss)	Pork LD n=312	pH, L*, a*, b* NIR spectroscopy	R^2=0.37-0.51, error=2.2-2.5%	Prevolnik et al., 2009
Sensory texture	Cooked sausage	Instrumental texture measurements	Lower errors as compared to regression analysis	Dong, 2009
Quality class	Cooked ham	Computer vision	84-96% correctness	Valous et al., 2010

LD – *longissimus dorsi*; TB – *triceps brahii*; LTL – *longissimus thoracis et lumborum*; R^2 – coefficient of determination; r – correlation coefficient; P – prediction; C – classification; WHC – water holding capacity; WBSF – Warner-Bratzler shear force; NIR – near infrared.

Table 1. Continued. Application of ANN in meat chemical composition and quality analysis

reported is high (70 to 85 %). In case where ANN approach was used for prediction, the results varied from moderate to excellent; however, for the most part the authors consider application of ANN as promising and successful.

5. Application of ANN for carcass quality or classification

Meat industry is interested in lean and conformed carcasses which provide high meat yields. The so called carcass grading or classification (used for pig, bovine, lamb carcasses) is performed at the end of the slaughter line and represents a basis for the payment to the farmer. Another example is in poultry, where the carcasses are inspected at the slaughter line for the wholesomeness and those with an abnormal aspect (tumorous, bruised, skin-torn, septicemic, cadaver, air-sacculitis) are discarded. The mentioned procedures are mostly based on the visual appraisal and thus subjected to human limitations (speed, error, fatigue). The overview of the problems encountered in this field of research, where possible application of

ANN was investigated, is given in Table 2. In regard to carcass classification of domestic mammals, the research was mainly focused on either improving or replacing methods that are currently used. Many studies were carried out on classification or carcass quality evaluation in bovine carcasses (Borggaard et al., 1996; Hwang et al., 1997; Díez et al., 2003; Hatem et al., 2003; Lu & Tan, 2004), but also for lamb (Chandraratne et al., 2007) or goat (Peres et al., 2010). In these *species* the principle of grading is similar and consists of visual notes given by the classifier, which are the indicators of lean meat quantity. In these cases the aim was either to predict carcass lean meat content (Hwang et al., 1997; Berg et al., 1998; Lu & Tan, 2004) or to replace the classifier using automated grading (Borggaard et al., 1996).

OBJECTIVE	SAMPLE	INPUT DATA	RESULTS	REFERENCE
Inspection – carcass wholesomeness	Poultry n=87	Multispectral imaging	83-97% success in sorting	Park & Chen, 1994
PConformation, fatness, fat colour, rib eye area, saleable meat %	Bovine n=3,500	Computer vision	R^2=0.66-0.93, 20% lower error as classifier	Borggaard et al., 1996
Inspection – carcass wholesomeness	Poultry n=559	VIS-NIR spectroscopy	93–97% success in sorting	Chen et al., 1996
Inspection – carcass wholesomeness	Poultry n=288	Multispectral imaging	91% success in sorting	Park et al., 1996
Inspection – carcass wholesomeness	Poultry	VIS-NIR spectroscopy	>95% success in sorting	Chen et al., 1998a
Inspection – carcass wholesomeness	Poultry	VIS-NIR spectroscopy	98% success in sorting	Chen et al., 1998b
Lean meat content prediction (carcass and prime cuts)	Pig n=50	Electromagnetic scanning	Improvement in comparison to linear regression	Berg et al., 1998
Inspection – carcass wholesomeness	Poultry n=91	Multispectral imaging	90-93% success in sorting	Park et al., 1998
Inspection – carcass wholesomenes	Poultry	Machine vision (dual-camera)	80-100% success in sorting	Chao et al., 2000

Table 2. Application of ANN for carcass classification

Other studied applications were interested in prediction of fat depots based on *in vivo* measurements (Peres et al., 2010) or prediction of carcass maturity (Hatem et al., 2003). In the case of pig classification, studies using ANN are rare (Berg et al., 1998), probably because the current classification methods are based on objective measurements on the carcass which are well correlated to lean meat content thus providing sufficient accuracy using standard regression methods. There was an interesting study in bovine carcass classification addressing the problem of classifier effect and repeatability in bovine carcass grading (Díez et al., 2003), demonstrating another possible application of ANN for the purposes of monitoring. Much work has also been devoted to the automatic inspection of wholesomeness of chicken carcasses using different optical techniques (Park & Chen, 1994; Chen et al., 1996, Park et al., 1996, 1998; Chen et al., 1998a,b; Chao et al., 2000, 2002; Ibarra et

OBJECTIVE	SAMPLE	INPUT DATA	RESULTS	REFERENCE
Inspection – carcass wholesomeness	Poultry	Spectral imaging	83–91% success in sorting	Park & Chen, 2000
Inspection – carcass wholesomeness	Poultry n=14,591	Machine vision (dual-camera)	87-94% success in sorting	Chao et al., 2002
Inspection – carcass wholesomeness-diseased air sacks	Poultry n=100	Computer vision - color classification	97% success rate	Ibarra et al., 2002
Classifier effect and repeatability	Bovine n=227	Computer vision (image analysis)	Higher uncertainty when grading light than standard carcasses	Díez et al., 2003
Skeletal maturity grading	Bovine cartilage n=138	Machine vision (colour features of cartilage)	65-75% correctness	Hatem et al., 2003
Lean weight and lean percentage prediction	Bovine n=241	Computer vision (image analysis)	No advantage to linear methods	Lu & Tan, 2004
Carcass grading	Lamb n=160	Computer vision (image analysis)	87-100% correctness	Chandraratne et al., 2007
Fat depots assessment	Goats, n=56	Ultrasound technology	R^2=0.82-0.96, RPD=1.7-4.3	Peres et al., 2010

LD – *longissimus dorsi*; VIS – visible; NIR – near infrared; R^2 – coefficient of determination; r – correlation coefficient; P – prediction; C – classification; RPD – residual predictive deviation.

Table 2. Continued. Application of ANN for carcass classification

al., 2002). The usefulness of ANN as coupled with computer vision for such purposes has been demonstrated by several studies. The success rate of such classification is very high, typically above 90%. In all studies dealing with carcass classification or inspection a supervised learning strategy was applied, mainly BP-ANN, with the exception of a few studies using other types of ANN such as RBF networks (Peres et al., 2010) or learning vector quantization (Ibarra et al., 2002). In general, ANN showed its potential and advantage over conventional regression methods especially in case of non-linearity between system inputs and outputs.

6. Application of ANN for spoilage identification/storage time assessment

Meat and meat products are highly susceptible to spoilage or contamination, affecting the quality and safety of the products. Many of the methods used for the detection of spoiled or contaminated meat are based on immunological or nucleic acid based procedures which are time consuming, laborious and demand trained personnel. At present no method is available for a real-time, non-destructive, reagentless, quantitative and relatively inexpensive monitoring. According to Ellis & Goodacre (2001) interesting analytical approaches include biosensors, electronic noses, infrared spectroscopy upgraded with machine learning methods (ANN, genetic algorithms).

OBJECTIVE	SAMPLE	INPUT DATA	RESULTS	REFERENCE
P storage time, spoiled meat	Ground beef, pork n=20	Electronic nose	Successful	Winquist et al., 1993
P Meat freshness	Chicken	Electronic nose	Successful prediction of storage time	Galdikas et al., 2000
P Bacterial growth (*L. sake)*	Cooked meat products	T, a_w, CO_2	Max. specific growth rate R^2=0.94, RMSE=0.011 Lag phase λ R^2=0.97, RMSE=6.70	Lou & Nakai, 2001
P Bacterial growth (*L. monocytogenes)*	Meat broth	Fluctuating conditions (T, pH, NaCl, a_w)	ANN can be used to describe/predict bacterial growth in dynamic conditions	Cheroutre-Vialette & Lebert, 2002
P Internal temperature estimation	Chicken n=85	IR and laser range imaging	R^2=0.94-0.96	Ma & Tao, 2005
P Shelf-life estimation	Cooked meat products	T, pH, NaCl, $NaNO_2$	Error, bias and accuracy factors show successful validation	Zurera-Cosano et al., 2005
C Identification of spoiled meat	Bovine LD n=156	Electronic nose	83-100% correctness	Panigrahi et al., 2006
P Survivival of *Escherichia coli*	Fermented sausage	pH, a_w, iso-thiocyanate concentration	Accurate ANN based models	Palanichamy et al., 2008
C,P Meat spoilage identification	Bovine LD n=156	Electronic nose	Sorting accuracy >90% Microbial count R^2>0.70	Balasubramanian et al., 2009
C,P Spoilage identification	Beef fillets n=74	FT-IR spectroscopy	Sorting accuracy 81-94% Satisfactory prediction of microbial counts	Argyri et al., 2010

LD – *longissimus dorsi*; R^2 – coefficient of determination; r – correlation coefficient; P – prediction; C – classification; IR – infrared.

Table 3. Application of ANN for spoilage or storage time prediction

7. Various other applications of ANN in meat science and technology

In addition to the mentioned subjects of interest for ANN application in meat science there are various other applications related to meat technology issues (Table 4). These involve identification of animal *species* in ground meat mixtures (Winquist et al., 1993) or fat tissue (Beattie et al., 2007), recognition of animal origin (distinction between Iberian and Duroc

OBJECTIVE	SAMPLE	INPUT DATA	RESULTS	REFERENCE
Species recognition	Ground beef, pork, n=20	Electronic nose	Successful	Winquist et al., 1993
Visual guidance of evisceration	Pig carcasses	Computer vision	Efficient ANN based system	Christensen et al., 1996
Lean tissue extraction (image segmentation)	Bovine LD n=60	Computer vision (hybrid image)	Better efficiency and robustness of ANN based system	Hwang et al., 1997
Fermentation monitoring	Sausage	Electronic nose	Lowest error in case of ANN compared to regression	Eklöv et al., 1998
Estimation of meat internal T	Cooked chicken meat	IR imaging	Great potential for monitoring of meat doneness (error of ±1°C)	Ibarra et al., 2000
Determination of RN^- phenotype	Pig n=96	NIR spectroscopy	96% correctness	Josell et al., 2000
Identification of feeding and ripening time	Pig; dry-cured ham	Electronic nose	Best prediction for N at 250°C; misclassified hams ≈8%	Santos et al., 2004
Species recognition on adipose tissue	Lamb, beef chicken,pork n=255	Raman spectroscopy	>98% correctness	Beattie et al., 2007
^{P}Cooking shrinkage	Bovine TB n=25	Computer vision technique	r=0.52-0.75	Zheng et al., 2007
Walk-through weighing	Pigs	Machine vision	relative error ≈3%	Wang et al., 2008
Differentiation of Iberian and Duroc	Pigs n=30	VIS-NIR spectroscopy	>95% correctness	del Moral et al., 2009

LD – *longissimus dorsi*; TB – *triceps brachii*; R^2 – coefficient of determination; r – correlation coefficient; P – prediction; C – classification; VIS – visible; NIR – near infrared; IR - infrared.

Table 4. Other applications of ANN in meat science and technology

pigs) as affected by rearing regime and/or breed (del Moral et al., 2009), hybrid image processing for lean tissue extraction (Hwang et al., 1997), detection of RN^- phenotype in pigs (Josell et al., 2000), the "walk-through" weighing of pigs (Wang et al., 2008), the efficiency of ANN for visual guidance of pig evisceration at the slaughter line (Christensen et al., 1996) and the use of ANN for the processing control of meat products (Eklöv et al., 1998; Ibarra et al., 2000; Santos et al., 2004). Again, in the majority of studies, ANN approach was an instrument to deal with the complex output signal of novel technologies applied. Again, based on the literature reports, supervised learning strategy of ANN (BP-ANN, RBF) was applied in the majority of studies. There were also a few studies where unsupervised learning has been tested (Winquist et al., 1993; Beattie et al., 2007). A bibliographic overview given in Table 4 demonstrates the efficiency and successful classification rate of ANN based systems.

8. Conclusions and future perspectives

The existing research work of ANN application in meat production and technology provided many useful results for its application, the majority of them in association with novel technologies. Among interesting ideas that have not been encountered in the literature review is the combination of ANN with bio-sensing technology. ANN shows great potential for carcass and meat (product) quality evaluation and monitoring under industrial conditions or bacterial growth and shelf-life estimation. However, the potentially interesting relevance of ANN, for which the literature information is scarce, is its application for meat authenticity or meat (product) quality forecast based on the information from rearing phase. Overall the presented applications are relatively new and the full potential has not yet been discovered.

9. References

Argyri, A. A., Panagou, E. Z., Tarantilis, P. A., Polysiou, M. & Nychas, G. J. E. (2010). Rapid qualitative and quantitative detection of beef fillets spoilage based on Fourier transform infrared spectroscopy data and artificial neural networks. *Sensors and Actuators B-Chemical*, 145, 1, 146-154, ISSN: 0925-4005

Balasubramanian, S., Panigrahi, S., Logue, C. M., Gu, H. & Marchello, M. (2009). Neural networks-integrated metal oxide-based artificial olfactory system for meat spoilage identification. *Journal of Food Engineering*, 91, 1, 91-98, ISSN: 0260-8774

Beattie, J. R., Bell, S. E. J., Borggaard, C., Fearon, A. M. & Moss, B. W. (2007). Classification of adipose tissue species using Raman spectroscopy. *Lipids*, 42, 7, 679-685, ISSN: 0024-4201

Berg, E. P., Engel, B. A. & Forrest, J. C. (1998). Pork carcass composition derived from a neural network model of electromagnetic scans. *Journal of Animal Science*, 76, 1, 18-22, ISSN: 0021-8812

Borggaard, C., Madsen, N. & Thodberg, H. (1996). In-line image analysis in the slaughter industry, illustrated by beef carcass classification. *Meat Science*, 43, 151-163, ISSN: 0309-1740

Brethour, J. (1994). Estimating marbling score in live cattle from ultrasoud images using pattern-recognition and neural-network procedures. *Journal of Animal Science*, 72, 6, 1425-1432, ISSN: 0021-8812

Broomhead, D. S. & Lowe, D. (1998). Multivariable functional interpolation and adaptive networks. *Complex Systems*, 2, 312-355, ISSN: 0891-2513

Cartwright, H. M. (2008). Artificial neural networks in biology and chemistry. In: *Artificial neural networks : methods and applications*. Livingstone, D. (Ed.), 1-13, Humana Press, ISBN: 978-1-58829-718-1, New York

Chandraratne, M. R., Samarasinghe, S., Kulasiri, D. & Bickerstaffe, R. (2006). Prediction of lamb tenderness using image surface texture features. *Journal of Food Engineering*, 77, 3, 492-499, ISSN: 0260-8774

Chandraratne, M., Kulasiri, D. & Samarasinghe, S. (2007). Classification of lamb carcass using machine vision: Comparison of statistical and neural network analyses. *Journal of Food Engineering*, 82, 1, 26-34, ISSN: 0260-8774

Chao, K., Park, B., Chen, Y. R., Hruschka, W. R. & Wheaten, F. W. (2000). Design of a dual-camera system for poultry carcasses inspection. *Applied Engineering in Agriculture*, 16, 5, 581-587, ISSN: 0883-8542

Chao, K., Chen, Y. R., Hruschka, W. R. & Gwozdz, F. B. (2002). On-line inspection of poultry carcasses by a dual-camera system. *Journal of Food Engineering*, 51, 3, 185-192, ISSN: 0260-8774

Chen, Y. R., Huffman, R. W., Park, B. & Nguyen, M. (1996). Transportable spectrophotometer system for on-line classification of poultry carcasses. *Applied Spectroscopy*, 50, 7, 910-916, ISSN: 0003-7028

Chen, Y. R., Nguyen, M. & Park, B. (1998a). Neural network with principal component analysis for poultry carcass classification. *Journal of Food Process Engineering*, 21, 5, 351-367, ISSN: 0145-8876

Chen, Y. R., Park, B., Huffman, R. W. & Nguyen, M. (1998b). Classification o in-line poultry carcasses with back-propagation neural networks. *Journal of Food Processing Engineering*, 21, 1, 33-48, ISSN: 1745-4530

Cheroutre-Vialette, M. & Lebert, A. (2002). Application of recurrent neural network to predict bacterial growth in dynamic conditions. *International Journal of Food Microbiology*, 73, 2-3, 107-118 ISSN: 0168-1605

Christensen, S. S., Andersen, A. W., Jørgensen, T. M. & Liisberg, C. (1996). Visual guidance of a pig evisceration robot using neural networks. *Pattern Recognition Letters*, 17, 4, 345-355, ISSN: 0167-8655

Craven, M. A., Gardner, J. W. & Bartlett, P. N. (1996). Electronic noses – Development and future prospects. *Trends in Analytical Chemistry*, 15, 9, 486-493, ISSN: 0167-2940

Del Moral, F. G., Guillén, A., del Moral, L. G., O'Valle, F., Martínez, L. & del Moral, R. G. (2009). Duroc and Iberian pork neural network classification by visible and near infrared reflectance spectroscopy. *Journal of Food Engineering*, 90, 4, 540-547, ISSN: 0260-8774

Díez, J., Bahamonde, A., Alonso, J., López, S., del Coz, J. J., Quevedo, J. R., Ranilla, J., Luaces, O., Alvarez, I., Royo, L. J. & Goyache, F. (2003). Artificial intelligence techniques point out differences in classification performance between light and standard bovine carcasses. *Meat Science*, 64, 3, 249-258, ISSN: 0309-1740

Dong, Q. L. (2009). BP neural network for evaluating sensory texture properties of cooked sausage. *Journal of Sensory Studies*, 24, 6, 833-850, ISSN: 0887-8250

Eklöv, T., Johansson, G., Winquist, F. & Lundström, I. (1998). Monitoring sausage fermentation using an electronic nose. *Journal of the Science of Food and Agriculture*, 76, 4, 525-532, ISSN: 0022-5142

Ellis, D. I. & Goodacre, R. (2001). Rapid and quantitative detection of the microbial spoilage of muscle foods: Current status and future trends. *Trends in Food Science & Technology*, 12, 11, 414-424, ISSN: 0924-2244

Galdikas, A., Mironas, A., Senuliené, D., Strazdiené, V., Šetkus, A. & Zelenin, D. (2000). Response time based output of metal oxide gas sensors applied to evaluation of meat freshness with neural signal analysis. *Sensors and Actuators B: Chemical*, 69, 3, 258-265, ISSN: 0925-4005

Harper, W. J. (2001). The strengths and weaknesses of the electronic nose. In: *Headspace analysis of foods and flavours*, Rouseff R. L. & Cadwallader K. R. , (Ed.), 59-71, Kluwer Academic/Plenum Publ., ISBN: 978-0-306-46561-1, New York

Hatem, I., Tan, J. & Gerrard, D. E. (2003). Determination of animal skeletal maturity by image processing. *Meat Science*, 65, 3, 999-1004, ISSN: 0309-1740

Hill, B. D., Jones, S. D. M., Robertson, W. M. & Major, I. T. (2000). Neural network modeling of carcass measurements to predict beef tenderness. *Canadian Journal of Animal Science*, 80, 2, 311-318, ISSN: 0008-3984

Huang, Y., Lacey, R. & Whittaker, A. (1998). Neural network prediction modeling based on elastographic textural features for meat quality evaluation. *Transactions of the ASAE*, 41, 4, 1173-1179, ISSN: 0001-2351

Hwang, H., Park, B., Nguyen, M. & Chen, Y. R. (1997). Hybrid image processing for robust extraction of lean tissue on beef cut surfaces. *Computers and Electronics in Agriculture*, 17, 3, 281-294, ISSN: 0168-1699

Ibarra, J. G., Tao, Y. & Xin, H. W. (2000). Combined IR imaging-neural network method for the estimation of internal temperature in cooked chicken meat. *Optical Engineering*, 39, 11, 3032-3038, ISSN: 0091-3286

Ibarra, J. G., Tao, Y., Newberry, L. & Chen, Y. R. (2002). Learning vector quantization for color classification of diseased air sacs in chicken carcasses. *Transactions of the ASAE*, 45, 5, 1629-1635, ISSN: 0001-2351

Josell, Å., Martinsson, L., Borggaard, C., Andersen, J. R. & Tornberg, E. (2000). Determination of RN- phenotype in pigs at slaughter-line using visual and near-infrared spectroscopy. *Meat Science*, 55, 3, 273-278, ISSN: 0309-1740

Li, J., Tan, J., Martz, F. A. & Heymann, H. (1999). Image texture features as indicators of beef tenderness. *Meat Science*, 53, 1, 17-22, ISSN: 0309-1740

Li, J., Tan, J. & Shatadal, P. (2001). Classification of tough and tender beef by image texture analysis. *Meat Science*, 57, 4, 341-346, ISSN: 0309-1740

Lohninger, H. (1993). Evaluation of neural networks based on radial basis functions and their application to the prediction of boiling points from structural parameters. *Journal of Chemical Information and Computer Sciences*, 33, 736-744, ISSN: 0095-2338

Lohninger, H. (1999). Teach/Me Data Analysis, Springer-Verlag, Berlin-New York-Tokyo, ISBN: 978-3-54014-743-5

Lou, W. & Naka, S. (2001). Artificial Neural Network-based predictive model for bacterial growth in a simulated medium o modified-atmosphere-packed coked meat products. *Journal of Agricultural and Food Chemistry*, 49, 4, 1799-1804, ISSN: 0021-8561

Lu, J., Tan, J., Shatadal, P. & Gerrard, D. E. (2000). Evaluation of pork color by using computer vision. *Meat Science*, 56, 1, 57-60, ISSN: 0309-1740

Lu, W. & Tan, J. (2004). Analysis of image-based measurements and USDA characteristics as predictors of beef lean yield. *Meat Science*, 66, 2, 483-491, ISSN: 0309-1740

Ma, L. & Tao, Y. (2005). An infrared and laser range imaging system for non-invasive estimation of internal temperatures in chicken breasts during cooking. *Transactions of the ASAE, 48, 2, 681-690*, ISSN: 0001-2351

Mittal, G. S. & Zhang, J. (2000). Prediction of temperature and moisture content of frankfurters during thermal processing using neural network. Meat Science, 55, 1, 13-24, ISSN: 0309-1740

Novič, M. (2008). Kohonen and counter-propagation neural networks applied for mapping and interpretation of IR spectra. In: *Artificial neural networks : methods and applications*. Livingstone, D. (Ed.), 45-60, Humana Press, ISBN: 978-1-58829-718-1, New York

Palanichamy, A., Jayas, D. S. & Holley, R. A. (2008). Predicting survival of Escherichia coli O157 : H7 in dry fermented sausage using artificial neural networks. *Journal of Food Protection*, 71, 1, 6-12, ISSN: 0362-028X

Panigrahi, S., Balasubramanian, S., Gu, H., Logue, C. M. & Marchello, M. (2006). Design and development of a metal oxide based electronic nose for spoilage classification of beef. *Sensors and Actuators B: Chemical*, 119, 1, 2-14, ISSN: 0925-4005

Park, B. & Chen, Y.-R. (1994). Intensified multispectral imaging system for poultry carcass inspection. *Transactions of the ASAE*, 37, 6, 1983-1988, ISSN: 0001-2351

Park, B. Chen, Y. R., Nguyen, M. & Hwang, H. (1996). Characterizing multispectral images of tumorous, bruised, skin-torn, and wholesome poultry carcasses. *Transactions of the ASAE*, 39, 5, 1933-1941, ISSN: 0001-2351

Park, B., Chen, Y. R. & Nguyen, M. (1998). Multi-spectral Image Analysis using Neural Network Algorithm for Inspection of Poultry Carcasses. *Journal of Agricultural Engineering Research*, 69, 4, 351-363, ISSN: 1095-9246

Park, B. & Chen, J. Y. (2000). Real-time dual-wavelength image processing for poultry safety inspection. *Journal of Food Processing Engineering*, 23., 5., 329-351, ISSN: 1745-4530

Peres, A. M., Dias, L. G., Joy, M. & Teixeira, A. (2010). Assessment of goat fat depots using ultrasound technology and multiple multivariate prediction models. *Journal of Animal Science*, 88, 2, 572-580, ISSN: 0021-8812

Prevolnik, M., Čandek-Potokar, M., Novič, M. & Škorjanc, D. (2009). An attempt to predict pork drip loss from pH and colour measurements or near infrared spectra using artificial neural networks. *Meat Science*, 83, 3, 405-411, ISSN: 0309-1740

Qiao, J., Ngadi, M. O., Wang, N., Gariépy, C. & Prasher, S. O. (2007a). Pork quality and marbling level assessment using a hyperspectral imaging system. *Journal of Food Engineering*, 83, 1, 10-16, ISSN: 0260-8774

Qiao, J., Wang, N., Ngadi, M. O., Gunenc, A., Monroy, M., Gariépy, C. & Prasher, S.O. (2007b). Prediction of drip-loss, pH, and color for pork using a hyperspectral imaging technique. *Meat Science*, 76, 1, 1-8, ISSN: 0309-1740

Rosenblatt, F. (1961). Principles of neurodynamics: perceptrons and the theory of brain mechanisms. Spartan Books, Washington D. C., Washington

Santé, V. S., Lebert, A., Le Pottier, G. & Ouali, A. (1996). Comparison between two statistical models for prediction of turkey breast meat colour. *Meat Science*, 43, 3-4, 283-290, ISSN: 0309-1740

Santos, J. P., García, M., Aleixandre, M., Horrillo, M. C., Gutiérrez, J., Sayago, I., Fernández, M. J. & Arés, L. (2004). Electronic nose for the identification of pig feeding and ripening time in Iberian hams. *Meat Science*, 66, 3, 727-732, ISSN: 0309-1740

Sebastián, A., Viallon-Femandez, C., Toumayre, P., Berge, P., Sañudo, C., Sánchez, A. & Berdague, J.-L. (2004). Evaluation of collagen and lipid contents and texture of meat by Curie point pyrolysis-mass spectrometry. *Journal of Analytical and Applied Pyrolysis*, 72, 2, 203-208, ISSN: 0165-2370

Sheridan, C., O'Farrell, M., Lewis, E., Flanagan, C., Kerry, J. & Jackman, N. (2007). A comparison of CIE L*a*b* and spectral methods for the analysis of fading in sliced cured ham. *Journal of Optics A-Pure and Applied Optics*, 9, 6, 32-39, ISSN: 1464-4258

Shiranita, K., Hayashi, K., Otsubo, A., Miyajima, T. & Takiyama, R. (2000). Grading meat quality by image processing. *Pattern Recognition*, 33, 1, 97-104, ISSN: 0031-3203.

Tan, F. J., Morgan, M. T., Ludas, L. I., Forrest, J. C. & Gerrard, D. E. (2000). Assessment of fresh pork color with color machine vision. *Journal of Animal Science*, 78, 12, 3078-3085, ISSN: 0021-8812

Tian, Y. Q., McCall, D. G., Dripps, W., Yu, Q. & Gong, P. (2005). Using computer vision technology to evaluate the meat tenderness of grazing beef. *Food Australia*, 57, 8, 322-326, ISSN: 1032-5298

Valous, N. A., Mendoza, F., Sun, D.-W. & Allen, P. (2010). Supervised neural network classification of pre-sliced cooked pork ham images using quaternionic singular values. *Meat Science*, 84, 3, 422-430, ISSN: 0309-1740

Wang, Y., Yang, W., Winter, P. & Walker, L. (2008). Walk-through weighing of pigs using machine vision and an artificial neural network. *Biosystems Engineering*, 100, 1, 117-125, ISSN: 1537-5110

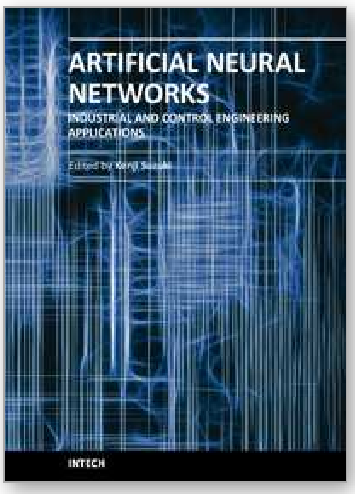
Winquist, F., Hörnsten, E. G., Sundgren, H. & Lundström, I. (1993). Performance of an electronic nose for quality estimation of ground meat. *Measurement Science & Technology*, 4, 12, 1493-1500, ISSN: 0957-0233

Zheng, C., Sun, D.-W. & Zheng, L. (2007). Predicting shrinkage of ellipsoid beef joints as affected by water immersion cooking using image analysis and neural network. *Journal of Food Engineering*, 79, 4, 1243-1249, ISSN: 0260-8774

Zou, J., Han, Y. & So, S.-S. (2008). Overview of artificial neural networks. In: *Artificial neural networks : methods and applications*. Livingstone, D. (Ed.), 15-23, Humana Press, ISBN: 978-1-58829-718-1, New York.

Zupan, J. (1994). Introduction to artificial neural network (ANN) methods: What they are and how to use them. *Acta Chimica Slovenica*, 41, 3, 327-352, ISSN: 1318-0207

Zurera-Cosano, G., Garcia-Gimeno, R. M, Rodriguez-Perez, M. R. & Hervas-Martinez, C. (2005). Validating an artificial neural network model of Leuconostoc mesenteroides in vacuum packaged sliced cooked meat products for shelf-life estimation. *European Food Research and Technology, 221, 5, 717-724,* ISSN: 1438-2377



Artificial Neural Networks - Industrial and Control Engineering Applications
Edited by Prof. Kenji Suzuki

ISBN 978-953-307-220-3
Hard cover, 478 pages
Publisher InTech
Published online 04, April, 2011
Published in print edition April, 2011

Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications. The purpose of this book is to provide recent advances of artificial neural networks in industrial and control engineering applications. The book begins with a review of applications of artificial neural networks in textile industries. Particular applications in textile industries follow. Parts continue with applications in materials science and industry such as material identification, and estimation of material property and state, food industry such as meat, electric and power industry such as batteries and power systems, mechanical engineering such as engines and machines, and control and robotic engineering such as system control and identification, fault diagnosis systems, and robot manipulation. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in industrial and control engineering areas. The target audience includes professors and students in engineering schools, and researchers and engineers in industries.