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Application of Artificial Neural Networks in Meat Production and Technology

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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 optimised: 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 \( W_j=(w_{j1}, w_{j2}, w_{j3}, \ldots, w_{jm}) \). 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 \((X_s=x_{s1}, x_{s2}, x_{s3}, \ldots, x_{sm})\). The winning neuron \( W_c \) is the neuron with weights closest to the input \( X_s \) 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 \( \text{Out}_s \) 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 \( (T_s - \text{Out}_s) \). 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](image-url)
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 spectroscoopy (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

<table>
<thead>
<tr>
<th>OBJECTIVE</th>
<th>SAMPLE</th>
<th>INPUT DATA</th>
<th>RESULTS</th>
<th>REFERENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>C Marbling</td>
<td>Bovine LD n=161</td>
<td>Ultrasonography, pattern recognition</td>
<td>84% correctness</td>
<td>Brethour, 1994</td>
</tr>
<tr>
<td>C Meat colour</td>
<td>Turkey breast, n=68+40</td>
<td>pH, L', a', b', T, haem pigment, dielectric loss factor</td>
<td>70% correctness</td>
<td>Santé et al., 1996</td>
</tr>
<tr>
<td>P WBSF, fat, moisture, collagen, sacromere length, calpastatine</td>
<td>Bovine LD</td>
<td>Wavelet textural features from ultrasonic elastograms</td>
<td>R²=0.91-0.99</td>
<td>Huang et al., 1998</td>
</tr>
<tr>
<td>P Cooked meat tenderness</td>
<td>Bovine loin n=97</td>
<td>Computer vision (digital colour image of meat)</td>
<td>R²=0.70</td>
<td>Li et al., 1999</td>
</tr>
<tr>
<td>C P WBSF</td>
<td>Bovine LTL n=1452</td>
<td>Carcass traits</td>
<td>Pr²=0.37-0.45 C=51-53%</td>
<td>Hill et al., 2000</td>
</tr>
<tr>
<td>P Meat colour</td>
<td>Pork LD n=44</td>
<td>Computer vision, image analysis</td>
<td>R²=0.56</td>
<td>Lu et al., 2000</td>
</tr>
<tr>
<td>P Temperature and moisture during cooking</td>
<td>Frankfurters</td>
<td>ratio fat/protein, initial &amp; ambient T, radius, initial moisture, relative humidity</td>
<td>System is convenient and accurate</td>
<td>Mittal &amp; Zhang, 2000</td>
</tr>
<tr>
<td>C Meat grade</td>
<td>Bovine loin n=36</td>
<td>Image processing</td>
<td>Effective system, difference in grades &lt; 1</td>
<td>Shiranita et al., 2000</td>
</tr>
<tr>
<td>C Meat colour</td>
<td>Pork LD n=200</td>
<td>Colour machine vision</td>
<td>86% correctness</td>
<td>Tan et al., 2000</td>
</tr>
<tr>
<td>C Meat tenderness (tough or tender)</td>
<td>Bovine loin n=59</td>
<td>Image texture analysis</td>
<td>83% correctness</td>
<td>Li et al., 2001</td>
</tr>
<tr>
<td>P WBSF, collagen and lipid content</td>
<td>Lamb LD n=120</td>
<td>Curie point pyrolysis/mass spectrometry</td>
<td>r=0.85-0.90, 10-12% error</td>
<td>Sebastian et al., 2004</td>
</tr>
</tbody>
</table>

Table 1. The application of ANN in meat chemical composition and quality analysis
OBJECTIVE | SAMPLE | INPUT DATA | RESULTS | REFERENCE
--- | --- | --- | --- | ---
P\(^{\text{Cooked meat tenderness}}\) | Bovine LD n=50 | Computer vision technology | \(R^2=0.62\) | Tian et al., 2005
FWBSF | Lamb loin n=160 | Image surface texture analysis | \(R^2=0.62-0.75\) | Chandraratne et al., 2006
PMoisture content | Cooked bovine joints | Computer vision (colour features) | \(r=0.75\) | Zheng et al., 2007
CPork quality class, marbling | Pork loin n=40 | Hyderspectral imaging | >70% correctness | Qiao et al., 2007a
PDrip loss, L*, pH | Pork loin n=80 | Hyderspectral imaging | \(P_r=0.77, 0.55\) and 0.86 for drip loss, pH and L*, respectively | Qiao et al., 2007b
CDiscoloration (fading) | Cured ham | L*, a*, b or spectral reflectance | Successful discriminating different stages of fading | Sheridan et al., 2007
PWHC (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 brachii; 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).

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

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

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

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

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

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

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

LD – longissimus dorsi; TB – triceps brachii; R² – 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

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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


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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.

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