Objective methods for pork quality evaluation
Literature Review

Canadian Centre for Swine Improvement

July 2018

Cluster 2 Project #1558 - Objective methods for the evaluation of marbling and other meat quality traits

This project was funded by Swine Innovation Porc within the Swine Cluster 2: Driving Results Through Innovation research program. Funding was provided by Agriculture and Agri-Food Canada through the AgriInnovation Program, provincial producer organizations and industry partners.

Table of Contents

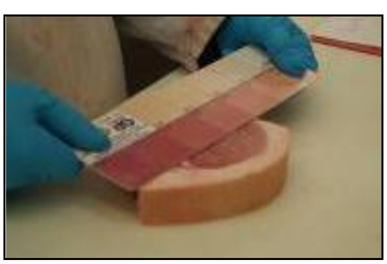
Table of Contents

1. Introduction

Meat is a perishable, nutritious and expensive food product, and its quality is related to biochemical changes affecting individual experience. As a result, pork quality is a complex combination of different properties of fresh meat affecting the processing of fat and lean tissues as well as the consumer acceptability and preference of both fresh and processed pork. Technological aspects such as colour, marbling, drip loss and firmness are the primary lean quality traits, which are affected by biochemical processes over time. Traditional evaluation process of meat quality is tedious, laborious, highly repetitive, costly, subjective, time-consuming and requires trained specialists. Yet, it is still the most used method in slaughterhouses. On the other hand, instrumental standard methods, relying on precision laboratory devices, suffer of some similar drawbacks. Nowadays, all food products need to be monitored, in order to ensure an acceptable level of quality and safety. In recent years, several food industries have seen human senses substituted with artificial sensors, used for various purposes: process, freshness and maturity monitoring, shelf life investigations, authenticity assessment and pathogen detection. Electronic senses offers various advantages over traditional analysis, such as the speed, accuracy, objectiveness, efficiency and non-destruction of the measurement with low cost, environmentally friendly nature and no sample pre-treatment (DiRosa *et al.*, 2017). This report provides an overview of published results on objective methods for pork quality assessment. It is largely based on information from the book entitled *Computer vision technology in the food and beverage technologies* (Woodhead Publishing Limited, 2012), several reviews on near infrared spectroscopy (Prevolnik *et al.*, 2004, Prieto *et al.*, 2009) and colour measurements by computer vision (Wu & Sun, 2013) as well as novel sensors for quality assessment (DiRosa *et al.*, 2017), as well as several recent articles about and application of objective pork quality assessment methods.

2. Subjective methods for pork quality assessment

In most countries, pork is typically marketed using a grid system based on cutability estimates that factor in carcass weight and instrumental measurements of carcass composition. Given the fact that pork does not currently receive quality grades like beef, measurements of quality, such as colour, marbling, and firmness, are typically not assessed for the purpose of assigning value in the commercial pork industry (North American Meat Institute, 2017). However, subjective scoring for colour, marbling and firmness is performed in most packing plants in order to monitor



and sort carcasses and meat cuts for added-value markets such as Japan and South Korea. Various standards are used, but the most popular ones are the NPPC standards for colour, marbling and firmness (NPPC, 1999), and the Japanese standards for meat and fat colour. More recently, Canadian pork quality standards for meat/fat colour and marbling were developed by Canada Pork International (CPI) in collaboration with Agriculture and Agri-Food Canada (AAFC) and the Canadian Centre for Swine Improvement (CCSI). These various standards were developed to be used on the fresh cut surface of the loin after a minimum 10-minute blooming time. In commercial conditions, unlike in the beef industry, pork loins are not cut, so visual scoring systems are sometimes adapted to be used on loin ends or on the primal or commercial loin cuts, which most likely amplifies the subjectivity of the scoring.

Meat scientists have worked together to establish industry standards for colour, marbling, and firmness (NPPC, 1999). In a recent meta-analysis review, Bohrer and Boler (2017) used 101 peer-reviewed studies that have used these industry standards and investigated the amount of inter-observer and between study variation. Subjective colour determined with NPPC colour standards was weakly correlated ($r \leq |0.35|$; $P < 0.01$) with instrumental L*, a*, and b* when measured with a Minolta colorimeter. Marbling evaluated using NPPC (1999) marbling standards was moderately correlated ($r = 0.48$; $P < 0.0001$) with intramuscular lipid percentage. The results of this review indicate the need for the meat science research community to acknowledge that visual colour and marbling scores may differ significantly on a study-to-study basis when attempting to standardize with Minolta colorimeter readings and intramuscular lipid percentage with various extraction procedures.

The pork industry may shift to a more quality-driven marketplace in the future. The ability to quickly and accurately predict quality characteristics of interest (most likely colour and marbling) in a commercial setting will be critical. Research groups working on many diverse areas of research have worked diligently on more efficient ways to evaluate multiple meat characteristics quickly and efficiently with devices such as a visible and near-infrared spectrophotometer (Prieto *et al.*, 2009) or hyperspectral imaging systems (Qiao *et al.*, 2007; Barbin *et al.*, 2012). It will be important to the pork industry to continue developing new technologies to measure pork quality rapidly and precisely with instrumental techniques.

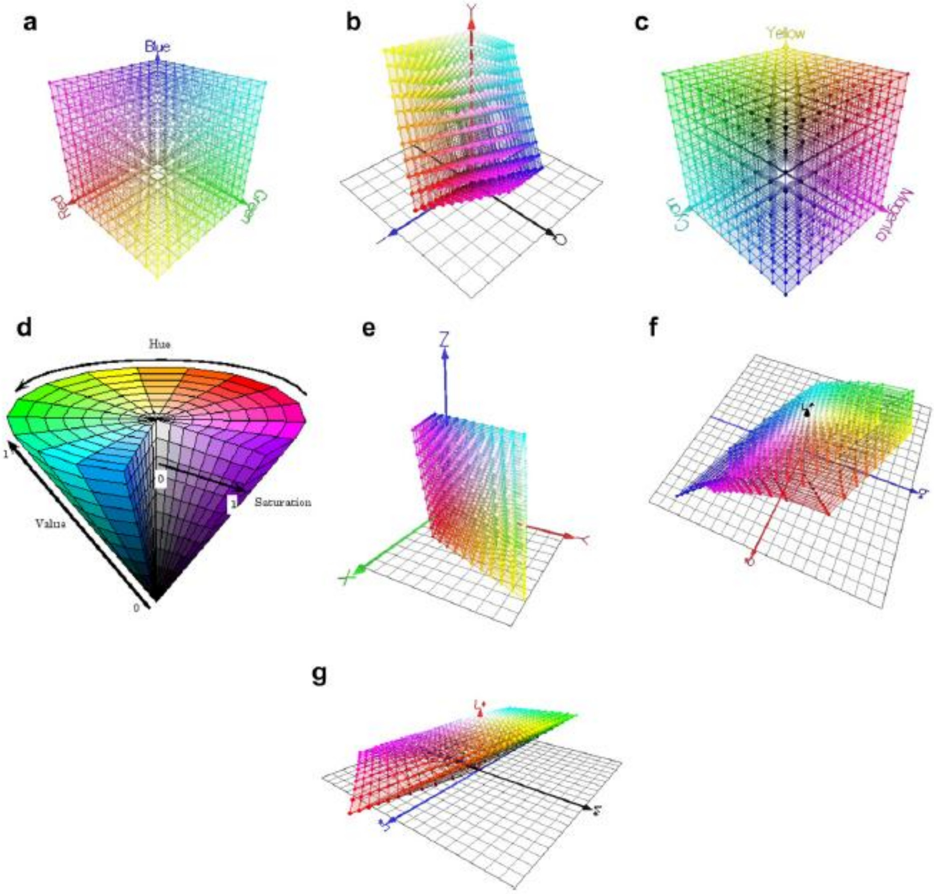
3. Objective methods for pork quality evaluation

3.1. Conventional/reference methods

Carcass composition and meat traits are important aspects of animal science relating to food production. This knowledge is fundamental to the study of genetics, nutrition, physiology, to marketing based on carcass value, as well as for monitoring body fat reserves. Dissection and chemical analysis have traditionally been used as the standard methods for determining carcass composition and meat quality. However, these procedures are expensive, laborious and destructive (i.e., an animal or carcass can be used only once). Non-destructive techniques are often required to test valuable animals or when repeated measures of the animals are necessary.

Instrumentation for meat quality assessment has been used for several decades, with the initial goal to detect meat with major quality issues such as PSE (pale, soft, exudative) or DFD (dark, firm, dry). This is still the case, even though the frequency of these defects is generally low in Canadian packing plants. The use of measurement tools is now more focused on classifying meat into quality classes and grades, which the aim of sorting fresh meat for specific markets or transformation processes. Instrumentation for objective quality assessment at the laboratory or directly on the slaughter line/cutting room was described and tested in many studies (Somers *et al.*, 1985; Chizzolini *et al.*, 1993; Garrido *et al.*, 1994; Berg, 2000).

Colour assessment - Classification of meat color can be performed with colorimeters or spectrophotometers. The CIE L*, a*, b* system is used to standardize products that have been pigmented or died such as textiles, paints, and plastics. This scale was designed to represent the human perception of colour. The a* scale is a measure of the relative intensity of red and green while b* considers the intensity of the colors blue and yellow (both sets of colors are considered opposite on the color scale). The L* value represents the overall lightness or darkness of the object (0 = black: 100 = white). The Minolta chromameter is one of the more common colorimeters used to measure meat lightness (L*), redness (a*), and yellowness (b*). The use of colorimeters has limited application as an on-line method of fresh pork color assessment due to accelerated line speeds and the absence of an exposed lean surface on the carcass (carcasses are not ribbed in the packing plant). Colorimeters are, however, widely used as a research tool to report differences in lean tissue colour brightness.



3D demonstration of some colour space images. (a) *RGB*, (b) YIQ, (c) CMY, (d) HSV (Mathworks, 2012), (e) *XYZ*, (f) $L^*a^*b^*$, (g) $L^*u^*v^*$.

Marbling and intramuscular fat (IMF) - Reference methods for IMF evaluation require meat sampling, grinding and chemical analysis of total fat using methods such as Soxhlet (AOAC, 1995). Other well documented and calibrated lab methods using near infrared spectroscopy to assess meat compositional traits are also well-known and used in research and in commercial conditions to monitor IMF and other meat components using randomly sampled products.

Firmness - Reference methods for meat firmness assessment rely on heavy instrumental methods to assess shear force. Rincker *et al*. (2007) looked at the feasibility of developing an objective method to measure pork loin firmness in order to score loins in parallel with a subjective method for determining pork firmness using the NPPC scale (score 1 to 5). The equipment used for the objective measurement of loin firmness was the TA.XT2 (Texture Technologies Corporation, 2005). The authors concluded that it was possible to create a standard protocol which could objectively assess the firmness of pork meat. The equipment used was not amenable for use under plant conditions. Yet, the results of this study could be used as part of projects that aim to develop portable tools that could be used in slaughter plants, on a production chain and for the objective assessment of loin firmness. Different laboratory devices are used routinely to carry out the characterization of meat firmness in different experiments, such as the TA XT-2i Texture Analyser (Stable Micro Systems Ltd., Surrey, UK) to assess the firmness of loins and dry hams as well as the Instron (Model 4464) Universal Testing apparatus to assess the firmness of different muscles in fresh hams. Many other laboratory equipment made by different manufacturers are available to assess meat firmness, including various types of durometers. The results obtained with such equipment are recognized by the scientific community. However, these apparatuses are not adapted to cutting room conditions at the slaughter plant where humidity is high and temperature is low.

Water-holding capacity (WHC) - Water holding capacity is the ability of meat to retain water during cutting, heating, grinding, and pressing. Water holding capacity of pork may be the single most important quality characteristic because poor WHC results in product weight and nutrient loss, and will affect texture, appearance, and juiciness of the cooked product. Percentage of lean tissue drip (purge or exudate) loss is often used as the most reliable method to estimate a muscle's WHC. Determining percentage drip loss is calculated as the loss in the meat sample weight (due to drip and evaporation) divided by the original sample weight, multiplied by 100, and reported as % drip. The original reference method was developed to be used in hanging plastic bags (Honikel, 1987), but it was adapted to be used in Styrofoam trays or plastic tubes (Rasmussen *et al.*, 1996; Correa *et al.,* 2007). This labor intensive and time-consuming procedure is, of course, not applicable in an industry setting. It is, however, widely used as a research tool. For on-line measures, the use of fiber optic probes (FOP) is based on the use of optical properties of meat to predict its quality: 1) wavelength of the emitted light; 2) the angle of the light to the muscle fibers; 3) the mode of light measurement (i.e., scattering, absorbance, or reflectance); and 4) contact at the meat-probe interface. The ability of FOP instruments to predict the functional component of pork (water holding capacity) is totally dependent on the marginal relationship between fresh pork color and WHC.

<u>Measurement of pH</u> - Early *post-mortem* measurement of pH and temperature are common measurements taken to identify potential meat quality problems. The value of pH measurement relates to the fact that pH directly affects meat colour, firmness and water holding capacity. When pH declines rapidly before the muscle has been significantly cooled, a partial denaturation of sarcoplasmic (proteins in the muscle cell's cytoplasm) and myofibrillar proteins occurs resulting in a pale appearance. Conditions affecting the structural integrity of *post-mortem* muscle will ultimately affect overall meat quality and functionality. The contractile proteins actin and myosin are the major proteins associated with formation of the myofibrillar protein lattice. Myosin binds to actin to initiate muscle contraction and forms a permanent rigor. The low pH may denature the globular protein head of myosin and affect myosin's ability to bind actin. The degree of myosin denaturation will affect both drip loss and softness associated with PSE meat. A reduced affinity of myosin for actin and (or) the shrinkage of the protein lattice can be associated with the softness of PSE lean. The net electrical charge of myosin becomes minimal as the pH of meat nears the isoelectric point (pI) of myosin (pI = 5.4) resulting in a low water binding capacity. Also, in fresh meat, the mobility of water is determined by the spatial arrangement of the muscle proteins. Therefore, the degree of myosin denaturation has an effect on the ability of muscle to hold moisture. Accurate, consistent, and rapid measurement of muscle pH is difficult to obtain at existing line speeds on the kill floor. It is more common for packing plants to measure pH at 20 to 24 h *post-mortem* (ultimate pH; pHult) when the carcasses are hanging stationary in the chilling cooler. Ultimate pH is not always indicative of final meat quality. Technologies such the PH-STAR pistol (SFK Technology, Denmark) were develop to provide rapid, on-line pH measurement.

The search for non-destructive methods to predict carcass composition or meat traits has led to the evaluation of numerous techniques such as real-time ultrasound (RTU), computer tomography (CT), magnetic resonance imaging (MRI), dual-energy X-ray absorptiometry (DXA), total body electrical conductivity (TOBEC), bioelectrical impedance and neutron activation analysis. Most of these technologies were shown to accurately assess carcass composition, and some of them have also been tested to predict meat quality traits on fresh and processed products.

3.2. Ultrasound technology

Techniques based on ultrasound have had great success in the fields of medical and animal science, as they are non-invasive, non-destructive and do not cause pain to the animal. For over 50 years, ultrasound techniques have been used to predict carcass composition and meat traits *in vivo*. Since its initial use, real-time ultrasound (RTU) has been demonstrated to be a valuable tool for the estimation of carcass composition and meat traits in living animals. The recent interest in the technique is almost certainly a result of the application of technology originally developed for computers, whereby a digital image formation process provides good quality black and white images. Furthermore, modern equipment is robust, easy to use and portable, and offers accurate imaging with great repeatability at relatively low cost, while also being well accepted by the public.

Ultrasound is sound waves with a frequency beyond the range of human hearing (above 20 kHz). These acoustic waves propagate through body tissues via compression and expansion of the tissues, and during propagation small particles of the material move back and forth in order to generate the compressions and expansions of the acoustic wave. In soft tissues (such as biological tissue), these particles move back and forth in the same direction that the acoustic wave is travelling. In soft tissues, the ultrasound waves propagate at a velocity of about 1500 m/s. Each change of tissue type causes a reflection and the greater the difference in acoustic impedance between the tissues the greater the proportion of the ultrasound wave to be reflected. For example, more energy is reflected in the passage from muscle to bone than from muscle to fat. The time taken for the echoes to reach the transducer is directly proportional to the thickness of the medium and inversely proportional to the velocity of ultrasound in that particular tissue. Thus, the time delay between the transmitted pulse and its echo is a measure of the depth of the tissue interface. The tissue thickness can be estimated on the basis of the time difference between the generation of the ultrasonic wave and the reception of the echoes. The spatial resolution of an image produced by ultrasound is limited by the wavelength of the ultrasound. The wavelength decreases with the increase in frequency: for example, at 2, 5 and 7.5 MHz the wavelength is approximately 0.77, 0.31 and 0.21 mm, respectively. The best resolution is obtained with higher frequencies, since these are associated with a higher attenuation by biological tissues.

The ability of RTU to measure carcass composition and meat traits in cattle, swine, sheep and goats has been the subject of a number of studies. The ability to model and predict the composition of the carcass is the basis for a decision support system that allows the producers to adjust animal feeding and handling strategies according to their specific needs. Intramuscular fat (IMF) content, particularly in cattle and swine, affects meat quality, especially the sensory properties of juiciness and flavour. IMF refers to the chemically extractable fat in a muscle and is an objective measurement, whereas marbling, assessed visually, refers to the appearance of evenly distributed white flecks or streaks of fatty tissue between bundles of muscle fibres and can be subjectively assessed with grading scores or objectively assessed when image analysis is used. Both are relevant for meat quality evaluation.

A number of authors reported results which undoubtedly suggest that IMF was accurately predicted with RTU and image analysis. In the early 1990s, Wilson (1992) stated that considerable research and development was needed before ultrasound could be effectively employed in cattle production and breeding. Since then, ultrasound technology has become a well-established and widely accepted method for predicting IMF in live cattle and swine. Recently, the RTU technology for predicting IMF was chosen as one of the 100 Innovations from Academic Research to Real-World Application (AUTM, 2007). The IMF is primarily determined by the distribution pattern of fat flecks in a cross-section of the logissimus muscle, usually between the 12th and the 13th thoracic vertebrae. Although IMF is present in other muscles, the assessment is generally performed on a loin muscle section. The IMF consists of deposits that occur within the muscle, which are irregular either in form or in their dispersal. These deposits represent a cluster of IMF cells. Individual cells can be very small (40–60 μm)

and are not visible to the human eye. The rough surface and small size of IMF deposits cause sound waves to scatter, producing spots on RTU images that are referred to as speckles. This is why ultrasound techniques have the potential to predict IMF in vivo after RTU image analysis. The same technology can be applied on hot carcasses shortly after slaughter. As an example, the BioQscan system was developed by Biotronics (Iowa) to measure carcass backfat, loin depth and marbling during carcass grading. The system includes the ultrasound scanning system, computer processing centre and scanning probe. An ultrasound probe is held up to the carcass as it passes by at line speed. Information about the percentage of intramuscular fat (IMF) in loins, and carcass percent-lean readings, is instantly available. The unit records multiple pictures of each carcass as the measurements are taken.

Advances in ultrasound such as synthetic aperture focusing, also known as zone sonography and elastrography are likely to be employed in animal science in the future. The zone sonography technology allows faster image acquisition and high image quality, which will prove particularly useful in situations in which multiple images of a subject are required during a scanning session. Elastrography is a technology with the potential to improve the accuracy with which marbling can be predicted. The use of three-dimensional (3-D) ultrasonography is another imaging technique with promising applications in the evaluation of carcass composition and meat traits. The use of volume measurements, along with image techniques such as MRI and CT, is an attractive approach for predicting carcass composition and meat traits. Although 3-D ultrasound is more costly than conventional ultrasound, it is not prohibitively expensive when incorporated into large breeding programmes.

Real-time ultrasonography imaging is a versatile and dynamic technology with many current and potential applications in animal science research and animal production. The attributes of the RTU technique have led to its current widespread use in animal science for the in vivo prediction of carcass composition and meat traits in several species. The results obtained with RTU are likely to play a major role in the meat industry by providing accurate and objective carcass and meat traits information in live animals. In the future, it is probable that modern ultrasound techniques will continue to be used in animal science, bringing further advances in value-based marketing and in precision meat production systems. Research will be focused on developments in ultrasound practicability, portability, cost and public acceptability, and the rapidly advancing field of molecular genetics and the dissemination of web-based databases will further expand the capabilities of RTU as a tool for evaluating carcass composition and meat traits.

3.3. Spectroscopy

The use of visible and near-infrared spectroscopy (Vis/NIRS) analysis for monitoring, quality control and analytical purposes is increasing in food and agricultural industries, and in this context, it can provide an objective, repeatable, rapid, accurate and non-destructive method of evaluating meat to predict qualitative attributes and the chemical composition in meat and meat products (Balage *et al*., 2015). Over the past three decades, near infrared reflectance (NIR) spectroscopy has been proved to be one of the most efficient and advanced tools for the estimation of quality attributes in meat and meat products, as outlined in two reviews published by Prevolnik *et al.* (2004) and Prieto *et al.* (2009).

Near infrared spectroscopy (NIRS) is an analytical technique that uses a source producing light of known wavelength pattern (usually 800–2 500 nm) and that enables to obtain a complete picture of the organic composition of the analysed substance/material. It is based on the principle that different chemical bonds in organic matter absorb or emit light of different wavelengths when the sample is irradiated. Nowadays NIRS is widely and successfully used in many different fields, also for feed and food analysis. NIRS offers a number of important advantages over conventional methods such as rapid and frequent measurements, fast and simple sample preparation, suitability for on-line use and simultaneous determination of different attributes. The main disadvantages of the method are its dependence on reference method, weak sensitivity to minor constituents, limited transfer of calibration between different instruments and complicated spectral data interpretation.

The potential of NIRS to predict chemical composition (crude protein, intramuscular fat, moisture/dry matter, ash, gross energy, myoglobin and collagen), technological parameters (pH value; L*, a*, b* colour values; water holding capacity; Warner–Bratzler and slice shear force) and sensory attributes (colour, shape, marbling, odour, flavour, juiciness, tenderness or firmness) was demonstrated in many studies. Secondly, the usefulness of NIR for classification into meat quality grades is presented and thirdly its potential application in the industry is shown. The review indicates that NIR showed high potential to predict chemical meat properties and to categorize meat into quality classes. In contrast, NIR showed limited ability for estimating technological and sensory attributes, which may be mainly due to the heterogeneity of the meat samples and their preparation, the low precision of the reference methods and the subjectivity of assessors in taste panels. Hence, future work to standardize sample preparation and increase the accuracy of reference methods is recommended to improve NIR ability to predict those technological and sensory characteristics. In conclusion, the review shows that NIR has a considerable potential to predict simultaneously numerous meat quality criteria such as drip loss, meat colour (Kapper et al., 2012), marbling scores (Huang *et al,* 2017), fatty acid profiles (Prieto et al., 2009).

Recent developments of NIRS instruments have increased the suitability of NIR spectroscopy for predicting meat quality at processing speed. NIR spectroscopy has considerable potential to predict simultaneously several meat chemical properties and to categorize meat into quality classes. Therefore, NIR is a suitable alternative to analytical procedures, which can be time-consuming, expensive and sometimes hazardous to health or the environment. On the contrary, NIR spectroscopy has only limited ability for estimating technological and sensory attributes of meat, mainly due to the heterogeneity of the meat samples (especially those in the intact form) and the low precision of the reference method (e.g., WBSF). Additionally, the sensory attributes obtained in taste panels are affected by the subjectivity of the assessors and only extreme samples (sensory scores deviating substantially from the mean) seem to be clearly differentiated by panellists. Consequently, better NIR calibrations for these technological and sensory characteristics are required, mainly with respect to a better sampling procedure and improvement of the precision of the reference methods. Recently, researchers and analysts are looking for wavelengths at which NIR measures are closely associated with the characteristics of meat quality. By understanding these critical wavelengths, it is possible to obtain more robust calibrations and to develop simple and low-cost instruments using only these wavelengths. Furthermore, the use of fibre-optic probes may improve the ability of NIR to monitor and control meat processing using remote on/in line detection. NIR spectroscopy will become more widely used in the meat industries as more attention is given to reduce errors in reference methods, more robust calibrations are developed by using larger sample sets showing wide ranges in reference values and transfer of calibration models is facilitated for commercial applications.

However, in NIR spectroscopy, the overtones of fundamental molecular vibration modes are being measured which are often overlapped to yield broad bands that do not provide high resolution spectroscopic fingerprints of different molecular functional groups, which subsequently limits the accuracy of the biochemical profiling of the meat. Mid-infrared Fourier Transform (FT-IR) spectroscopy has also been explored for meat characterization. Although FT-IR yields high-resolution spectroscopic profiles for meat samples, it suffers from strong interference from omnipresent water in the meat samples. Raman spectroscopy is another alternative vibrational spectroscopic method that has a considerable number of advantages compared to other food analysis techniques (Wang et al., 2012). It is a non-invasive spectroscopic technique providing in situ information about the composition and structure of proteins and lipids, which are main components of pork. Raman spectroscopy is relatively insensitive to water and hence does not suffer from water interference, which is a severe problem in mid-IR spectroscopy like FT-IR, since foods commonly contain ≥75% water. In addition, it does not require any sample preparation and is non-destructive while at the same time providing high-resolution, detailed spectral information about the chemical composition of the sample. Raman spectroscopy is getting more and more interest thanks to its portability and was applied on pork samples to predict sensory quality traits (Wang et al., 2012; Santos et al., 2018).

3.4. Computer vision systems (CVS)

Computer vision is the science that develops theoretical and algorithmic basis to automatically extract and analyse useful information about physical objects from images (Wu and Sun, 2013).

It encloses the capturing, processing and analysis of two-dimensional images, with others noting that it aims to duplicate the effect of human vision by electronically perceiving and understanding an image. In general, the hardware configuration of a computer vision system consists of an illumination device, a camera, a personal computer and a high-resolution monitor. As in the case of the human eye, the operation of CVS depends on the intensity of lighting. Properly designed lighting can improve the precision of analysis and decrease analysis time. Fluorescent and incandescent bulbs are the most frequently used light sources. Luminescent electric diodes (LEDs), quartz halogen lamps, metal halide lamps and high-pressure sodium lamps are also used. Moreover, a camera converting photons to electrical signals is used (Wu and Sun, 2013). There are two types of cameras, that is, analog and digital cameras, which are equipped with CCD (Charged-coupled device) or CMOS (Complementary metal-oxide semiconductor) sensor arrays. In an analog camera, the recorded image is transformed into the analog signal and then transferred to a frame grabber, which transforms the analog signal into a digital data stream and sends it to the computer memory. In digital cameras, a frame grabber is not needed because the analog signal is sent directly to the computer via a USB or FireWire adapter. The image processing and the image analysis represent the core of computer vision. Image processing involves a series of operation that enhance the quality of an image in order to remove defects. Image analysis is the process of distinguishing the objects from the background and producing quantitative information. As a non-destructive detecting approach, CVS have been used increasingly in the food industry for inspection and evaluation purposes as they provide suitably rapid, economic, consistent and objective assessment. Precisely, CVSs are feasible to classify food products into specific grades, detect defects and estimate properties such as colour, shape, size, surface defects, and contamination

Results show how CVS applications are targeted at those food products for which the appearance is the main key quality attribute evaluated by the consumers. The application of computer vision techniques could offer several advantages, including:

- The rapidness, preciseness, objectiveness, efficiency and non-destruction of the measurement with low cost and no sample pre-treatment
- The permanent storage of data, allowing further analysis later
- Image capturing and illumination devices are easy to mount, remove, replace, and upgrade;
- The possibility of automation for in-line monitoring and controlling of industrial scale food operations

Computer vision systems are ideally suited for routine inspection and quality assurance tasks which are common in the food industry. Backed by powerful machine intelligence and state-of-the-art electronic technologies, machine vision provides a mechanism by which the human thinking process is simulated artificially. Depending on the nature of application and the sensitivity needed to perform the inspection, an image can be acquired at different wavelengths, extending from visible to invisible electromagnetic spectrum.

However, extra chemical composition information cannot be extracted by using CVSs. With the help of spectrometry, chemical composition information can be obtained successfully. With hyperspectral imaging technique, several authors achieved excellent results in a variety of applications. Further, the employment of 3-dimensionals cameras may help to improve analysis, provide more information and allow the study of complex or irregular-shape materials with fewer errors and less time. In addition, these devices may find application in texture analysis, so far based on 2D image sequences, where the texture distribution is limited to a single plane. The use of three-dimensional images could help to avoid the loss of information when texture features are studied from different orientations.

Many studies looked at using CVS to detect defects in meat, more specifically to detect PSE and DFD meats (Chmiel & Slowinski, 2016; Chmiel *et al.*, 2016) using a standardized setup to capture digital images for real-time or delayed analysis with a basic image analysis software (Image Analyzer software from Warsaw University) to extract lightness and colour information from pictures. In that study they were able to accurately detect PSE and DFD meat, but the system was not discriminant enough to differentiate between RSE and RFN meats. Several studies looked at using CVS to predict pork colour (Lu *et al.*, 2000), pork marbling (Da Costa Barbon *et al.*, 2017; Liu *et al.*, 2018) or both (Sun *et al.*, 2016; Sun *et al.*, 2018) with various statistical approaches including stepwise regression, multiple linear regression, support vector machine models and artificial intelligence.

3.5. Infrared imaging techniques

Presumably, when both computer vision and ultrasound systems failed to produce the desired images, food engineers and technologists could resort to the use of much longer wavelength for image acquisition. The IR range lies in the region of 700–1000 nm, and the technique responsible for generating such images is called thermographic photography. Thermographic imaging is based on the simple fact that all objects emit a certain amount of thermal radiation as a function of their temperature. Generally, the higher temperature the object is at, the more IR radiation it emits. A specially built camera, known as the IR camera, can detect this radiation in a similar way to an ordinary camera detecting visible light. However, unlike computer vision, thermal imaging does not require an illumination source for spectral reflectance, which can be affected by the varied surface colour of a target or by the illumination set-up.

3.6. Hyperspectral and multispectral imaging

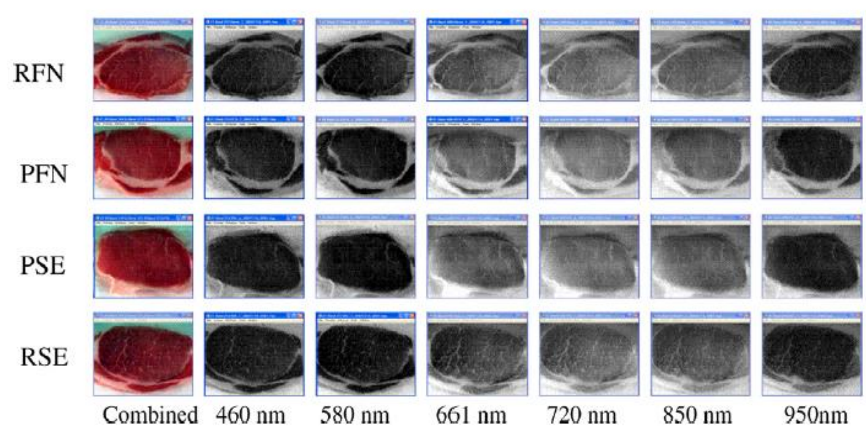
Traditional optical sensing techniques, such as imaging and spectroscopy, have limitations for acquisition of adequate information for non-destructive evaluation of food and agricultural products. In recent years, spectral imaging (i.e., hyperspectral and multispectral) has emerged as a better tool for quality and safety inspection of various agricultural commodities. Spectral imaging techniques combine conventional imaging and spectroscopy techniques; it is possible to obtain both spatial and spectral information from the target, which is essentially useful for evaluating individual food items. The technique has drawn tremendous interest from both academic and industrial areas, and it has been developed rapidly during the past decade.

Spectral images are three-dimensional (3-D) in nature, with two spatial dimensions and one spectral dimension. Based on the continuity of the data stored in the wavelength domain, spectral imaging can be divided into two main techniques: hyperspectral imaging and multispectral imaging. The hyperspectral technique acquires images with abundant (tens or hundreds) and continuous wave (CW) bands, while the multispectral technique acquires images with few (generally less than ten) and discrete wavebands. A full spectrum can be extracted from each pixel in hyperspectral images. Multispectral images produce a set of isolated data points for each pixel due to the separate wavebands stored in the dataset.

Hyperspectral imaging is intended to collect images with high spatial and spectral resolutions for fundamental research. The process usually involves a relatively long time for image acquisition under laboratory conditions and relatively complicated procedures for offline image analysis. Generally, there are three approaches for acquiring 3-D hyperspectral cubes [hypercubes (x,y,λ)].

Multispectral imaging aims to acquire spatial and spectral information that is directly useful for real-time applications in the field (e.g., fruit packing and food processing). The process generally involves fast image acquisition and simple algorithms for image processing and decision-making. Reducing the total volume of the data required in collecting both spatial and spectral domains is the key for building multispectral imaging systems. In practice, this means acquiring images with relatively low spatial resolutions at few important wavelengths. Hyperspectral images are usually used as fundamental datasets to determine optimal wavebands that can be used by a multispectral imaging solution for a particular application.

Hyperspectral imaging was used successfully to classify PSE, RFN and DFD meat with a high accuracy (Barbin *et al.*, 2012) and predict key traits such as moisture, salt content, lipid content and Minolta colour. It was also used to predict marbling scores and IMF (Quiao *et al.*, 2007; Liu *et al.*, 2010; Liu *et al.*, 2012; Huang *et al.*, 2017) and has the potential to predict texture and tenderness (Tao & Peng, 2014).



Acquired hyperspectral images, the colored images were obtained by combined images at wavelengths of 460 nm, 580 nm and 720 nm.

3.7. Tomographic techniques

While a computer vision system is useful for surface-type inspection, in many specialized investigations, food technologists and scientists frequently need to 'see' the internal view of the sample. The term 'tomography' refers to the general class of devices and procedures for producing two-dimensional cross-sectional images of a three-dimensional object. Therefore, tomographic imaging is a technique which is capable of revealing internal structures through the use of ionizing or non-ionizing penetrating waves in a non-invasive and non-destructive manner. Ionizing sources include X-ray, while electrical techniques and microwaves belong to the class of non-ionizing radiation. With the safety advantage of non-ionizing radiation, the use of soft-field sensors for food imaging has been a subject of interest for several decades, realizing the potential and challenges, and exploring several techniques.

Previously known as nuclear magnetic resonance (NMR) imaging, MRI gives the density of protons or hydrogen nuclei of the body at resonant frequency. Unlike CT, MRI provides excellent rendition of soft and delicate materials. This unique characteristic makes MRI suitable for visualizing most food objects. The applications range from non-invasive to real-time monitoring of dynamic changes as foods are processed, stored, packaged and distributed (Caballero *et al.*, 2017).

3.8. E-Nose, E-Tongue, E-Eye and sensor fusion

In the food industry, monitoring of products, in terms of quality and control of production processes, are performed via physico-chemical measurements, despite the extreme importance of aroma as an indicator of quality and product conformity. This was mainly due to the lack of reliable odour assessing instruments. The electronic nose is a technology designed to mimic the olfactory system of humans (DiRosa *et al.*, 2017). An electronic nose as an instrument that comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern-recognition system that is capable of recognizing simple or complex odours Before the advent of solid-state gas sensors arrays, the term "electronic nose" was related to the techniques used in the identification and quantification of volatile compounds, in the headspace of a product, such as gas chromatography-mass spectrometry (GC-MS), gas chromatography-flame ionization detector (GC-FID) and solid-phase micro extraction-mass spectrometry (SPME-MS), coupled with multivariate statistical analysis. Today, the electronic noses are instruments, based on the interaction of semi-selective sensors with volatile compounds. In the pork and beef production sectors, electronic noses are currently developing at a quick pace, especially in the area of shelf-life prediction, detection of meat spoilage, detection of tainted meat, etc. (Di Rosa *et al.*, 2017).

The taste we perceive is composed of five kinds of taste qualities: sourness, saltiness, sweetness, bitterness and umami. The objective of the electronic tongue technology is to study the chemical substances showing the five basic taste qualities. Other tastes like astringent and pungent substances were investigated. The electronic tongue can be described as an analytical tool, including an array of non-specific, poorly selective chemical sensors, with partial specificity, coupled with chemometric processing, for recognizing the qualitative and quantitative composition of multispecies solutions. A variety of chemical sensors can be employed in the design of electronic tongues: electrochemical (voltametric, potentiometric, amperometric, impedimetric, conductimetric), optical or enzymatic sensors (biosensors). However, most of these systems are based on potentiometric sensors. In potentiometry, a potential is measured between two electrodes under the conditions of no current flow. The measured potential may then be used to determine the analytical quantity of interest, generally the concentration of some component of the solution. Ion-selective electrodes (ISEs) represent the largest group among potentiometric sensors. The development of electronic tongues to assess fresh and cooked meat quality was recently seen for monitoring of physical, chemical and microbiological changes under cold storage, testing of various salt formulations on ham quality, detection of ammonia and putrescine (Di Rosa *et al.*, 2017).

Computer vision systems (CVS), also known as E-eye, were already quickly described in previous sections. They can use traditional, 2D images in the visible spectrum to mimic human vision, but can also use 3D vision as well as collect information outside of the visible spectrum, which makes them so much more powerful than the human eye, by gathering compositional and structural information on the product of interest. The various sensors described here generate a vast volume of data and require statistical analysis methods allowing for data classification, such as multivariate analysis methods, including principal component analysis (PCA), artificial neural networks (ANN), linear discriminant analysis (LDA), partial least square regression (PLSR) and support vector machines (SVM). A major trend is currently for sensor fusion, in order to combine and optimise the use of data from various sensors. Despite the promising results obtained so far, there is still room for improvement. Novel artificial sensing devices are being studied, such as E-Noses and E-Tongues based on hybrid or bioelectronic sensors. Recently, bioelectronic noses using human olfactory receptors as primary recognition elements and nanomaterials as secondary transducers have been reported. A prototype of a sensor, inspired by human teeth, was successfully applied to food texture measurements. Research in this area is moving very quickly and will bring novel tools with the increasing application

4. Conclusions

Traditionally, food quality evaluation has been performed by panels of trained human experts; despite this approach still suffers from several disadvantages, such as being time consuming, expensive and subjective, it is the most common used. On the other hand, instrumental standard methods, relying on precision laboratory devices, also suffer of similar drawbacks, being time-consuming, labour intensive and expensive. In recent years, human senses were substituted with artificial sensors, which have been increasingly employed in the food industry for quality control purposes; process, freshness and maturity monitoring; shelf life investigations; authenticity assessments and microbial pathogen detection. Electronic senses offer various advantages over traditional analysis, such as the rapidness, preciseness, objectiveness, efficiency and non-destruction of the measurement with low cost, environmentally friendly nature and no sample pre-treatment. Nevertheless, the permanent storage of data and the possibility of automation for on-line monitoring of industrial scale operations should be considered. These techniques used all together are called “electronic panel” and this approach is possible due to the fusion of data coming from complementary sensors. Data fusion has been applied to a wide range of food and beverages to authenticate origin and assess quality, enhancing significantly the performance of classification or quality evaluation.

In several countries, pork industries and companies are currently considering the inclusion of quality in their grading systems. This will be very beneficial to domestic and international marketing, consumer satisfaction and will also provide great benchmarking opportunities, however the technological challenge to meet this objective is huge. However, past research and recent applications in other species (beef, fish, etc) indicate that several potential technologies could be used to develop good grading systems. Another aspect to be considered is to use potential synergies between technologies since most meat quality traits of interest in pork quality are correlated with each other. Many research studies focus on one trait (colour or marbling very often). A good technology or combination of technologies should provide information on all the traits of interest in terms of visual appraisal, sensory quality and economic importance. Computer vision systems and hyperspectral imaging seem to be the most promising technologies in this context, but ultrasound technology and spectroscopy are also very versatile and powerful, as they keep evolving over time with novel sensors and enhanced statistical approaches boosted with artificial intelligence.

References

- AOAC, 1995. Official Method 960.39, Fat (Crude) or Ether Extract in Meat. In *Official Methods of Analysis, Meat and Meat Products, Suppl March 1997,* Chapter 39, p 2
- Balage J. M., Da Luz E.S.S., Gomide C. A., Bonin M.N., Figueira A. C., 2015. Use of visible and near infrared spectroscopy to predict beef and pork quality. *Meat Science*, 108, 37-43.
- Barbin D., Elmastry G., Sun D.W., Allen P., 2012. Near-infrared hyperspectral imaging for grading and classification of pork. *Meat Science*, 90, 259-268.
- Berg E.P, 2000. Instrumentation to Measure Pork Quality. American Meat Science Association.
- Bohrer B.M., Boler D.D., 2017. Review: Subjective pork quality evaluation may not be indicative of instrumental pork quality measurements on a study-to-study basis. *The Professional Animal Scientist,* 33, 530–540.
- Caballero D., Pérez-Palaciosa T., Caro A., Amigo J.M., Dahl A.B., ErsbØll B.K., Antequera T., 2017. Prediction of pork quality parameters by applying fractals and data mining on MRI. *Food Research International*, 2017, 739-747.

- Correa, J.A., Méthot, S. and L. Faucitano. 2007. A modified meat juice container (EZ-DripLoss) procedure for a more reliable assessment of drip loss and related quality changes in pork meat. *Journal of Muscle Foods*, 18, 67-77.
- Chizzolini R., Novelli E., Badiani A., Rosa P., Delbono G., 1993. Objective evaluation of pork quality: evaluation of various techniques. *Meat Science*, 34, 49-77.
- Chizzolini R., Novelli E., Badiani A., Delbono G., Rosa P., 1993. Objective evaluation of pork quality: results of on-line measurements. *Meat Science*, 34, 79-93.
- Chmiel M., Slowinski M., 2016. The use of computer vision system to detect pork defects. *Food Science and Technology*, 71, 473-480.
- Chmiel M., Slowinski M., Dasiewicz K., Florowski T., 2016. Use of computer vision system (CVS) for detection of PSE pork meat obtained from m. *semimembranosous*. *Food Science and Technology*, 65, 532-536.
- Da Costa Barbon A.P.A.., Barbon S., Centini Campos G.F., Seixas J.L., Peres L.M., Mastelini S.M. Andreo N., Ulrici A., Bridi A.M., 2017. Development of a flexible Computer Vision System for marbling classification. *Computers and Electronics in Agriculture*, 142, 536-544.
- Di Rosa A.R., Leone F., Cheli F., Chiofalo V., 2017. Fusion of electronic nose, electronic tongue and computer vision for animal source food authentication and quality assessment – A review. *Journal of Food Engineering*, 210, 62-75.
- Garrido M.D., Pedauyé J., Banon S., Laencina J., 1994. Objective assessment of meat quality. *Meat Science*, 37, 411-420.
- Honikel, K.O. 1987. The water binding of meat. *Fleischwirtschaft*, 67, 1098-1102.
- Huang H., Liu L., Ngadi M.O., 2017. Quantitative evaluation of pork marbling score along *Longissimus thoracis* using NIR images of rib end. *Biosystems Engineering*, 164, 147-156.
- Kapper C., Klont R.E., Verdonk J.M.A.J., Urlings H.A.P., 2012. Prediction of pork quality with near infrared spectroscopy (NIRS) - 1. Feasibility and robustness of NIRS measurements at laboratory scale. *Meat Science*, 91, 294-299.
- Kauffman, R.G. and Animal Science 405 (Livestock and Meat Distribution Class). 1997. National Pork Quality Project. pp 119-184. *In Proc. of Pork Quality Summit.* National Pork Producers Council. Des Moines, IA.
- Larsen A.B.L., Hviid M.S., Jorgensen M.E., 2014. Vision-based method for tracking meat cuts in slaughterhouses. *Meat Science*, 96, 366-372.
- Liu J.H., Sun X., Young J.M., Bachmeier L.A. Newman D.J., 2018. Predicting pork loin intramuscular fat using computer vision systems. *Meat Science*, 143, 18-23.
- Liu L., Ngadi M.O, Prasher S.O., Gariépy C., 2010. Categorization of pork quality using Gabor filter-based hyperspectral imaging technology. *Journal of Food Engineering*, 99, 284-293.
- Liu L., Ngadi M.O, Prasher S.O., Gariépy C., 2012. Objective determination of pork marbling scores using the wide line detector. *Journal of Food Engineering*, 110, 497-504.
- Lu J., Tan J., Shatadal P., Gerrard D.E., 2000. Evaluation of pork color by using computer vision. *Meat Science*, 56, 57-60.

- NPPC. 1999. Official Color and Marbling Standards. *Natl. Pork Prod. Counc.,* Des Moines, IA.
- North American Meat Institute. 2017. The Pork Book: Fundamentals of the Pork Trade from Farm to Table. 1st ed. Urner Barry, Toms River, NJ.
- Prevolnik, M., Candek-Potokar, M., Škorjanc, D., 2004) Ability of NIR spectroscopy to predict meat chemical composition and quality: a review. *Czechoslovak Journal of Animal Science*, 49, 500–510.
- Prieto, N., R. Roehe, P. Lavín, G. Batten, and S. Andrés. 2009. Application of near infrared reflectance spectroscopy to predict meat and meat products quality: A review. *Meat Science*, 83, 175–186.
- Quiao J., Ngadi M.O., Wang N., Gariépy C., Prasher S.O., 2007. Pork quality and marbling level assessment using a hyperspectral imaging system. *Journal of Food Engineering*, 83, 10-16.
- Rasmussen, A.J. and M. Anderson. 1996. New methods for determination of drip loss in pork muscles. In meat for the Consumer, *42nd International Congress of Meat Science and Technology*, Lillehammer, 1-6 September : 286-287.
- Rincker P.J., Killefer J., McKeith F.K., 2007. Evaluating an objective method to measure fresh pork loin firmness. *Meat Science*, 77, 213-219.
- Santos C.C, Zhao J., Dong X., Lonergan S.M., Huff-Lonergan E., Outhouse A., Carlson K.B., Prusa K.J., Fedler C.A., Yu C., Shackelford S.D., King D.A., Wheeler T.L., 2018. Predicting aged pork quality using a portable Raman device. *Meat Science*, 145, 79-85.
- Somers C., Tarrant P.V., Sherington J., 1985. Evaluation of some objective methods for measuring pork quality. *Meat Science*, 15, 63-76.
- Sun D.W, 2012. Computer vision technology in the food and beverage technologies. *Woodhead Publishing Limited*, 2012. 499 pp.
- Sun X., Young J., Liu J.H., Bachmeier L., Somers R.M., 2016. Prediction of pork color attributes using computer vision systems. *Meat Science*, 113, 62-64.
- Sun X., Young J., Liu J.H., Newman D., 2018. Prediction of pork loin quality using online computer vision system and artificial intelligence model. *Meat Science*, 140, 72-77.
- Tao F., Peng Y., 2014. A method for non-destructive prediction of pork meat quality and safety attributes by hyperspectral imaging technique. *Journal of Food Engineering*, 126, 98-106.
- Wang, Qi ; Lonergan, Steven M. ; Yu, Chenxu, 2012. Rapid determination of pork sensory quality using Raman spectroscopy. *Meat Science*, 91, 232-239.
- Wu D., Sun D.W., 2013. Colour measurements by computer vision for food quality control – A review. *Food Science and Technology*, 29, 5-20.

.

Cluster 2 Project #1558 - Objective methods for the evaluation of marbling and other meat quality traits
Summary Table of papers in the literature review
The table below shows references in chronological order, showing the trend in technology and the emergence of computer vision and artificial intelligence applications in recent years.

Reference	Country(ies)	Technology(ies)	Traits measured	#samples	Muscle/site	Main results
Somers et al, 1985	Ireland	pHmeter Fibre optic probe EEL reflectometer Kapillarvolumeter	pH Light scattering Reflectance Drip loss Panel assessment (extreme DFD to extreme PSE) Pigment analysis	169	*Longissimus dorsi* and *rectus femoris*	FOPu and reflectometer values agreed most closely with panel results in cold carcasses. In the hot carcass, FOP1 was better than pH1 to predict paleness. FOPu gave a good estimate of drip loss.
Chizzolini et al, 1993a	Italy	pHmeter Fibre optic probe Conductimeter MS tester Minolta Chromameter	pH45' and 24h Light scattering Conductivity Dielectric loss factor Minolta colour L* a* b*	700	*Semimembranosus*	Meat could be classified by colour intensity (a*), type of colour (hue angle) and by exudative phenomena (L*)
Chizzolini et al, 1993a	Italy	pHmeter Minolta Chromameter	pH45' and pH24h Minolta colour L* a* b*	>5,000	*Semimembranosus* and *Biceps femoris*	Cold carcass weight and lean content only slightly related to meat quality. Importance of pH and colour parameters for the evaluation of pork quality
Garrido et al, 1994	Spain	pHmeter Fibre optic probe Quality meter Minolta Chromameter	pH45' and pH24h Internal light scattering Electrical conductivity Minolta colour L* a* b* Water holding capacity Moisture %	312	*Semimembranosus* and *Longissimus thoracis*	Good correlations between pH, EC and FOP measurements. PCA analsysi showed that the first 3 components explain 60.3% of the total variation. The most important variables

			IMF% Pigment concentration Chemical composition			are pH45 and EC45.
Lu et al, 2000	USA	Computer vision using multiple linear regression and neural networks	Colour score	44	Bone-in pork loins ribbed at the 10th rib	Prediction error < 0.6 for 93% of the samples with neural network approach, vs 84 with statistical predictions. Image processing system + neural networking = effective tool for evaluation fresh pork colour
Qiao et al, 2007	Canada China	Hyperspectral imaging system and artificial neural networks	Marbling score RFN, PFN, PSE, DFD classes based on colour, texture and exudation	40	*Longissimus dorsi*	Appropriate spatial features were obtained for marbling distribution in pork meat. RFN and RSE samples were successfully grouped with a ratio of 75 to 80%.
Rincker et al 2007	USA	TA.XT2 Texture Analyzer (lab device)	Firmness score (NPPC 1-5) assessed by a panel	275	Boneless pork loins	It is possible to build a prediction equation using an objective measurement method that will correlate reasonably well with subjective firmness scores of fresh pork loins.
Liu et al, 2010	Canada	Hyperspectral imaging (HSI) and Gabor filter-based processing	Marbling score	40	*Longissimus dorsi*	
Liu et al, 2012	Canada	Hyperspectral imaging (HSI) and pattern recognition technique	Marbling score	40	*Longissimus dorsi* (centre cut)	Potential for automatic and objective determination of pork marbling scores using pattern recognition. Efficiency of the marbling extraction procedure,

						alleviating the contrast problem in PSE and PFN meat.
Barbin et al, 2012	Ireland	Near-infrared hyperspectral imaging	Moisture Water activity Salt content Lipid content Minolta colour L* a* b*	75	*Longissimus dorsi*	PSE, RFN and DFD classes precisely discriminated (96%)
Kapper et al, 2012	The Netherlands	Near Infrared Spectroscopy (NIRS)	Drip loss Minolta colour L* a* b* Ultimate pH	131	*Longissimus dorsi*	NIRS prediction equations could be developed to predict drip loss and colour (L*) of pork samples. NIRS equations for colour a* and b* and pHu were not applicable.
Wnag et al, 2012	USA	Raman spectroscopy	Tenderness Juiciness Chewiness	169	*Longissimus dorsi* (centre cut)	The method was demonstrated to yield good performance in identifying pork loins that belong to extreme categories of their sensory quality (i.e., superior and inferior). Good agreement (>83%) with sensory panel results for tenderness and chewiness.
Larsen et al, 2014	Denmark	Kinect cameras		211	*Bone-in pork loins*	Combining off-the-shelf vision and image processing technology can allow tracking pork cuts along the processing line. Alternative method to current more intrusive tracking methods.
Tao & Peng, 2014	China	Hyperspectral imaging	Shear force	31	*Longissimus dorsi*	HSI technique combined with Gompertz function was

					(centre cut)	potential for rapid determination of pork meat tenderness and E.*coli* contamination.
Tao & Peng, 2014	China	Hyperspectral imaging	Shear force	31	*Longissimus dorsi* (centre cut)	HSI technique combined with Gompertz function was potential for rapid determination of pork meat tenderness and E.*coli* contamination.
Balage et, 2015	Brazil Portugal	Visible and near-infrared spectroscopy	Ultimate pH Colour Intramuscular fat Shear force	134	*Longissimus dorsi*	The Vis/NIRS offered great potential for correctly classifying pork Longissimus into two tenderness and two juiciness classes. Good predictive models for pHu and colour, more research required for IMF and shear force
Chmiel et al, 2016a	Poland	Computer vision system (CVS) pHmeter Minolta Chromameter	pH45’ and pH24h Electrical conductivity Minolta colour L* a* b* Drip loss Water holding capacity Thermal drip Total heme pigment content Chemical composition	100	*Semimembranosus*	Limited possibility of CVS application for m.semimembranosus classification (for detection of PSE pork)
Chmiel et al, 2016b	Poland	Computer vision system (CVS) pHmeter Minolta Chromameter	pH45’ and pH24h Minolta colour L* a* b* Drip loss Water holding capacity Thermal drip	230	*Longissimus lumborum*	It is possible to use CVS to detect PSE and DFD meat and to classify meat into quality groups. It was not possible to differentiate RSE and RFN

			Total heme pigment content Chemical composition			meat
Sun et al, 2016	USA China	Computer Vision System (CVS) using high resolution digital camera with 2 adjustable LED lighting systems	Marbling score Colour score Minolta colour L* a* b*	100	*Longissimus dorsi* (centre cut)	Good correlations between Minolta measurements and image processing L* (r=0.91) a* (r=0.80) b* (r=0.66). Linear regression model provided better prediction then stepwise model for score prediction (R2=0.83 vs 0.70)
Da Costa Barbon et al, 2017	Brazil Italy	Computer Vision Systems (CVS)	Marbling	335	*Longissimus thoracis*	Flexible system using machine learning based on scores assigned by panel. 76% accuracy when 3 samples used for each score for learning process.
Caballero et al, 2017	Spain Denmark	Magnetic resonance imaging (MRI)	Moisture Water activity Salt content Lipid content Minolta colour L* a* b*	20	*Longissimus dorsi*	Moderate to excellent correlations for most physico-chemical parameters Alternative technique to determine physico-chemical traits of fresh and dry-cured loins in a non-destructive way with high accuracy
Huang et al, 2017	China Canada	Near Infrared Spectroscopy (NIRS)	Marbling score	24	*Longissimus thoracis* (rib end)	Correlation coefficients of prediction>0.89 Potential of using NIR images of rib ends for the assessment of marbling score along *Longissimus thoracis*

Liu et al, 2018	USA	Computer Vision System (CVS) using stepwise regression and support vector machine models	Marbling score IMF	85	*Longissimus dorsi* (centre cut)	Predicted IMF had a 66% correlation with chemical IMF Accuracy rates for regression models = 0.63 for stepwise and 0.75 for support vector machine. Subjective scores sowed better predictions.
Santos et al, 2018	USA China	Raman spectroscopy (portable device)	Sensory tenderness Slide shear force (SSF) at day 1 and day 15	800	*Longissimus dorsi*	Sensory tenderness attributes lowly correlated to their Raman spectroscopic characteristics. Moderate performance in identifying pork samples that belong to extreme categories. Classification more accurate when using spectra from aged samples.
Sun et al, 2018	USA	Computer Vision System used with artificial intelligence model	Marbling score Crude fat percentage Colour score Minolta colour L* a* b*	1400	*Longissimus dorsi* (centre cut)	CVS with support vector machine modelling reached the highest prediction accuracy (92.5% for colour score and 75% for marbling score)