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Report Title: Compare objective carcase measurement technologies for pig classification systems

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Abstract

Carcass classification systems within the pork industry are based on lean meat yield (LMY). Thus, accurate tools to measure the carcass characteristics predicting LMY are essential to underpin grading systems given they inform pricing grids, herd genetics, product segregation and support consistent trade language, which is essential for industry sustainability. This review summarised the accuracy of several commercially available technologies used for prediction of pork carcass composition. Both optical probes and ultrasound-based devices demonstrated comparable accuracy in the prediction of backfat depth, loin muscle depth, lean meat content and saleable meat yield. Ultrasound devices may have the advantage in that they are non-invasive and in the case of the AutoFom can also predict primal LMY values and cut weights. Some variation in predictions was observed across technologies that could be attributed to operator effect, device settings, reference methods used, and variables included in prediction equations. This highlighted the need for consistent testing methodology, and reference standards to train devices against. Rather than manual dissection methods, which are time consuming, destructive and subject to variation, computed tomography (CT) provides a non-invasive, rapid and highly accurate reference method to train and test device performance against. Continued research into objective measurement technologies for LMY in the Australian pig industry is recommended, given most investigations have been conducted internationally to date.

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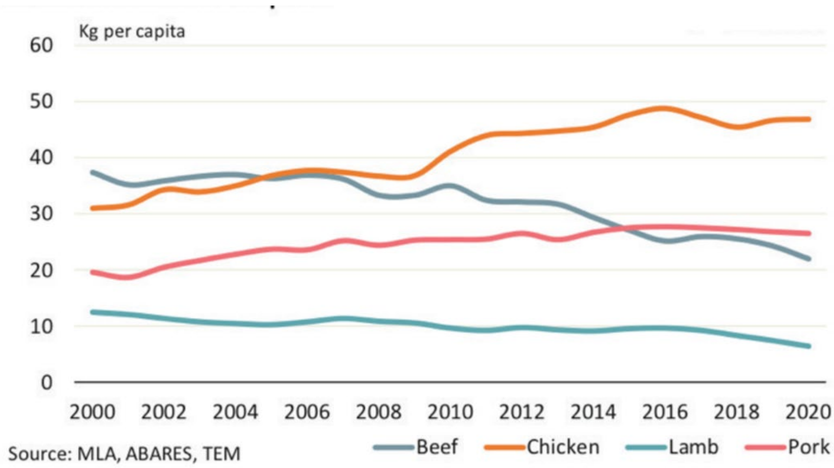
1 Introduction

The European Union (EU), USA and Canada are the top three exporters of pork internationally (based on volume), while Australia is placed 19th, occupying a share of 0.3% of total global trade for the last five years. The top importers of pork globally are China, Japan, and Mexico, while Australia ranks 17th with a 1.7% share of the global import market for frozen, fresh and chilled pork products (APL, 2021). Global demand for pork is expected to increase, alongside domestic consumption of pork and chicken as red meats have started to lose favour in the last few decades (Figure 1). While domestic pork consumption has increased by 35% in the last 20 years, the retail share for pork products is still lower than other proteins on the market with the retail spend on beef and chicken still around three times greater than pork (APL, 2021). To ensure the pork industry remains competitive, consumer demands for consistent quality products are required, for both domestic and international markets.

Figure 1. Per capita domestic meat consumption by meat type (APL, 2021).



In order to detemine the quality and value of carcasses at slaughter, accurate evaluation of carcass characteristics is critical. Carcass evaluation can provide feedback to producers for genetic improvements, inform pricing grids, improve product segregation, increase boning room efficiency, and add value across the entire supply chain (Allen, 2009). Therefore it is essential that reliable and accurate means of carcass evaluation are established; subjective evalution has been the starting point in all carcass classification and grading systems, however in recent decades industry has begun adopting objective measurement (OCM) technologies to improve accuracy (Delgado-Pando et al., 2021). In the pork industry, the classification of carcasses is based on lean meat yield (LMY) for many countries, and a range of OCM devices have been adopted commercially for carcass measurement, including but not limited to: optical probes: Hennessy Grading Probe (HGP), and Destron Pork Grader (DPG); ultrasound devices: PorkScan Lite, Carcass Value Technology system (CVT-1 and CVT-2); and the UltraFom 300 device; and ultrasound array, the AutoFom III (Fortin et al., 2004). The focus of this literature review will be the performance of technologies currently utilised by the Australian pork industry (HGP, ultrasound probes, AutoFom), with reference to other devices for comparison.

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2 Carcase classification

2.1 Lean meat yield (LMY)

Carcase classification systems are required to underpin trade language and ensure transparency in transactions (Polkinghorne and Thompson, 2010). They were initially developed as a quality control measure for commercial trade between livestock producers and processors but now also inform genetic programs, and improve processor efficiency and product segregation through additional knowledge on composition and quality (Delgado-Pando et al., 2021). Since the 1970's, Australian pig carcasses have increased in weight at an average of 587 g per year, and are now 60% heavier than the 70's with the average national pig carcass weight ranging from 72kg to 80kg (APL, 2021). However, weight alone does not give a clear indication of the economic value of a carcase, it can be represented by both the LMY (proportion of lean) and saleable meat yield (SMY). SMY can be defined as the amount of meat trimmed to commercial specifications ready for the point of sale, saleable yield has a strong influence on profitability as it can vary substantially between carcasses due to variation in fatness observed for carcasses of the same weight (Delgado-Pando et al., 2021). SMY is subject to market specifications, thus can include variations for quantity of fat and lean, and can include/exclude bone. For this reason, countries seeking to offer price incentives for high yielding carcases find it difficult to define a standardised SMY specifications to underpin trade. An alternative approach, is to establish a standardised cutout or dissection method that separates carcases more completely into their fat, lean and bone components, with the lean then expressed as a percentage of the weight of the whole carcase and termed "lean meat yield percentage" (LMY%) (Marcoux et al., 2007).

2.2 Reference methods for lean meat prediction

Manual dissection or cutout methods have been utilised to determine lean yield and calculate carcase value (Marcoux et al., 2007). They can act as a calibrating standard for technologies to predict, and in turn underpin pork classification and grading systems as is done in a number of countries (Delgado-Pando, Allen, Troy et al. 2021). This approach has several limitations. Firstly, it is destructive and time consuming, and therefore expensive. Furthermore, variation between individual boners reduces its reliability as a calibration tool (Vester-Christensen et al., 2009; Olsen et al., 2017), and within individual boners its repeatability cannot be demonstrated due to the destructive methodology. In addition, dissection techniques are not standardised across nations. In France a simplified dissection method was adopted for cost and time saving benefit, while the US pig industry has adopted a definition of lean yield expressed as a standardised fat-free lean yield. There is a high amount of variation in yield definitions in relation to selected tissues of interest (numerator) and the denominator (Marcoux et al., 2007).

Another historic method is to undertake a proximate analysis of a carcase to determine the fat, protein and ash content (which reflects fat, lean and bone). Yet similar to manual dissection, it is also time consuming and destructive, hence it cannot be fully replicated. However, the laboratory step of proximate analysis can be replicated, at least enabling comparison of the repeatability of this step. None-the-less assumptions are required to convert fat, protein and ash content into the equivalent mass of carcase fat, lean, and bone,

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also imposing some extrapolated error. Therefore, an alternative methodology for determining carcase composition is required.

A non-invasive approach for LMY determination is x-ray computed tomography (CT) (Vester-Christensen et al., 2009; Olsen et al., 2017). In CT scanners, an x-ray source rotates around the carcase, and attenuation is measured by stationary ring detectors after x-rays have passed through the tissues of interest. The relative attenuation of x-rays through different tissues (density) is measured on the Hounsfield scale. It can be used to accurately measure the proportions of lean, fat and bone within a whole carcase with mass attenuation coefficients transformed into Hounsfield Units (HU) ranging from 0 to 100 for lean, –100 to –50 for fat and greater than 250 for bone (Vester-Christensen et al., 2009; Olsen et al., 2017). CT scanners are consistently calibrated with an air equivalent to –1000 Hounsfield Units (HU), and water to 0 HU, thus these fixed calibrations allow for a reasonable comparison of HU values across different scanners with variations to settings.

The first use of CT in the meat industries for estimation of carcase composition was in live pigs (Kolstad and Vangen, 1996; Font-i-Furnols et al., 2015). Advancements in chemometrics and technology have improved prediction accuracy of CT to a level such that it is considered the "gold standard" for LMY determination. In live pigs, R^2 values have been observed from 0.98-0.99 for protein, moisture and fat, and RMSEP values 0.63, 1.03, and 1.14 for protein, moisture and fat percentages (Font-i-Furnols et al., 2015). And in primal cuts from the carcase, accuracy of prediction for fat and lean tissue has been reported at 0.994 and 0.993 respectively (Carabús et al., 2015). The application of CT for on-line determination of LMY is challenging for several reasons: logistically, CT machine are expensive, operation speeds are slow, radiation safely requires many safe-guards, and aperture size can prevent scanning of entire sides. Operationally, some tissues can have similar HU values (skin and lean; fat and marrow; fat and mammary tissue) causing overlap in tissue types, and differences in operating protocols and scanner brands can introduce some variance between machines. However, this can be overcome through standardisation of the protocols and HU coefficients with the use of phantoms of equivalent tissues densities and adjustments to HU outputs (Olsen et al., 2017). Regardless of on-line use, its demonstrated accuracy has confirmed CT to be included as an EU legislated reference method for calibration of devices to predict pork carcass composition (Font i Furnols and Gispert, 2009; Gangsei et al., 2016). In Australia, CT has been used as a "gold standard" to compare devices that predict carcass composition for the sheepmeat industry (Gardner et al., 2018), and now acts as the reference method for the new sheepmeat carcase composition trait. This is due to its strong associations with other measures of whole carcase composition including proximate analysis of carcase chemical constituents (Gardner *et al*., 2007a; Mata *et al*., 2021), manual dissection (Gardner *et al*., 2007b), and commercial cut weight (Gardner et al., 2021). Furthermore, CT scanning lamb carcases has shown excellent repeatability, demonstrated when scanning the same carcases within the same scanner and across separate scanners (Mata *et al*., 2021), reinforcing this technology as an ideal reference method regardless of species.

2.3 Carcase classification within Australia

In Australia, producer payments for pork carcases are based on hot carcase weight and fat depth at the P2 site, located 59 mm from the midline of the carcase at the last rib (Figure 2) (Moore et al., 2016; AUS-MEAT, 2021). These measures are taken approximately 35

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minutes post exsanguination and before chiller entry (Moore et al., 2016). The carcase weight must be measured hot. Abattoirs accredited by AUS-MEAT may trim carcases to one of 24 combinations, however all operators must report all pig weights in terms of the Standard Carcase Definition. To ensure fair trading irrespective of trim Conversion Factor guidelines are provided for processors (the Standard Carcase has a conversion factor of 1). There are different scales for carcases over and under 60kg. See Figure 3 for an example of the conversion factors

Figure 2. Illustration of P2 measurement site *(image courtesy of AUS-MEAT- Pigmeat Language Guide)*.

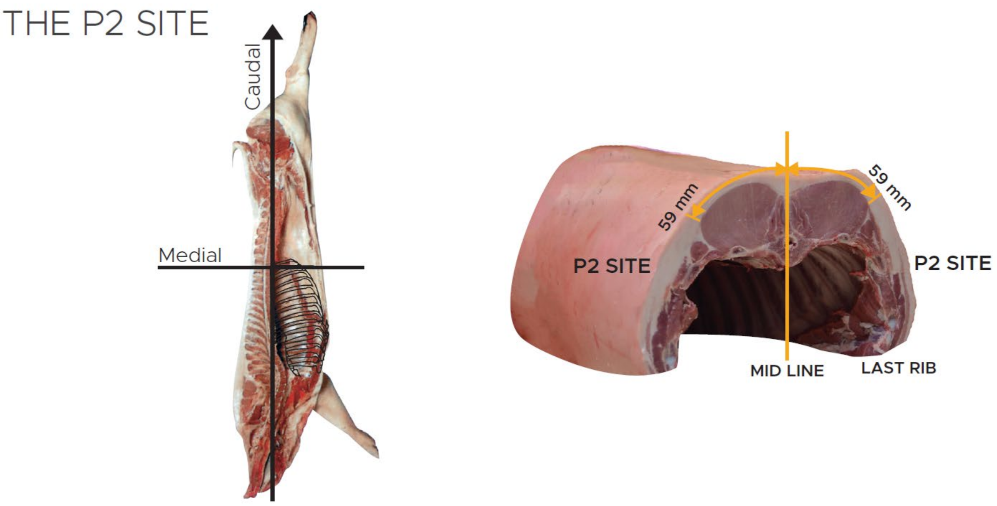
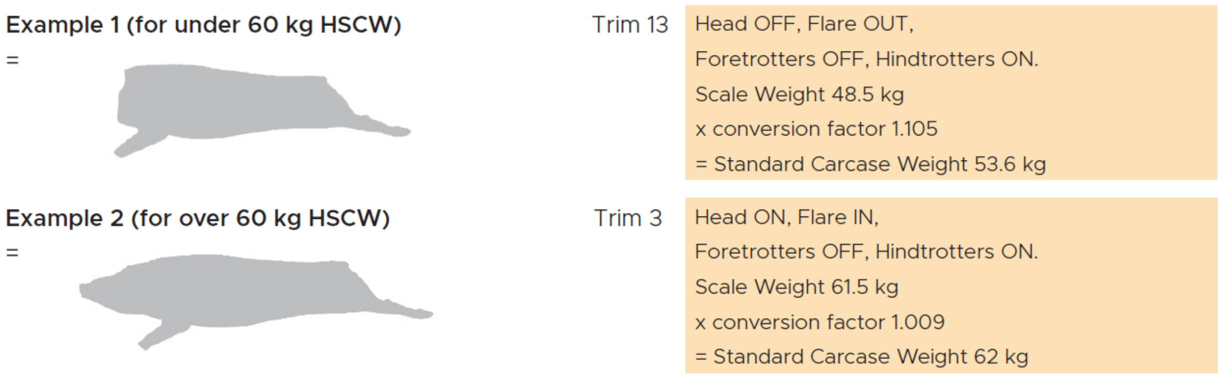


Figure 3. Illustration of P2 measurement site *(image courtesy of AUS-MEAT- Pigmeat Language Guide)*.



In the majority of countries, pig carcases are classified according to a LMY estimation based on a measure of fat thickness and carcase weight (Table 1) (Delgado-Pando et al., 2021). The only exception is Japan who include secondary measures of meat and fat colour, marbling, drip loss and texture in their classification system (Delgado-Pando et al., 2021). The majority of European, Canadian and US pork producers use either optical probe or ultrasound measurement to predict carcass lean composition and inform subsequent pricing grids (Berg et al., 1999; Fortin et al., 2004; Schinckel et al., 2010).

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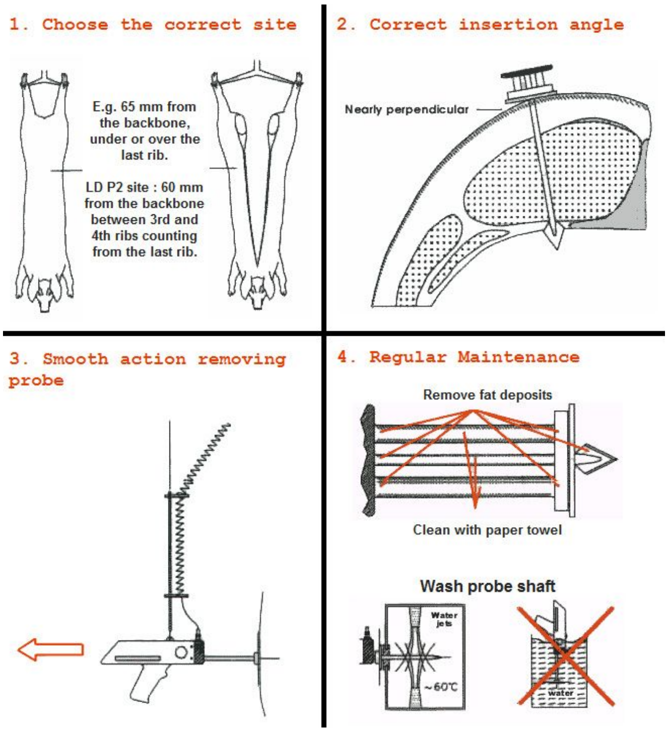
3 Objective carcase measurement technologies

Objective carcase measurement technologies are required to ensure accurate and precise estimates of carcase composition can be provided to underpin classification systems, provide feedback to producers and ensure consistent product specifications are achieved. The premise of using backfat thickness in lean meat prediction models is its inverse relationship with the lean content of a carcase (Callow, 1948). Thus in order to predict LMY, a high correlation between lean meat yield and the carcass site measures is required (Vítek et al., 2008)

3.1 Hennessy Grading Probe (HGP)

The Hennessy Grading Probe (HGP) is an optical device that operates on the principle pf light reflectance to objectively measure back fat thickness and muscle depth in pork carcases at a single site (Pomar and Marcoux, 2005). Originally developed as the Fat Depth Indicator in the 1980's for use in pork, it later became the HGP, and is commonly utilised in Australia and worldwide in carcase classification systems (Delgado-Pando et al., 2021). Backfat and loin muscle depths are automatically generated using differential light reflectance as the probe tip passes through the various tissue types. The probe records ten measurements a millimetre at a speed of up to 2,000 measures per second, typically taking less than one second to measure a carcase. The probe requires manual operation, with basic operator training only taking a few minutes, see Figure 4 for user instructions. The probes are robust enough for on-line use and are supplied with pre-installed software (Hennessy Technology, 2023). Within Australia, HGPs are used at the P2 measurement site to output a P2 value (fat class score for classification grids), muscle depth measure and provide a prediction of LMY%.

Figure 4. Operator instructions for use of Hennessy Grading Probe *(image courtesy of Hennessy Grading Systems Limited, New Zealand)*.



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Some limitations of the HGP include its lack of automation and physical destruction of the muscle tissue at the insertion site. Also industry concerns around the accuracy of optical probes used at a single site (Schinckel et al., 2010), encouraged development of more extensive carcass scanning technologies such as ultrasound devices and arrays.

3.2 PorkScan Lite and Plus

The PorkScan Lite device is a non-invasive ultrasound probe that measures fat and muscle depth at the P2 site on a pig carcase, it is AUS-MEAT accredited for use in Australia for measuring carcass quality (AUS-MEAT, 2021). There are several other commercially available ultrasound probes used internationally including the Carcass Value Technology (CVT) system (AUS, Ithaca, NY, US), and the UltraFom 300 device (SFK Technology A/S, Herlev, DK (Fortin et al., 2004; Pomar and Marcoux, 2005). Ultrasound has been successful in predicting LMY in pigs and has thus been opted for by large processors with justified throughput, in favour of optical probes which still require manual operation (Choi et al., 2018a; Delgado-Pando et al., 2021). Ultrasound imaging measures the echo of ultrasonic waves reflected off the fat/muscle interface to differentiate fat and muscle tissues (Houghton and Turlington, 1992). The PorkScan system captures and stores measurements for every carcase on the slaughter floor, allowing for producer feedback, and rapid processor sorting decisions for product.

The PorkScan Plus system was developed to enable Australian pork processors to predict LMY% for a relatively low investment cost. The Porkscan Plus LMY prototype uses laser light scanning to capture depth measures along a line that represents the curved contour of a carcase. The degree of curvature of these beams at specific sites on the carcass surface are captured and interpreted using image analysis software. Each scan results in 231 vectors of information for each carcase, including 15 radius of curvature (RCUB) measures, 108 angles of curvature (‘z’) measures and 108 2D segment (‘x’) measures. Simple carcase measures are also captured to measure the 2-dimensional width of the carcase at several points (top, chest, shoulder and upper chest). This information is incorporated into a complex algorithm to predict the LMY% of the carcass. This device was designed for faster chain speed performance, and cost efficiency with an aim of improved accuracy in LMY% prediction. Previous analysis demonstrated the PorkScan Plus system had some capacity to predict ultrasound P2 fat depth in pork carcasses, however inconsistency in performance was observed between different subsets of this data suggesting low commercial viability, refer to ALMTech Technical report 3.14.2. (Calnan and Gardner, 2019). Assessment of the predictive ability of whole carcass composition was required, given other sheepmeat technologies have demonstrated poor accuracy of a single site fat depth prediction but good whole carcass and cut weight prediction commercially.

3.3 AutoFOM III

The AutoFom III is an automated ultrasound imaging device that can provide real-time prediction of lean meat percentage, P2 fat site depth, loin muscle depth, and a grading class in European systems (Frontmatec, 2023). The device is currently AUS-MEAT accredited for P2 determination within Australia, and LMY prediction in several European nations (Frontmatec, 2023). The machine uses 16 2.0MHz transducers set apart at 25 mm intervals in a U-shaped frame to measure fat and muscle depths (Figure 5) (Busk et al., 1999; Choi et al., 2018b). Entire carcasses are scanned as they are pulled over the transducer arrays to

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gather the ultrasound readings, which are processed using advanced image analysis software, at a line speed of up to 1,400 carcasses per hour. As carcasses are scanned 48 image parameters are generated providing information on skin, fat and lean measures. The carcass must be wet to ensure good contact between the skin and transducers, thus the AutoFom device is usually situated between the dehairing and singing ovens on the processing line (Frontmatec, 2023). The AutoFom III can provide predictions for P2 fat depth, LMY%, weight of lean meat and total bone-in/bone-out weight of four primal cuts of shoulder, loin, belly and ham with a high degree of accuracy (Busk et al., 1999). This device is unique as it is able to predict lean meat yield at the primal cut level, enabling optimised cut floor performance to meet market specifications.

Figure 5. AutoFom device schematics, Top: u-shaped frame with transducers; Bottom: representation of the on-line set-up in the abattoir (Busk et al., 1999).

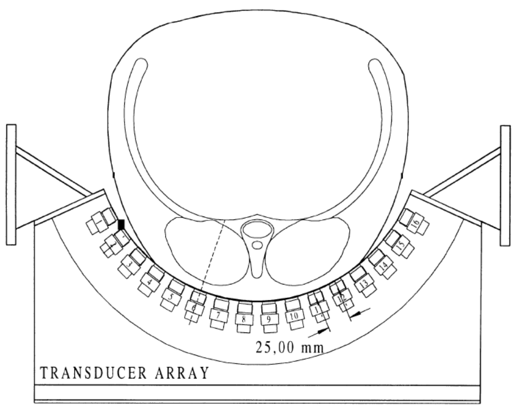

Fig. 1. U-shaped frame with transducers.

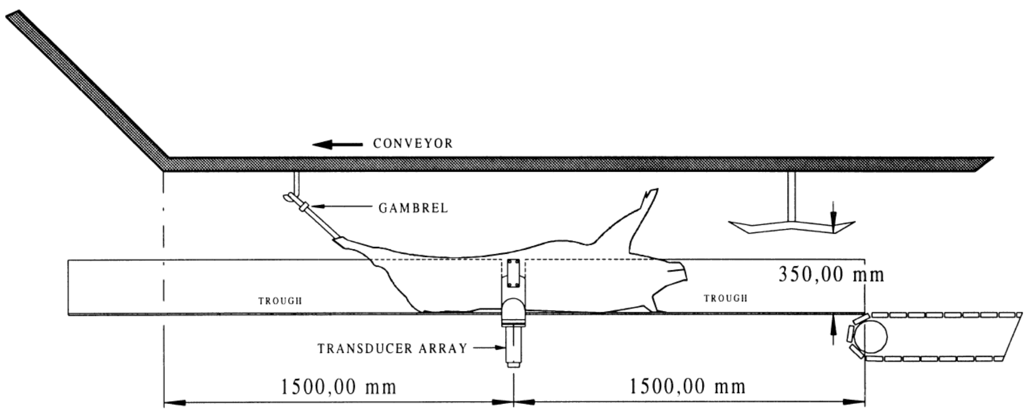

Fig. 2. Outline of the measurement system at the abattoir.

3.4 Comparison of technologies

3.4.1 Measurement of backfat and loin muscle depth

Prediction equations for lean meat content are underpinned with fat and muscle measures taken at specific carcass sites, hence a strong relationship between these measures and lean meat yield must be evident in order for accurate prediction of lean yield (Vítek et al.,

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2008). Both optical and ultrasound measures have demonstrated good accuracy in multiple studies comparing their performance (Vítek et al., 2008; Schinckel et al., 2010).

The published correlations between HGP measured backfat depth and carcass lean tissue content are strong with values ranging from – 0.83 to – 0.829, measured in American (n= 153) and Czech (n= 168) barrows and gilts (Vítek et al., 2008; Schinckel et al., 2010). Similarly, a strong relationship between backfat depth and total fat percentage has been reported (r= 0.843) (Schinckel et al., 2010). Conversely, HGP predicted loin muscle depths are weakly correlated with lean tissue and total fat percentages across several studies (lean tissue content: r = 0.31 to 0.37; total fat percentage: – 0.24) (Vítek et al., 2008; Schinckel et al., 2010). Thus perhaps unsurprisingly, Pomar and Marcoux (2005) demonstrated much higher accuracy in HGP predicted backfat depth compared to loin muscle depth (R^2 = 0.89 and 0.31) when compared to digitized images of the grade site in Canadian pig carcasses (n=207). Results indicate that the HGP tends to overestimate backfat depth in lean carcasses and underestimate backfat depth in fatter carcasses (Pomar and Marcoux, 2005; Vítek et al., 2008). Figures 6 and 7 demonstrate the relationship between HGP predictions, and backfat and loin depth measures, with over/under estimation evident for fat thickness and a consistent underestimation for loin muscle depth (Pomar and Marcoux, 2005). Compared to other commercially available optical probes i.e. Destron Pork Grader (DPG) and Capteur Gras Maigre (CGM), the HGP was the most precise device for measuring backfat thickness (R^2 = 0.89 versus 0.81 and 0.82) and only slightly less accurate for muscle depth (R^2 = 0.31 versus 0.31 and 0.35) (Pomar and Marcoux, 2005).

Figure 6. Hennessy Grading Probe (HGP) compared to digitized image generated backfat thickness values (n= 268). —— = regression line, —— = equality line with an intercept of 0 and slope of 1 (Pomar and Marcoux, 2005).

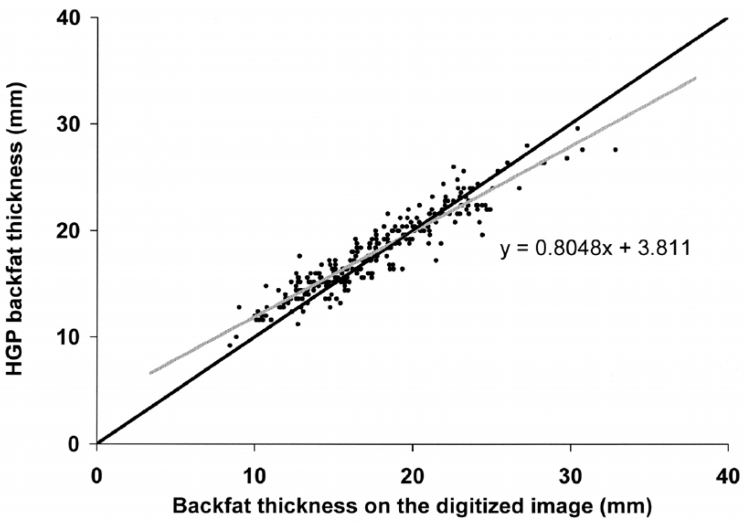

Figure 7. Hennessy Grading Probe (HGP) compared to digitized image generated loin muscle depth values (n= 268). —— = regression line, —— = equality line with an intercept of 0 and slope of 1 (Pomar and Marcoux, 2005).

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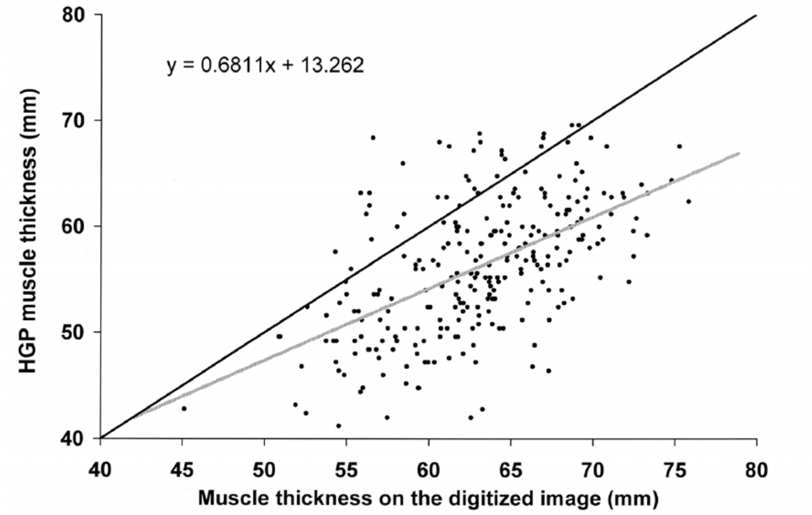

Ultrasound measures used to predict backfat thickness and loin muscle depth demonstrate similar accuracy, and correlations to lean meat yield as the optical HGPs (Pomar and Marcoux, 2005; Vítek et al., 2008). The CVT-1 (long transducer) and CVT-2 (short transducer) were able to predict back fat depth (R^2= 0.82 and 0.86) with a high degree of accuracy and loin muscle depth at a more moderate level (R^2=0.40 and 0.41) (Pomar and Marcoux, 2005). Similar to the HGP results, the CVT probes overestimate fat depth in leaner carcasses and underestimate fat depth in fat carcasses but to a slightly lesser degree (Pomar and Marcoux, 2005; Vítek et al., 2008), in addition there is consistent underestimation loin muscle depth (see Figures 8 and 9) (Pomar and Marcoux, 2005). Correlations between CVT predicted fat thickness and lean meat content determined by dissection are high at r = –0.82 , while correlations between loin muscle depth and lean meat content awere more moderate (r = 0.37) (Vítek et al., 2008).Comparison of optical and ultrasound devices by Pomar and Marcoux (2005) indicated the CVT's were generally more precise for loin muscle measurement than the optical devices, while the HGP was more precise at measuring back fat thickness. Despite this, ultrasound devices have the logistical advantage of being non-invasive.

Figure 8. Carcass Value Technology (CVT) predicted backfat compared to digitized image generated backfat thickness values (n= 268). — = regression line, — = equality line with an intercept of 0 and slope of 1. (left) CVT-1 = long transducer, (right) CVT-2 = short transducer (Pomar and Marcoux, 2005).

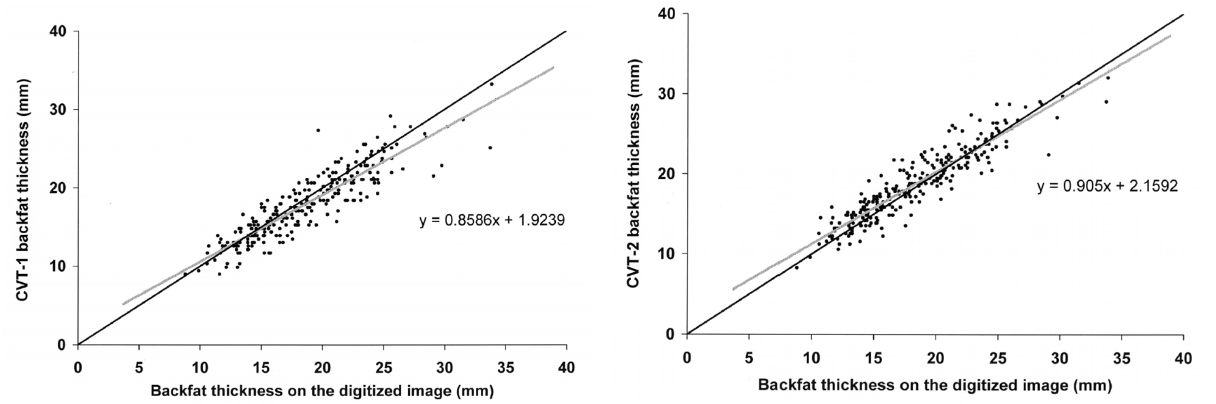

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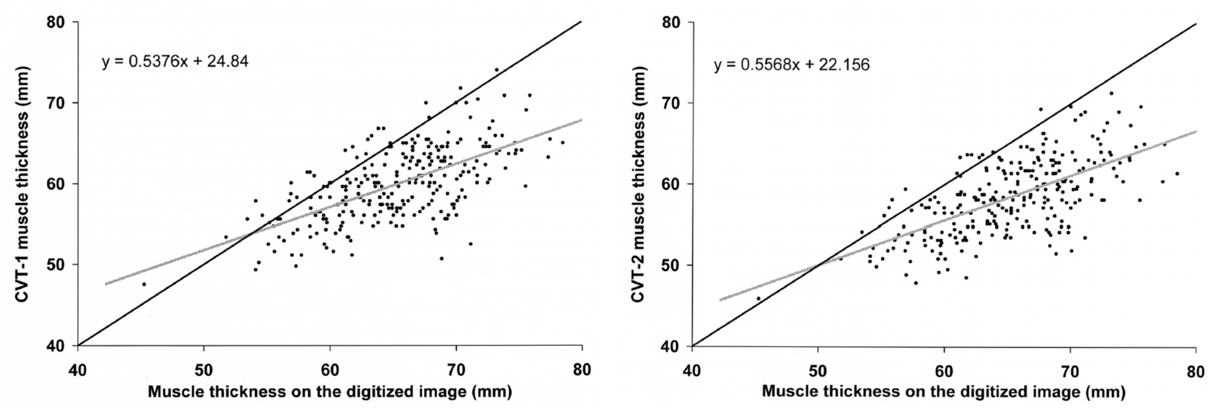
Figure 9. Carcass Value Technology with long transducer (CVT-1) compared to digitized image generated loin muscle depth values (n= 268). —— = regression line, —— = equality line with an intercept of 0 and slope of 1. (left) CVT-1 = long transducer, (right) CVT-2 = short transducer. (Pomar and Marcoux, 2005).



3.4.2 Prediction of lean tissue content

Classification of pig carcasses is based on carcass lean meat yield values, hence accurate prediction of lean content is essential to ensure appropriate product segregation, manage processing floor decisions, inform pricing grids, and allow for transparent trade (Delgado-Pando et al., 2021). A range of commercially available optical and ultrasound technologies currently output lean meat values for industry with a high degree of accuracy (Busk et al., 1999; Fortin et al., 2004; Vítek et al., 2008).

Across the literature, accuracy is comparable for devices with RMSE values ranging from 1.71 – 2.54% for optical devices,1.61 – 2.48% for ultrasound probes, and 1.58 – 2.48% for the AutoFom in its various iterations (adapted from Fortin et al. 2004; Vitek et al. 2008; Schinckel et al. 2010). Prediction bias has been demonstrated for the optical HGP and ultrasound devices (Vítek et al., 2008), with lean meat content overestimated in carcasses of less than 55% lean meat content, and underestimated in carcasses over 55% lean meat content (up to 1.1% and 2.8% respectively), this is similarly reflected in the backfat predictions for these devices (Pomar and Marcoux, 2005; Vítek et al., 2008).

Attempts to improve accuracy through additional measurement sites has been examined (for optical and ultrasound probes), however where successful, the magnitude of effect was often deemed too negligible for implementation commercially. One example, Vitek et al. (2008) improved the accuracy of lean meat content prediction for both HGP (R^2= 0.73 versus 0.83 and RMSE= 2.41% versus 1.93%) and ultrasound device (R^2= 0.71 versus 0.83 and RMSE= 2.48% versus 1.94%) with the inclusion of additional carcass characteristics in equations i.e. proportion of leg without fat cover proportion to total carcass weight, average of fat thickness measures at three sites along the midline, cold carcass weight, and proportion of fat cover above the loin muscle in proportion to total loin muscle area. However, collecting these measures in an abattoir is impractical thus their use is encouraged only for experimental purposes or when investigating carcass value for new genetic lines (Vítek et al., 2008).

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The AutoFom is unique in that it incorporates multiple fat and muscle depth measurements into lean meat yield prediction equations and also outputs lean meat values and cut weights at the primal level of shoulder, loin, belly and ham (Frontmatec, 2023). Choi et al. (2018b) demonstrated high accuracy of AutoFom III to predict weights of deboned shoulder blade, shoulder picnic, loin, belly and ham (R^2= 0.77 to 0.86) however lower accuracy with smaller cuts including the tenderloin, spare rib, diaphragm, jowl, and back rib (R^2= 0.34 to 0.62). In a Canadian study by Fortin et al. (2004), the AutoFom was able to predict saleable meat yield with a moderate to high degree of accuracy (R^2 = 0.75, RMSE = 1.68). However, performance was slightly better for the HGP2 probe and CVT-2 ultrasound device in the same study (R^2 = 0.74, RMSE = 1.56; R^2 = 0.75, RMSE = 1.57).The AutoFom is advantageous in that it is fully automated and can be easily integrated into the processing plant providing real-time information for rapid decisions (Fortin et al., 2004). However, given each technology operates in a different manner, it may be prudent to develop thresholds or grids specific to each technology in order to optimise accuracy for segmentation of products (Pomar and Marcoux, 2005).

4 Conclusion

This review summarised the performance of some commercially available technologies used for prediction of pork carcass composition. Generally, both optical probes and ultrasound-based devices demonstrated comparable accuracy in the prediction of backfat depth, loin muscle depth, lean meat content and saleable meat yield. There was some variation across the literature which could be attributed to differences in lean and fat determination techniques, dissection methods, operator error, device settings, and the variables included in prediction equations. Improvement in accuracy was shown with the inclusion of additional carcass site measures (more than backfat and loin depth) in prediction equations, however the magnitude of difference was usually too low to warrant the logistics required for their inclusion on-line. The AutoFom may prove advantageous to other technology in that it is completely automated and can predict the yield values of primal cuts and individual cut weights, in addition to the total carcass yields. Furthermore, some of the highest accuracy values were shown for this system, likely due to the inclusion of over 36 site measures in equations generating a slightly better predictions. For most other technologies, carcass weight, backfat and loin muscle depth remain the most practical inclusions in equations to predict lean meat yield. A clear set of standards for calibration of devices would improve consistency and transferability of device results. CT could be implemented as the “gold standard” reference method to achieve this in Australia, similar to Europe. Research into device performance using Australian pork herds is recommended as a paucity of data on this has been noted. More accurate descriptors of the carcass will allow processors to improve feedback for producers, meet market specifications and improve the efficiency of operations.

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