# THERMAL IMAGING TECHNOLOGY FOR RAPID *IN-VIVO* EVALUATION OF CARCASS COMPOSITION IN GROWING-FINISHING PIGS

**by**

**VERONICA NDAMS**

A Thesis Submitted to The Faculty of Graduate Studies of

The University of Manitoba

In partial fulfillment of the requirements for the degree of

**MASTER OF SCIENCE**

Department of Animal Science

University of Manitoba

Winnipeg

**ABSTRACT**

Selecting market hogs' antemortem is labour-intensive and time-consuming, involving evaluations based on weight and conformation. However, most hog markets pay the producer based on pork carcass merit, which is determined at postmortem by carcass leanness percentage. The objective of this study was to predict carcass traits and composition of live animals by using multispectral thermal imaging with computer vision models. A total of 243 finishing pigs (crossbred Large White × Landrace barrows and gilts; average body weight 122 kg) were used for that purpose. Three days before slaughter, dorsal images were captured using a multispectral camera (5–15 µm wavelength range). Once pigs were slaughtered, lean depth, fat depth and leanness percentage were obtained from hot carcasses using a Destron probe. After 24 hours postmortem, chilled carcasses were fabricated into primal cuts and analyzed for leanness percentage via dual-energy X-ray absorptiometry (DEXA). Images were preprocessed, and 238 were selected based on quality and complete data. Computer vision models were trained with data augmentation techniques to predict carcass traits and classify carcasses based on lean grade index (higher lean grade indexes > 109 scores; between 57.7 to 64.2% of leanness and 80 to 105 kg of hot carcass weight). Bayesian optimization was applied to fine-tune model hyperparameters. The models showed low performance in predicting individual carcass traits and composition variables with an (RMSE of 4.93mm, an ooSR2 of 0.04) for fat depth and (RMSE of 5.77mm, and an ooSR2 of -0.14) for lean depth. The classification model moderately distinguished high and low lean-grade indexes based on DEXA lean yield (F1 score: 0.73), while Destron assessments showed a lower F1 score (0.38). Multispectral imaging technology could enable producers to market hogs based on the best grid grade. Future research should focus on increasing sample size, integrating additional measurements, like phenotypic (e.g., body weight, sex classification, feed efficiency,

and age), and genomic data, (e.g., breed type, sire, and dam lineage) and advancing from 2D to 3D imaging to enhance model accuracy and reliability.

Keywords: Carcass composition, Destron fat depth, Destron lean depth, DEXA, Lean grade index, Total lean, Total fat, Multispectral camera, Thermal imaging technology

## ACKNOWLEDGEMENTS

First and foremost, I thank God for His steadfast guidance, grace, and strength throughout this journey. I am deeply grateful to my supervisor, Dr. Argenis Rodas-Gonzalez, for his invaluable mentorship and consistent support. His guidance and encouragement have been instrumental in my academic growth

My sincere thanks go to my co-advisor, Dr. Gabriel Dallago, for his steadfast support and thoughtful advice, which has helped me persevere through challenges. I am grateful for his constant guidance throughout this process.

I am appreciative of Dr. Manuel Juarez from Agriculture and Agri-Food Canada, and Dr. Victor Lei from Topigs Norsvin Canada Inc., for serving on my thesis committee. Your expertise and insightful feedback have greatly enriched this work.

To my immediate family, especially my husband, Mr. Sannar Ndams, and my children, Hovai, Otah, and Rademene-Rejoice, your love, support, and understanding have been the foundation of my success.

Lastly, I thank all those who have supported me in various ways throughout this journey.

## TABLE OF CONTENTS

## LIST OF TABLES

## LIST OF FIGURES



.

## LIST OF ABBREVIATIONS

AAFC = Agriculture and Agri-Food Canada

FFLM = Fat-Free Lean Muscle

2D = 2D Dimensional

3D = 3D Dimensional

DPG = Destron Pork Grader

HGP =Hennessy Grading Probe

CLY = Canadian Lean Yield

NPPC =National Pork Producers Council

FOM = Fat-O-Meater

$R^2$ =Coefficient of Determination

RMSE =Root Mean Square Error

CT =Computed Tomography

VIA = Visual Image Analysis

US = Ultrasound

DEXA =Dual Energy X-ray Absorptiometry

MRI =Magnetic Resonance Imaging

CVS =Computer Vision Systems

CNN =Convolutional Neural Networks

DL = Deep Learning

FAO =Food and Agriculture Organization

CCAC =Canadian Council on Animal Care

NRC = National Research Council

RFID =Radio Frequency Identification

OOS$R^2$ = Out of Sample Coefficient of Determination

$^0C$ =Degree Celsius

KG= Kilograms

mm = millimeters

# CHAPTER 1: GENERAL INTRODUCTION

Pork producers select pigs for slaughter based on the evaluation of live pig conformation and weight, which are labour-intensive and stressful for the pigs (Jeon et al. 2025). However, most hog markets pay the producer based on pork carcass merit, which is determined post-mortem by the percentage of carcass fat-free-lean muscle (FFLM). The FFLM is determined post-mortem using various carcass measurements, which is also time-consuming, requires skilled personnel, and uses invasive and destructive techniques (i.e. ribbing or penetrating an optical probe) (Pomar & Marcoux,2003; Benjamin &Yik, 2019). They are, therefore, unsuitable for use on farms to select market animals. As a result, a large number of pigs sent to slaughter do not meet the target specifications set by the packing plant, leading to frequent penalization for animals that are too lean or over-fat (Boler, 2017). For efficiency, the producer requires a non-invasive, labour-efficient and real-time monitoring system to keep track of growth curves, feed efficiencies and degree of muscling/leanness for individual pigs at each production phase (growing and finishing), which could help in making real-time management adjustments (e.g. diet) (Zhao et al. 2024).

The agricultural industry is progressively implementing cutting-edge technologies to improve productivity and sustainability. A notable innovation in this area is precision livestock farming, which utilizes various technologies for more effective monitoring and management of livestock. Imaging technologies are non-invasive and non-destructive technologies such as 2D and 3D digital imaging that have demonstrated their usefulness in determining live weight, body condition score, animal welfare and health in the livestock sector (Miller et al.2019). However, their performance depends on illumination conditions and depth distance (distance between the camera and the object) (Kim et al. 2013). A multispectral camera typically consists of an image sensor, a spectral filter array, a sensor board, and a driving board. These components capture images across multiple spectral bands (Mohammadi et al. 2022). Multispectral cameras have been used in several fields, such as aerospace and pharmaceutical production to assess tablet coating defects, hardness, and surface density profiles (Klukkert et al. 2016); to differentiate active pharmaceutical ingredients from the tablet matrix and to distinguish between their crystalline and amorphous forms within tablets (Wu et al. 2014). In livestock, this approach has been used to characterize several different abnormal poultry carcasses, including bruised, tumorous, and skin-torn carcasses (Sun, 2017), real-time detection of diseases in chicken (Chao et al. 2001), and detect fecal and ingested contaminants on broiler carcasses (Park et al. 2007).

Multispectral cameras capture images across multiple spectral bands, ranging from visible (0.4 to 0.7 μm) to near-infrared (0.7 to 1 μm), and occasionally mid-infrared (3.5 to 5 μm) (Coffey, 2012; Smeesters et al. 2023). These cameras, equipped with advanced sensors, provide high spatial and spectral resolution, making them essential for precision agriculture and environmental monitoring. By detecting subtle variations in light absorption, reflection, and emission, they generate detailed data that can be integrated with technologies such as convolutional neural networks, sensors, and automated systems to establish a comprehensive approach to livestock management (Vollmer et al. 2022; Torres & Kämäräinen,2023).

Multispectral imaging provides a non-invasive option that can rapidly and precisely estimate characteristics such as muscling, leanness, growth patterns, and feed efficiency by examining the spectral signatures of pigs' bodies. Tracking these features at various production stages (growing, finishing), can assist farmers in making real-time adjustments to management strategies, such as dietary changes (Zhao et al. 2024).

# CHAPTER 2: LITERATURE REVIEW

## 2.1. Pig carcass traits, composition and importance

Pig carcass composition is important for farmers since packing plants are inclined to reward them according to lean muscle percentage (Engel et al. 2012). Composition refers to the proportionate quantity of lean pork or muscle in a carcass. The degree of fatness and the extent of muscling, which reflect variations in the muscle-to-bone ratio, are the primary parameters associated with carcass composition (Beermann et al.1994). Carcasses should contain the maximum amount of muscle and the minimal quantities of fat, bone, and skin within biological limits as this enhances lean yield. Over the past three decades, various technologies have been employed to measure lean meat percentage in pork carcasses. These efforts primarily aim to determine the carcass' commercial value for processors and producers (Swatland et al. 1994). In North America, the most prevalent method involves using an optical probe (e.g., Destron and Hennessy Grading Probe) to assess fat and loin muscle depths, with these measurements converted through standardized equations to estimate lean yield (Busk et al. 1999; Zhou and Bohrer, 2019). Consequently, fat depth, muscle depth, and predicted leanness are the primary parameters assessed in commercial pigs. Additionally, traits like backfat thickness and loin eye area are reliable indicators of carcass lean meat content (Johnson et al. 2004). To optimize efficiency and profitability, pork processors prioritize consistent products that align with industry standards for weight and yield (Barducci et al. 2020).

Since the 1960s, the value of a carcass has been closely linked to its leanness (Fredeen et al. 1964), and this relationship remains relevant in many countries. Depending on the region, carcasses are evaluated based on different criteria, such as lean content (e.g., Canada), saleable meat yield (SMY = [weight of the commercial cuts (loin; ham; picnic; butt; belly; side ribs and hock)] × 100/[weight of the four primal cuts) loin; ham; belly; shoulder)]; Marcoux et al. 2003)), standardized fat-free lean (e.g., United States), or measurements of backfat and loin muscle depth (e.g., United Kingdom, New Zealand, Australia). Importantly, these evaluation systems assume that improving yield criteria enhances the commercial value of carcasses, as lean meat typically has a higher market price than fat. Therefore, carcass lean yield has been defined as the proportion of tissues of interest in a carcass, determined through a standardized reference method. This method specifies the preparation process and the type and extent of dissected tissues. While lean tissue is the primary focus, it is important to note that the tissues of interest may also include fat and bones, depending on the evaluation objectives (Pomar et al. 2009).

### 2.2. Factors affecting pig carcass traits and composition

A combination of genetic factors, environmental factors, and management practices such as sex class, age, nutrition, and rearing conditions influences carcass composition. Livestock producers can manipulate these factors to achieve desired carcass outcomes (Irshad et al. 2013).

#### 2.2.1. Sex class

Sex class in pigs refers to the classification based on their reproductive status: barrows (castrated males), gilts (young females), and boars (uncastrated males). This classification significantly impacts carcass composition (Fortin et al. (1987).

Malgwi et al. (2022) reported that gilts typically exhibit higher lean yields than barrows due to reduced fat deposition and increased muscle. Similarly, Manchisi et al. (2010) found that gilts demonstrated approximately 2.92% higher dissected carcass lean yields than barrows, highlighting the impact that the sex class of an animal has on carcass composition. Moreover, when comparing wholesale primal cuts like the loin, ham, and shoulder, along with their sub-primal by-product, which includes trimmings, bones, fat and skin of varying types and quantities, gilts generally yield a higher proportion of lean meat than barrows (Elbert et al. 2020). Other researchers have found similar results (Smit et al. 2014).

In a recent study by Lei et al. (2022), the significant impacts of carcass weight and sex class on meat cuts were investigated. They revealed that as carcass weight increased, the proportion of muscle and bone decreased while the proportion of fat increased. Additionally, the four-point backfat thickness, which measures the amount of adipose tissue at four specific locations (the shoulder, located at the front above the shoulder blade; the mid-back, positioned centrally between the tenth and eleventh ribs; the loin, near the last rib; and the hip, located at the rear above the hip bone) increases significantly with carcass weight, indicating increased fat deposition. Barrows exhibit higher proportions of shoulder cuts and back fat compared to sows, whereas sows demonstrate higher proportions of leg cuts. Moreover, barrows display lower proportions of loin and loin muscle area but higher proportions of fat areas relative to sows.

### 2.2.2. Genetic

Genetic factors are fundamental in determining carcass traits, including fat and lean content in pigs. Different breeds demonstrate noticeable genetic predispositions that affect fat deposition and muscle mass. In an investigation, Latorre et al. (2009) evaluated the impact of the sire lines (Duroc and Pietrain) on carcass traits, as well as meat and fat characteristics, in pigs raised outdoors for dry-cured meat production. The study found no significant differences in carcass fat thickness between the two sire lines. However, carcasses from Duroc-sired pigs were longer and showed a tendency for higher yields of trimmed shoulders and hams compared to those from Pietrain-sired pigs.

Edwards et al. (2006) also found that Duroc-sired pigs had heavier and longer carcasses than Pietrain-sired pigs; however, Pietrain-sired pigs exhibited less backfat at the first rib, last lumbar vertebrae and fat depth. Also, Pietrain progeny had a greater percentage of their carcasses of ham and loin primals, while Duroc progeny had a higher belly yield. Consequently, Pietrain-sired pigs had a higher percentage of leanness than their Duroc counterparts. Furthermore, Fortin et al. (1987) investigated how breed and sex influenced carcass composition in entire male and female Iron Age, Pietrain, and Large White pigs. Their findings emphasized that Pietrain pigs demonstrated a notably higher muscle-to-bone ratio (6.2 at the average side weight) compared to Large White (5.2) and Iron Age pigs (5.3). The differences in carcass composition between entire males and females varied by breed, with entire male carcasses being slightly leaner overall but showing a lower muscle-to-bone ratio than female carcasses. Comparing modern meat-type pig breeds (e.g., Large White) versus 'older' fatty Saddle Back breeds (e.g., Meishan, Basque breeds); Large White exhibits higher lean content and lower lean meat content (Rehfeldt et al. 2011).

The choice of parent line significantly influences carcass composition and traits in pigs. Selecting superior sire and dam lines within breeds for terminal crossbreeding aims to enhance offspring performance.  At the same time, genetic selection for feed efficiency has enhanced swine production, improving growth performance and carcass yield traits (Patience et al. 2015). This approach uses estimated breeding values to evaluate an animal's genetic potential for traits like feed efficiency and carcass composition (Van Der Peet-Schwering et al. 2021). Feed efficiency is commonly expressed as the feed conversion ratio, defined as the ratio of feed intake to body weight gain (Hoque et al. 2007). Animals with a lower feed conversion ratio are more desirable, as they require less feed to achieve the same weight gain compared to those with a higher feed conversion ratio, which consume more feed for equivalent growth (Bergamaschi et al. 2020). In line with this, Saikia et al. (2024) and Beens (et al. 2024) selected for feed efficiency (low and high) based on estimated breeding value for feed conversion ratio within a Large White dam and sire genetic lines.

Regardless of the efficiency group, the results indicated that sire line boars were significantly heavier, with larger loin areas and greater loin depth, lower trimmed fat and higher lean compared to proportions dam line boars. On the other hand, high-efficient animals showed advantageous performance in most carcass yield traits, which provide a favourable response in leaner animals. Furthermore, Elbert et al. (2020) compared two sire lines of the same breed, Synthetic (A) and Piétrain (B), and found that pigs from line B had leaner carcasses and heavier primal cuts compared to those from line A.

### 2.2.4 Rearing condition (confinement vs free range)

The study by Sather et al. (1997) compared pigs raised in confinement versus free-range systems, investigating their growth and carcass composition, where free-range pigs took longer to reach market weight but showed higher muscle depth with an average increase of 2.4 mm and lean yield, from 59.1% to 59.8% compared to confinement pigs. Specifically, free-range-reared pigs exhibited heavier butts, loins, and hams, along with lighter bellies, contributing to a 2.9% increase in wholesale carcass value. Moreover, they had greater dissected lean in various cuts, such as the picnic butt (2.0%), butt (4.0%), loin (4.5%), and ham (2.0%), with no compromise to pork quality. These findings suggest the benefits of outdoor rearing for enhancing carcass quality and emphasize the potential advantages of improved carcass grading technologies.

### 2.2.5. Nutrition

Nutrition plays a critical role in determining body composition. Inadequate protein or an imbalanced amino acid profile can hinder skeletal muscle growth while promoting fat deposition. Conversely, providing a high-energy ration ad libitum without a balance in amino acid intake can lead to excessive fat accumulation (Van Milgen & Dourmad, 2015).

Schinckel et al. (2012) examined how high-energy and low-energy diets influenced the carcass composition of pigs. The findings showed that the overall lean percentage was slightly higher in pigs fed the low-energy diet (56.1%) compared to those on the high-energy diet (55.9%, $p = 0.034$). Similarly, the fat-free lean percentage was significantly greater in pigs consuming the low-energy diet (51.6%) than those on the high-energy diet (50.8%, $p = 0.028$). Feeding low-energy diets consistently increased the predicted lean percentage across all sire lines in the study.

An optimal diet, rich in essential vitamins, minerals, and energy, is essential. Mooney and Cromwell (1995) observed that chromium supplementation led to increased rates of muscle accretion and decreased rates of fat accretion. Moreover, O'Quinn et al. (1998) found a reduction of 13.5% in carcass fat percentage and 11.1% in average backfat thickness with chromium supplementation. Wang & Xu, (2004) noted that pigs fed chromium nanoparticles exhibited higher percentages of carcass lean meat, larger loin muscle areas, and reduced backfat thickness

Jackson et al. (2009) reported that the addition of chromium reduced the $10^{th}$ rib backfat thickness and increased muscle percentage. Similarly, Kim et al. (2010) observed a significant reduction in average backfat thickness, particularly in castrated pigs, with chromium picolinate supplementation, considering that chromium methionine supplementation is cost-comparable to other organic chromium complexes, it may offer an economically feasible approach to enhancing the nutritional quality of pork.

Feeding regimes, including the frequency and quantity of feed provided, can also affect body composition. The investigation by Dalla Bona et al. (2016) compared ad libitum feeding with restricted feeding regimes and found that pigs on a restricted feeding regime had lower feed intake but improved feed efficiency (Lebret et al. 2008). The restricted feeding regime resulted in leaner carcasses with less fat deposition, which is required for producing consumer-desired pork.

Additionally, the timing and duration of feed restriction can influence carcass composition. Shurson et al. (2016) reported that moderate feed restriction during the finishing phase improved feed efficiency and reduced the proportion of saturated fatty acids in the intramuscular fat without adversely affecting carcass value. This indicates that planned feed management can improve carcass traits and enhance the economic efficiency of pork production (Lebret et al., 2008).

### 2.3 Hog grading system in Canada

Pork producers are economically motivated by consumer demand and carcass-value marketing programs to produce lean pork efficiently. The absolute and relative rates of lean and fat gain determine the efficiency of lean gain and carcass composition. Therefore, to increase lean growth rates, pork producers need to implement genetic and management improvement strategies (Schinckel & Einstein, 1995). Commercial pork producers typically focus on metrics such as live weight gain, feed conversion, and feed intake. In Canada, actual grading methods using Destron (DPG) and Hennessy (HGP) probe measurements were authorized in 1994. The Canadian grading system categorizes pork carcasses into indexes based on their lean yield content and warm carcass weight, which includes the head, kidney, leaf lard, and feet (Canada Gazette, 1986). This index is used to adjust the average market price to compensate producers for the relative value of each carcass fairly. The primary goal of grading pork carcasses in commercial packing plants is to ensure that producers receive a fair and unbiased return based on the lean yield of their carcasses (Fredeen et al. 1964; Daumas, 1999). Additionally, it offers clear indicators to seed stock producers regarding the commercial worth of their carcasses. The carcass lean yield, often called the cutout, is predicted using backfat and loin muscle thickness measurements. In Canada, as in many other countries, these measurements are taken on the carcass at a specific grading spot after slaughter using an optical probe. The prediction of lean yield is based on the strong correlation between carcass lean yield and the measurements of backfat and loin muscle thickness (Fredeen and Bowman, 1968; Fortin et al. 1984).

However, the measurements of backfat and muscle thickness are distinct to each optical probe, as these probes function uniquely based on factors such as the wavelength of light emitted, the sensitivity of the reflection measurement device, and its software interpretation. The probe itself, with the probing technique (including location, angle, movement, etc.), and the equation used to predict lean yield collectively form a grading method. The most used measuring devices in Canada are the HGP2 Hennessy probe (Hennessy Grading System Ltd., New Zealand) (HGP) and the PG-100 Destron probe (Anitech Identification System Inc., Canada) (DPG).

The yield, estimated as the percentage of lean, is determined through a mathematical formula derived from extensive carcass cutouts. This formula incorporates two main variables: fat thickness and lean depth, both measured using the Destron Electronic Probe. Among these variables, fat thickness exerts the most significant influence, accounting for more than 90% of the variation in calculating the lean yield percentage. In contrast, the lean measurement has a minimal effect, acting as a minor adjustment factor in the equation. Generally, lower fat measurements correspond to higher estimated lean yield percentages (Canada Gazette, 1986).

The lean yield equations for the HGP and DPG probes currently utilized at many Canadian slaughter plants were established in 1994 by the Canadian Pork Council (CPC 1994). The selected lean yield prediction equations for these probes are as follows (CPC 1994):

- HGP: $CLY (\%) = 67.2327 – 0.7877f + 0.1086m + 0.0087f^2 – 0.0004m^2 – 0.0002fm$
- DPG: $CLY (\%) = 68.1863 – 0.7833f + 0.0689m + 0.0080f^2 – 0.0002m^2 + 0.0006fm$

Here, CLY represents the Canadian lean yield of the carcasses, while f and m denote the backfat thickness (mm) and muscle thickness (mm), respectively, measured by their respective probe. The potential for profit after raising a hog is dependent on the final step: marketing, which is primarily determined by the targeted carcass weight specified by a hog grading grid. Several factors, such as pig variation and herd uniformity, can impact this timing, sometimes resulting in a less-than-ideal fit with the target range of the grading grid (Price, 2020). However, some of these factors can be managed to maximize profit through constant monitoring of individual pigs' growth curves throughout the production phases. This allows for real-time adjustments in management strategies to enhance financial returns.

The grading grid combines two key pork value factors: dressed carcass weight and estimated percent lean yield, into a single grading system, and the grid determines the grade index for each pork carcass (Canada Gazette, 1986). The premium-grade indexes within this grid are determined by where the plant identifies the optimal carcass value and meat yield. However, to secure the maximum premium grade index from a grading grid, pork producers should aim for the optimal dressed carcass weight range and the desired estimated lean yield by effectively controlling fat at the market weight (Canada Gazette, 1986). Table 1. shows the various hog grade classes in the Canadian hog grading system.

**Table 1.** Canada Hog carcass grades

| Hog Grade Classes | Number of Grades | Hog Criteria |
|---|---|---|
| Canada Yield with 7 classes | 1 | Weight must be 40kg (88lb) or more |
| Canada Emaciated | 1 | Weight must be 40kg (88lb) or less |
| Canada Ridgling | 1 | Has one or two undescended testicles or has both male and female sex organs |
| Canada Sow 1-6 | 6 | Must be a sow with the required back fat levels, good muscling, straight to convex profile, and barely visible shoulders |
| Canada Sow 7 | 1 | Must be a sow deficient in muscling and finish |
| Canada Stag | 1 | A mature porcine animal, castrated before slaughter, and exhibiting pronounced masculinity at the time of slaughter |
| Canada Boar | 1 | Must be a male carcass with one or more testicles but not a carcass of a ridgling |

### 2.4. Methods for measuring carcass composition

Methods for measuring carcass composition vary from country to country and even between processing plants in a country and are directly related to carcass value, i.e., carcass and/or primal weights or primal lean content. Indirect measurements start from visual carcass conformation assessments to the use of sophisticated instruments, such as fibre optic probes like Fat-O-Meat'er, Hennessey Grading Probe or Destron PG-100, and ultrasound devices like BioQScan or AutoFOM which is currently the most accurate system for commercial on-line grading of carcass (Sosnick & Knap, 2024).

Over the past three decades, various technologies have been employed to predict the leanness of pork carcasses online, with the primary objective of determining the true commercial value of the carcass for processors and offering appropriate guidance to pig producers by providing important data which helps producers in making real-time management changes like feed adjustment (Swatland et al. 1994). In North America, the prevailing method for assessing carcass lean yield involves utilizing an optical probe to measure fat and muscle depth in the loin. These measurements are used in specific equations to estimate the predicted lean yield (Busk et al. 1999; Zhou & Bohrer, 2019). Consequently, fat depth, muscle depth, and predicted leanness are solely the general parameters for evaluating carcass leanness in commercial pigs (Barducci et al. 2019).

### 2.4.1. Carcass evaluation

The composition of meat animal carcasses has long been a critical focus for livestock producers and meat processors. The economic value of the main tissue components in carcasses varies based on their utilization and current consumer demand. Accurate carcass evaluation techniques are essential, with their effectiveness determined by how precisely they assess carcass value. According to Forrest, (2020), realistic carcass values are calculated by determining the worth of products derived from the carcass, factoring in their selling price minus production costs and profit margins.

In most markets, the value of pork carcasses is influenced by the percentage of fat-free lean, which is estimated using carcass weight, backfat depth, and loin muscle measurements. Packers utilize various tools to measure backfat and loin muscle, with measurement sites differing by packer. Each processor applies its method to predict carcass fat-free lean for pigs in their market (Johnson et al. 2004). Typically, backfat thickness is measured at a specific location, often at the last rib, while loin muscle depth is assessed at the loin eye area. Carcass weight generally refers to the hot carcass weight (AMSA/NPPC, 2001).

### 2.4.2. Carcass dissection

The gold standard for assessing meat and fat contents in a carcass is dissection. Traditionally, carcass dissection has been the benchmark for evaluating new estimation formulas for lean content. Dissection involves a more detailed manual separation of the carcass into different components, including lean tissue, subcutaneous fat (external fat), intermuscular seam fat, bone, and skin. This is often done for scientific analysis to study the composition and yield of the carcass. The carcass is then cut into primal cuts, such as the shoulder, loin, belly, and ham, and further divided into subprimal cuts. Finally, weighing occurs at different stages, including before and after dressing and during portioning, to monitor yield and ensure accurate pricing and portion sizes (NPPC, 2001). However, dissection is costly, labour-intensive and requires expertise (Bernau et al. 2015). In addition, fatigue and variability in operator technique can reduce the precision and accuracy of dissection, leading to mistakes that compromise the uniformity of cuts, hinder the proper separation of muscle groups, and result in inaccurate yield data or the loss of valuable meat (Olsen et al. 2017). Despite its drawbacks, dissection remains crucial for accurately identifying differences in lean meat percentage, although at the expense of time and resources.

### 2.4.3. AutoFom

Brøndum et al. (1998) introduced the Automatic Fat-O-Meat'er as a technology designed to assess the distribution of lean meat within pork carcasses and to estimate the weights of primal and boneless sub-primal cuts. The system comprises a structure equipped with 16 ultrasound transducers. It automatically measures the carcass at 3,200 positions, penetrating to a depth of approximately 12 cm with a depth resolution of 0.19 mm. The resulting ultrasound data is processed to generate a three-dimensional image, which undergoes noise reduction, orientation detection, and extraction of 127 features to characterize the carcass composition (Brøndum et al. 1998). The author reported that online tests conducted at line speeds of up to 1,150 carcasses per hour provide predictions of the meat percentage with an accuracy ranging from 1.58% to 1.95%. The system has also demonstrated accurate predictions of fat thickness and primal meat cuts.

The AutoFom device offers significant advantages for carcass analysis in slaughterhouses. Its software automatically adjusts data analysis based on carcass rotation, eliminating the need for precise positioning within the transducer array (Brondum et al. 1998). This feature not only enhances efficiency but also reduces the likelihood of errors during measurement. Additionally, AutoFom achieves remarkable throughput, capable of measuring up to 1250 carcasses per hour, facilitating rapid processing in slaughter facilities.

However, despite these advantages, AutoFom is susceptible to measurement variability, primarily due to differences in tissue characteristics, especially temperature-dependent variations in ultrasound and sound velocity. These variations may impact the accuracy and consistency of measurements across carcasses.

### 2.4.4. Single point measuring devices (FOM, Destron, HGP)

Many pork processors still utilize technologies that rely on single-point measurements to determine lean yield. Examples include optical grading probes like the Hennessy, Fat-O-Meat'er, and Destron probes (Knecht et al. 2016). These devices operate on the principle that white fat reflects more light than darker lean tissue (Berg et al., 1999; Balas, 2009). The Destron PG-100 employs reflectance spectroscopy, capturing profiles of measurements by recording fractions of millimetres of penetration and backscattered light signals. With an impressive precision of 0.03 mm, the system can operate efficiently at high line speeds. Specifically designed for pig carcasses, it measures back fat thickness and loin muscle depth at predetermined locations. The fat and muscle depths are assessed using a Destron PG-100 probe, inserted perpendicularly between the third and fourth last rib, and positioned 7 cm off the mid-line, adhering to Canadian grading standards (Pomar and Marcoux, 2003).

Goenaga et al. (2008) demonstrated the effectiveness of the Fat-O-Meat'er (FOM) and Henessy grading probe (HGP) devices in predicting carcass lean content using multiple regression equations. They achieved coefficients of determination ($R^2$) of 0.801 and 0.794 for the FOM and

HGP equations, respectively, with residual standard deviations of 2.40% and 2.45%, indicating high precision and accuracy suitable for national carcass grading (Goenaga et al. 2008).

However, challenges associated with these technologies include operator and random measurement errors, and the assumption that a single carcass location accurately represents the entire carcass. To address these challenges, the European Union has established threshold requirements for grading equipment, with a root mean square error (RMSE) of prediction set at less than 2.5 (Dorleku et al. 2023).

**2.4.5. UltraFom 300**

The UltraFom 300, like the Fat-O-Meat'er, is a handheld ultrasound probe that operates in real time. It incorporates 64 sensor elements to emit sound pulses into the carcass, enabling the measurement of ultraFom backfat thickness and ultraFom loin muscle depth (Johnson et al. 2004). The accuracy of UltraFom can be affected by variations in muscle shape and fat distribution within the carcass, which can lead to less precise results. The definition of the probing position does not always coincide with the anatomical position of the intended superficial layer of muscle underneath the subcutaneous fat (Hulsegge et al. 2010).

**2.4.6. Computed tomography (CT)**

Computer tomography is a non-invasive technique that captures internal images of livestock animals based on X-ray attenuation. The attenuation, expressed in Hounsfield values, presents a grey scale from black to white, representing low to high density. Pixels, forming voxels, enable the resolution of structures regardless of nearby densities. The capability of the 3-D imaging feature of computer tomography devices makes it a reliable predictor of body composition in live pigs (Luiting et al. 1995) and carcasses (Font-i-Furnols & Gispert, 2009). In another investigation, Font-i-Furnols et al., (2014) demonstrated an accurate estimation of carcass lean meat percentage and slice composition using CT images. Gjerlaug-Enger et al. (2012) employed CT technology to compute genetic parameters concerning muscle growth rate, carcass fat, bone development, and non-carcass tissue from birth until pigs reached a live weight of 100 kg, focusing on Landrace and Duroc genotypes. Additionally, Carabús et al. (2015) utilized CT scans to investigate phenotypic traits across three different genotypes at weights of 30, 70, 100, and 120 kg. Their findings revealed that the Pietrain cross-type exhibited notably greater ham development, offering valuable insights for companies selecting Pietrain pigs for their lean attributes.

However, X-ray emission requires isolation in leaded rooms, with operators monitoring from shielded areas. In addition, although widely available for human clinical studies, CT equipment is costly (Mitchell & Scholz, 2004).

### 2.4.7. Visual image analysis (VIA)

The VIA, also known as video image analysis and computer-aided design, employs one or more cameras to capture 2D or video images for online estimating carcass characteristics. While primarily used online, VIA has been utilized offline to predict lean meat yield in live pigs (Doeschl-Wilson et al. 2005). The study further examined pig growth in terms of size and shape and found a significant relationship ($p<0.05$) between shape data analysis and carcass composition at various growth stages, with variations among genetic populations. VIA has also been extensively applied for classifying carcasses into payment categories and enhancing SEUROP classification (a system used to evaluate carcasses based on their conformation and fat cover, listed as S-Superior, E-Excellent, U-Very good, R-Good, O-Fair and P-Poor) consistency compared to visual appraisal (Font-i-Furnols & Gispert, 2009; Craige et al. 2012; Engel et al. 2012).

The technique offers advantages in agricultural applications, particularly in eliminating the need for human-animal interaction. However, it solely provides external body information without internal imaging of the pig. Factors such as proximity of electrical outlets for non-portable cameras, proper camera positioning, light intensity, sensor sensitivity, flash type, field of view, farm cleanliness, and dust control are crucial considerations when using VIA equipment (Carabús et al. 2016).

### 2.4.8. Ultrasound

Ultrasonic imaging offers a significant advantage over visual image analysis (VIA) by enabling the acquisition of internal images for body composition evaluation. It operates by propagating acoustic waves through materials, reflecting perturbations in their physical structure, which allows for correlating acoustic properties with macroscopic composition and structure.

Two models for ultrasonic imaging are commonly used: A-mode (amplitude modulation) and B-mode (brightness modulation). A-mode involves a single transducer scanning a line through the body, with echoes plotted on the screen relative to depth. B-mode, also known as 2D mode, utilizes a linear array of transducers to scan a plane through the body, presenting a two-dimensional image on the screen. Ultrasonic imaging has been in use since the early 1950s, facilitating measurements of fat thickness and meat quality assessment in live animals or carcasses (Fortin et al. 2003). Ultrasonic imaging (US) has been employed to examine intramuscular fat in live pigs (Newcom et al. 2002) and has been utilized, both in vivo and post-mortem, to assess raw meat attributes, particularly intramuscular fat content, achieving the highest R2 value of 0.92 in pork (Newcom et al., 2002). Nonetheless, the precision of the US in estimating carcass traits varies and relies on factors such as species, ultrasonic equipment, and the proficiency of the operator. Most US assessments typically demand about 1-2 minutes per image acquisition (Newcom et al., 2002; Mörlein et al. 2005).

### 2.4.9. Dual Energy X-ray Absorptiometry (DEXA)

DEXA operates by measuring the attenuation of X-rays (photons) as they pass through either a living body or a carcass. Specific tissues or elements within the body or carcass exhibit distinct mass attenuation coefficients, which vary based on the energy level of the photons used for measurement (Magnusson et al. 2011). Various generations of DEXA machines employ either pencil or fan-beam technology, with advancements such as cone-beam or flash-beam techniques. A full-body scan using a pencil-beam scanner, although accurate, may take up to 35 minutes, whereas a high-speed cone-beam scanner can complete the same scan in less than 3 minutes (Scholz et al. 2015).

DEXA technology has been applied across various farm animals, including pigs (Mitchell et al. 1996; Kremer et al. 2012), chickens (Swennen et al., 2004), and calves (Scholz et al., 2003), for predicting carcasses and body composition. Studies on DEXA measurements in pigs have shown notable precision compared to chemically determined values (Mitchell et al. 1998). However, concerns persist regarding variable bias linked to body size, gender, and adiposity (Wells, 2009), as well as concerns regarding radiation exposure and the cost of acquisition of the equipment.

### 2.4.10. Magnetic Resonance Imaging (MRI)

The MRI is a valuable non-invasive diagnostic tool used in various fields, including livestock assessment and carcass evaluation. The fundamental principle of MRI relies on the behaviour of atomic nuclei with an odd number of protons or neutrons when subjected to a strong magnetic field, absorbing and reemitting radio waves (Carabús et al., 2016). During MRI scans, the atoms within the body absorb energy from an external source and emit signals over time. These signals, characterized by longitudinal relaxation (T1) and spin-spin relaxation (T2) times, correspond to different tissues and their proton densities. MRI scanners come in two types: closed (high-field) and open (low-field). High-field scanners, typically operating at 1.5-3 Tesla, offer superior resolution and speed compared to open scanners, which typically operate at around 0.23 Tesla (Carabús et al., 2016). MRI holds significant promise for livestock assessment and is particularly useful for estimating the composition of pigs across different weight ranges (Mitchell et al. 2001; Kremer et al. 2013). However, MRI scans may take longer to acquire due to the magnetic field involved. Despite its availability for animal research, MRI equipment is costly to acquire and maintain.

### 2.4.11. Computer Vision

In the early 1970s, computer vision systems emerged as the visual perception aspect of a grand initiative aimed at emulating human intelligence and granting robots the capability of intelligent actions (Szeliski, 2011). Computer vision constitutes an aspect of artificial intelligence (AI) dedicated to the instruction of computers and systems in obtaining meaningful insights from digital images and videos. Computer vision systems, a subset of artificial intelligence, enable computers to analyze and interpret visual data, such as images and videos, by using cameras, algorithms, and data processing techniques to replicate human vision (Szeliski, 2011; Goodfellow et al. 2016). Computer vision involves three fundamental tasks among others: image classification, where the objective is to assign one or more labels to an image in either single-label or multi-label formats; image segmentation, which involves partitioning an image into distinct areas, each typically representing a specific category; and object detection, aimed at identifying objects of interest by drawing bounding boxes around them and associating each box with a corresponding class (Chollet et al. 2022).

Convolutional Neural Networks (CNNs) are advanced artificial intelligence models that operate on intricate multilayer neural networks. They demonstrate proficiency in recognizing, categorizing, and identifying objects within images, detecting and segmenting objects. Referred to as Conv Nets, CNNs stand out as a well-established deep-learning model possessing the ability to make precise distinctions. Importantly, they demonstrate the capability to learn directly from input images without requiring human intervention in feature extraction, making them more efficient compared to regular networks (O'Shea et al. 2015). Unlike regular networks that may lose some information during feature extraction as they require the flattening of images before input, convolutional neural networks can directly process raw images. By analyzing all the pixel data, the network can identify features more effectively and the relationships within the image, improving performance in tasks such as image recognition or classification (O'Shea et al. 2015). In convolutional networks, the essential components include convolutional layers for feature extraction, pooling layers to reduce dimensionality, and fully connected layers for flattening and combining features for final prediction in the output layer. The convolutional layers are the foundational components, applying filters to the input image to detect features such as edges, textures, and patterns. Pooling layers (such as max pooling) follow, reducing the dimensionality of the feature maps, which helps to decrease computational load and control overfitting while preserving essential information. Fully connected layers come next, flattening the feature maps into a single vector and combining the features to make final predictions. These layers interpret the high-level features and make decisions based on the patterns learned. Activation functions (like ReLU) introduce non-linearity, enabling the network to learn complex relationships. Collectively, these layers transform raw pixel data into meaningful outputs, whether for classification, object detection, or other tasks (Elgendy, 2019; Albawi et al. 2017; Chollet et al. 2022).

### 2.4.12 The Application of convolutional neural networks in the swine industry

Convolutional neural network algorithms have been utilized for computer vision purposes, comprising image processing, object identification, and prediction of body and carcass composition of animals in the livestock industry with promising outcomes.

Fernandes et al. (2019) demonstrated the use of a DL algorithm, utilizing raw 3D images to predict muscle depth and back fat thickness of pigs. The results showed a predictive Mean Absolute Scaled Error (MASE) of 5.10% and 13.62%, a Root-Mean-Square Error (RMSE) of 4.35mm and 1.10mm, and an $R^2$ of 0.51 and 0.45 for muscle depth and backfat, respectively. This suggests successful prediction of muscle depth and back fat using autonomously collected 3D images in farm conditions. Similarly, Pan et al. (2021) conducted experiments involving 40 pigs using a bidirectional convolutional residual framework, a specialized type of CNN designed to enhance the segmentation of complex structures, such as internal organs in CT scans, by considering information in both forward and backward directions within the network architecture. When weighed their approach against manual dissection, the outcomes strongly agreed with the traditional manual dissection method, affirming the method's ability to precisely measure the body composition ratios of fat, lean meat, and bone in live pigs. The application of CNNs has also been reported in a study by Alsahaf et al. (2019) that utilized RGB-Depth computer vision and machine learning to score pig muscularity automatically. The tenfold cross-validation resulted in a mean absolute error of 0.65, which both end users and field experts deemed satisfactory for replacing human assessors.

Utilizing measuring procedures like CVS, ultrasound, MRI, CT, etc., to access pork carcass composition significantly improves the accuracy and consistency of hog grading systems, including those in Canada. These technologies provide precise, real-time data on important attributes such as backfat thickness, muscle depth, and overall carcass composition, which are fundamental for verifying carcass value (Delgado-Pando et al. 2021; Newman, 2009).

### 2.5 Summary

This literature review has highlighted the current methods for determining lean yield, which are mainly invasive and time-consuming, creating a demand for more efficient, non-invasive on-farm selection methods. The proposed research, utilizing a camera system combined with artificial intelligence models, offers a promising solution for predicting carcass traits and leanness. These capabilities show the viability of this method in improving swine producer profitability and optimizing time to market while also enhancing the sustainability of swine production.

Moreover, the review systematically examined the role of multispectral imaging technologies in advancing precision livestock farming. These technologies, particularly computer vision systems, show substantial potential to improve the accuracy and efficiency of carcass evaluation in the swine industry. The significance of carcass grading was also investigated, highlighting its role in standardizing carcass trait assessments and providing fair incentives for producers. Overall, integrating multispectral imaging technologies represents a key advancement in precision livestock farming, enabling rapid, accurate, and non-invasive assessment of carcass traits. In addition to addressing existing challenges, these innovations also contribute to the industry's long-term sustainability and efficiency.

# CHAPTER 3: RESEARCH HYPOTHESIS AND OBJECTIVES

## 3.1 Research Hypothesis:

The hypotheses that were tested in this thesis are as follows:

1. Multispectral imaging will predict in-vivo carcass traits and carcass leanness in growing-finishing pigs.

2. Multispectral imaging will classify growing pigs into higher and lower lean grade indexes within the grid grade index (based on carcass weight and estimated percent lean yield) for a pork carcass.

## 3.2 Research Objectives:

The objectives of this study are:

1. To predict in-vivo carcass traits and carcass leanness levels of live pigs.

2. To predict the classification of live pigs into higher and lower lean grade indexes (defined based on carcass weight and estimated percent lean yield for a pork carcass).

3. To contrast the lean yield classification obtained by DEXA vs Destron

# CHAPTER 4: MANUSCRIPT 1

Developing predictive models for carcass composition of finishing pigs using multispectral imaging technology

## 4.1 Abstract

Most hog markets pay the producer based on pork carcass merit, which is determined at postmortem by carcass leanness percentage. Thermal image analysis could enable producers to predict live animals' leanness, avoiding excessively lean or overly conditioned animals being selected for slaughter. The objective of this study was to use multispectral thermal imaging with computer vision models to predict carcass traits and composition of live animals. A total of 243 finishing pigs (crossbred Large White x Landrace barrows and gilts; average body weight 122 kg) were used in the experiment. One dorsal image per pig (500 × 600 pixels) was captured with a multispectral camera (between 5-15 μM). Three days after scanning, pigs were slaughtered. After 24 hours postmortem, chilled carcasses were fabricated (e.g., picnic, butt, ham, and loin primals) and assessed for composition using dual-energy x-ray absorptiometry technology. A subsample of 238 images was selected based on complete data availability. Images were segmented to remove the background, and then computer vision models were trained using data augmentation. The models performed poorly ($R^2 \leq 0.09$) when predicting individual traits, including total lean, total fat, lean depth, and fat depth. However, when a model was trained to classify the images based on lean grade index (> 109 scores; carcasses between 57.7 to 64.2% of leanness and 80 to 105 kg of hot carcass weight) a moderate performance was obtained (F1 score = 0.73). Multispectral imaging could enable producers to select and market their hogs based on the best grid- grade. However, future studies should focus on increasing the sample size to improve the precision and reliability of the model predictions.

## 4.2 Introduction

Global demand for meat products is expected to increase by 57% between 2005 and 2050 (FAO, 2006). Satisfying this demand is a global challenge for future food security. In addition, since 2020, the Canadian swine industry has experienced unprecedented challenges caused by the COVID-19 pandemic affecting swine producers such as the inability to find a market for finished pigs and labour shortage. Thus, minimizing input waste and costs is a critical strategy for improving farm viability, as it allows farmers greater control over their resources. Achieving optimal input efficiency is vital for all producers, as higher technical efficiency reduces resource usage, lowers production costs, and increases profitability, which serves as a key motivator for adopting innovative practices (Galanopoulos et al. 2006).

Pork producers select pigs for slaughter based on live pig conformation and weight, which is labour-intensive and stressful for the pigs, but not based on carcass merits. However, most hog markets are based on pork carcass merit, which is determined at postmortem by the percentage of carcass fat-free-lean muscle (leanness). As a result, many pigs do not meet the target specifications set by the packing plant, leading to frequent penalization for animals that are too lean or over-fat. Leanness is determined by using various invasive and destructive techniques on the carcass (i.e. ribbing or penetrating an optical probe) and cannot be used on farms to select market animals. Thus, a non-invasive real-time monitoring system, in terms of their growth rates and in vivo carcass composition could give producers the ability to make real-time management modifications (e.g., diet) as pigs are growing for better use of resources. The proposed technology can promote sustainable intensification, enhance animal welfare and alleviate the shortage of specialized labour.

Recent efforts have shown the potential of 2D, 3D and thermal infrared image analysis in chicken, pig, beef and dairy cattle to estimate live weight, body score condition, lameness, lying behaviour, milking traits, carcass characteristics, abnormal poultry carcasses, (including bruised, tumorous, and skin-torn carcasses) and identify metabolic efficient animals (Sun,2007 Benjamin & Yik, 2019; Miller et al. 2019; Schaefer et al. 2018). In addition, multispectral imaging has been used in several sciences (e.g., aerospace) and industry fields (e.g., pharmaceutical production) (Calvini et al. 2020), but has had limited use in the livestock sector (Sun,2007) with no known reports where multispectral imaging has been applied to estimate both carcass traits and live carcass composition of swine.

Therefore, this study aims to predict in-vivo carcass traits and carcass leanness levels, predict growing pig classes (higher and lower lean grade indexes defined based on carcass weight and estimated percent lean yield for a pork carcass), and to compare the lean yield classification obtained by DEXA vs Destron.

### 4.3. Materials and methods

The experimental procedures were approved by the University of Manitoba Animal Care Committee (F20-026) to ensure conformity with the Canadian Council on Animal Care (CCAC) guidelines (2009).

#### 4.3.1. Animal and carcass management

A total of 243 hundred finishing pigs (barrow 125 and gilt 118; Duroc boars× (Landrace × Large White Sows; Genesus) were evaluated in a swine unit located in Alberta (Lacombe Research Centre). The pigs were fed a commercial finisher diet (a corn-wheat meal-base diet), and diets were formulated to meet the nutrient requirements recommended by the National Research Council (NRC, 1999). Animals had ad libitum access to feed and water throughout the experiment. When animals reached the endpoint of 122kg± 7, images of the pigs were captured, and pigs were slaughtered

### 4.3.2. Image acquisition

The pigs were calmly moved through the chute using rattles paddles in a single file towards the imaging area, where the scale and camera were located. Once the pig was placed on the scale, the image of each pig was captured from the dorsal view. One dorsal image (640 × 512 pixels) per pig was captured from all pigs at a focal distance of approximately 2 meters with a multispectral camera (between 5-15 µM; capture speed of 30 Hz; FLIR A 65 (FLIR System, Inc., Wilsonville, Oregon) (Taylor et al.2023). A total of 243 images were captured. The setup for image acquisition (Fig 1) was composed of an overhead camera, with a proper lighting system and a non-reflective uniform background. Each pig was assigned unique Radio Frequency Identification (RFID tags) to keep track of the images and corresponding data.

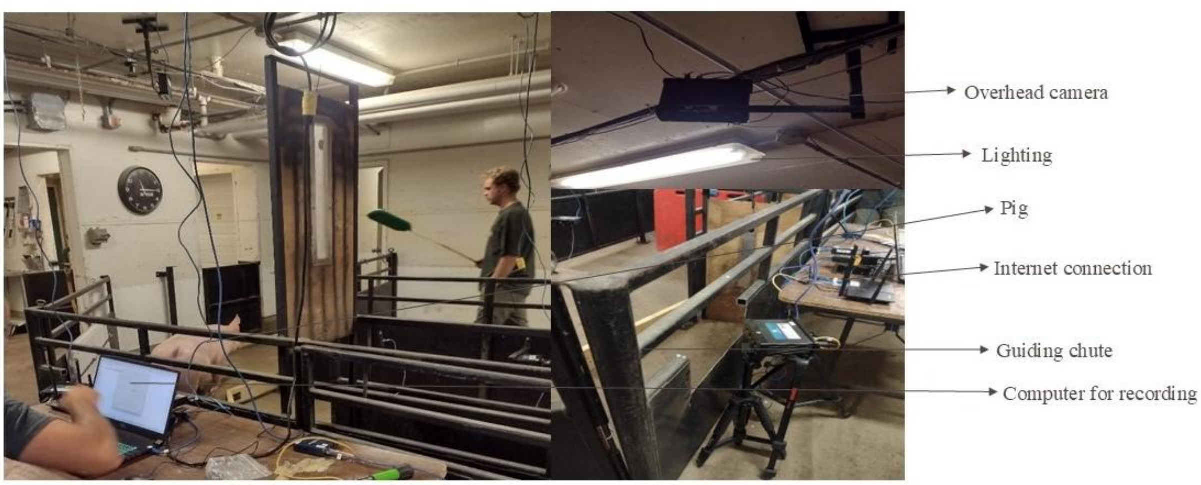


Figure 1. Set up for image acquisition

### 4.3.3. Slaughter and carcass fabrication

Three days after the images were taken, pigs were slaughtered. After dressing, carcasses were split into two halves and weighed, and the left carcass sides were applied to the Destron electronic probe Viewtrak PG-309 (Viewtrak Technologies Inc., Markham, ON, Canada) to determine fat depth, lean depth, and leanness. The Destron was inserted perpendicularly into the carcass between the third and fourth last rib, approximately 7 cm off midline, to measure the fat depth and lean tissue (Barducci et al. 2020). Carcass sides were then moved into the cooler with a temperature set to 2 °C. After a 24-hour postmortem, chilled carcasses were weighed, and carcass shrink was calculated. The left carcass sides were further divided into primal cuts, including picnic shoulder, butt, ham, loin, and belly (CPI, 1995) and then DEXA was applied to determine the total yield of the product (i.e., leanness of individual primal cuts and total) and co-product components were computed as proportions (%) of the cold carcass weight (Soladoye et al. 2016).

#### 4.3.4. Data preprocessing

Data collected were analyzed using R (R Core Team, 2023). Descriptive statistics of central tendency and dispersion were determined for the studied variables. Additionally, considering DEXA leanness as the golden standard for its high accuracy ($R^2 > 0.90$) with the manual dissection method (Soladoye et al., 2016), Destron leanness was contrasted with DEXA leanness, through a linear regression model. It was used: $Y_j = \beta_0 + \beta_1 \text{ Destron}_j + \varepsilon_j$, in which $Y_j$ represented the lean yield measured by DEXA (%), $\beta_0$ was the intercept, $\beta_1$ was the linear regression coefficient, $\text{Destron}_j$ was the coefficient associated with the lean yield measured by Destron (%), and $\varepsilon_j$ was the residual error ~ N (0, σ2). The coefficient of determination ($R^2$) and p-value were used to evaluate the model. The statistical significance level was set at $\alpha < 0.05$. A scatter plot was used to visualize the relationship between the two variables.

The lean grade index was determined for the carcasses. Lean grade index (from 10 to 116 scores) is a combination of the hot carcass weight and the lean percentage, where carcasses were classified into higher (> 109 scores; carcasses between 57.7 to 64.2% of leanness and hot carcass weight ranging from 80 to 105 kg) and low lean grade indexes (< 109 scores). This was done using the measure of carcass leanness obtained from DEXA and Destron. The obtained classes from both methodologies were compared as well as used as labels for training the models.

A total of 238 images were selected based on complete data availability. Using an open-source pre-trained segmentation model (Ravi et al. 2024), the images were segmented to remove the background and maintain only the pigs (i.e., the region of interest) as suggested by Chollet et al. (2022) and Zheng et al. (2014). As a result, the images varied in size due to the segmentation process, and a padding technique was implemented by adding zeros (i.e., empty pixels) based on the largest image to ensure all images were the same size to train the models. The final images were 296 × 610 pixels and had one channel (i.e., black and white colour).

The image dataset was split into a training set, used to train the model, a validation set, for hyperparameter tuning and model evaluation during training, and a test set used to assess the model performance on unseen data. The split was done using the ratio of 70%, 15% and 15%, respectively, for the train, validation, and test sets. The split was stratified based on the distribution of the outcome variables.

Data augmentation (Fig 2.) was implemented in the training set as a strategy to increase the number of observations (from 166 to 1,162) available for model training, as suggested by Hodnett & Wiley (2018). The following augmentation procedures were implemented: A horizontal flip of the images at 180 degrees was applied. Shifting 1: shifted the image 50 pixels to the x-axis and 50 pixels to the y-axis. Shifting 2: shifted the image -80 pixels to the x-axis and -80 pixels to the y-axis. Blurring: A Gaussian blur with a kernel size of 1 × 15 pixels and a standard deviation of.5 for the blur intensity. Noise was added by sampling from a Gaussian distribution (mean = 0, standard deviation = 1) and scaling it by 0.80 to control its magnitude relative to the original images. After adding noise, pixel values were normalized back to the original range of 0 (i.e., fully black) to 1 (i.e., fully white).

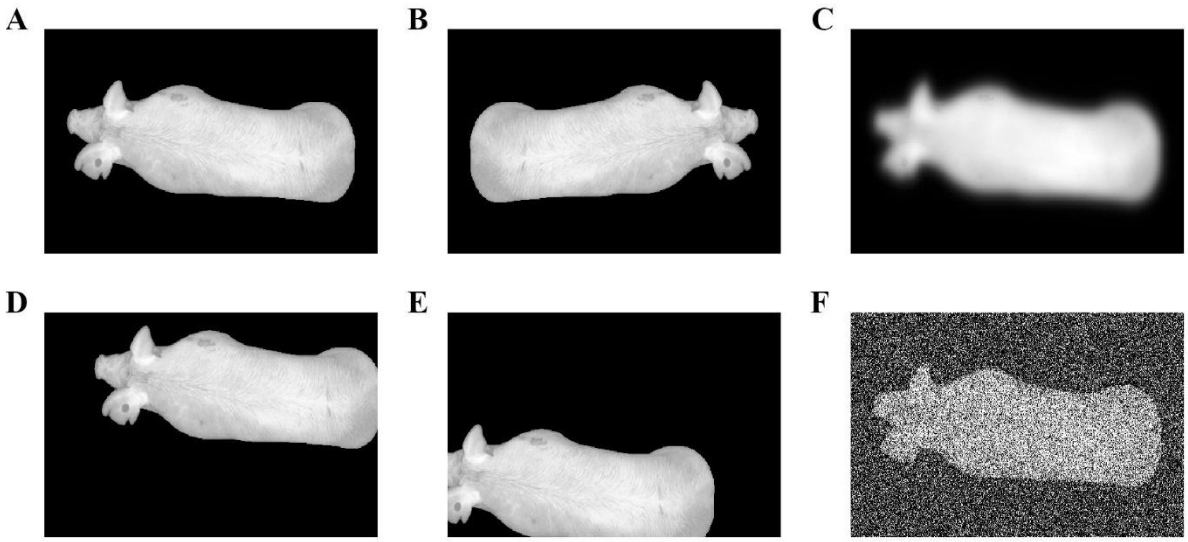

Figure 2. Various data augmentation strategies were implemented. A show the original image. B, the image is flipped over by 180 degrees horizontally. C, blur dimensions were added to the image. D, the image was shifted by 50 pixels. E, the image was shifted by -80 pixels. F, noise from a Gaussian distribution (mean = 0 and standard deviation = 1) was added to the image.

### 4.3.5. Model Training

Computer vision models based on convolutional neural networks were trained for regression (prediction of individual variables) and classification analysis (high or low lean grade index). The outcome variables fat depth, lean depth, total lean and total fat were used in the regression models. For the classification models, carcass classes determined based on either DEXA or Destron were used as outcome variables.

We used a Bayesian optimization procedure to select the hyperparameters for the models (Eriksson et al. 2021; Nguyen, 2019). The hyperparameters evaluated were as follows: the number of convolutional layers (1 to 4), the number of filters in the convolutional layers (32, 64 or 128), the kernel size (3, 5 or 7), the number of dense layers (1 to 3), and the number of units in the dense layers (64 or 128).

Early stop and learning rate reduction on the plateau were implemented to avoid overfitting and improve model learning, respectively. The maximum number of epochs during hyperparameter optimization was set to 250, but the training was stopped if the validation loss did not decrease after 15 epochs. The learning rate was decreased by a factor of 0.1 until a minimum rate of $1 \times 10^{-5}$ if the training loss did not decrease after 10 epochs.

Once the best hyperparameter combination was identified, the final models were also trained for a maximum epoch number of 250, along with early stop and learning rate reduction on the plateau. Final model training was repeated 5 times to account for the random initializations of weights at the beginning of the training process of the convolutional neural networks.

### 4.3.6 Model evaluation

For the regression analysis, models were evaluated based on the root mean squared error (RMSE), mean absolute error (MAE), and the out-of-sample coefficient of determination ($osR^2$) (Hawinkel et al. 2024). For RMSE and MAE, lower values are desired as they indicate how close the predicted value is to the actual value, while values close to 1 indicate a better model fit for $osR^2$. For the classification analysis, the models were evaluated using precision, accuracy, recall, and F1 score, which range from 0 to 1 and the closer to 1, the better the predictive performance of the model performance.

## 4.4 Results

### 4.4.1 Descriptive statistics of carcass traits and composition variables

The descriptive statistics of carcass traits and composition variables observed in the present study are shown in table Table 2. A wide range of carcass fatness traits were observed (fat depth and total fat percentage), which corresponded with a moderate variation (CV > 10%). In contrast, a low variation was detected (CV < 10%) for slaughter and carcass weights, lean depth and total lean percentage.

**Table 2. Descriptive statistics of carcass traits and composition variables (N=238).**

| Variable | Mean | STD | CV | Min | Median | Max |
|---|---|---|---|---|---|---|
| Slaughter weight, kg | 121.6 | 6.55 | 5.39 | 102.5 | 122.0 | 145.0 |
| Hot carcass weight, kg | 102.1 | 5.74 | 5.62 | 88.6 | 102.1 | 122.0 |
| Fat depth, mm* | 23.0 | 5.21 | 22.65 | 12.0 | 22.4 | 45.3 |
| Lean depth, mm* | 63.7 | 5.81 | 9.12 | 40.5 | 64.1 | 78.3 |
| Total lean, %[y] | 57.7 | 3.50 | 6.07 | 47.2 | 58.1 | 66.0 |
| Total fat, %[y] | 32.6 | 3.74 | 11.47 | 23.2 | 32.5 | 44.0 |

*Measured with Destron electronic probe
[y]Total lean muscle and fat measured by using DEXA

### 4.4.2 Contrasting DEXA and Destron based on lean yields and lean grade index

The scatter plot in Figure 3 shows the relationship between the DEXA and Destron lean yields. A moderate relationship ($p < 0.001$; $R^2 = 0.64$) was observed between lean yield estimates from DEXA (as standard method) and Destron, indicating that Destron was less accurate. Also, it was denoted in the distribution of the carcasses segregated in low and a high lean-grade index (Table 3), high percentage of animals were considered as high lean score based on Destron. It might indicate that Destron overestimates carcass leanness and could not be an alternative predictor to train the models.

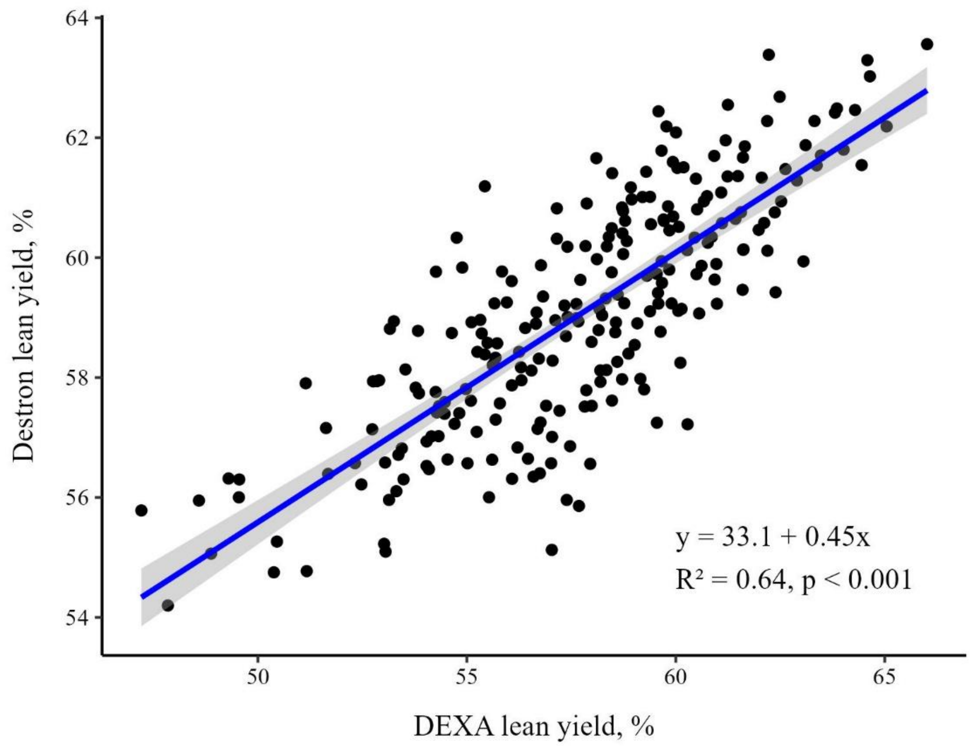


**Figure 3.** Contrasting lean yield obtained by DEXA vs. lean yield from Destron.

**Table 3. The distribution of the carcass classes as having a low and a high lean-grade index (N=238).**

| Carcass score* | N | % |
|---|---|---|
| DEXA | | |
| Low lean-grade index | 137 | 57.6 |
| High lean-grade index | 101 | 42.4 |
| Destron | | |
| Low lean-grade index | 103 | 43.3 |
| High lean-grade index | 135 | 56.7 |

*The percentage of higher and lower grade indexes obtained based on carcass leanness and hot carcass weight. Leanness was measured separately using DEXA and Destron methods.

### 4.4.3 Predicting individual traits

The CNN models trained for the regression analysis to predict individual carcass leanness- and fatness-related traits performed poorly (ooS$R^2$ < 0.30; Table 4). Although lean depth had moderate performance during the training stage (os$R^2$ = 0.62), validation and testing stages decreased its performance to low (os$R^2$ < 0.30).

**Table 4. The performance of convolutional neural network models in predicting fat and lean depth, and total lean and fat across the data set.**

| Variable | Data set | RMSE | MAE | os$R^2$ |
|---|---|---|---|---|
| Fat depth, mm* | Training | 5.02 ± 0.03 | 3.97 ± 0.04 | 0.12 ± 0.01 |
| | Validation | 4.67 ± 0.02 | 3.83 ± 0.03 | 0.01 ± 0.01 |
| | Testing | 4.93 ± 0.08 | 3.86 ± 0.11 | 0.04 ± 0.03 |
| Lean depth, mm* | Training | 3.34 ± 0.67 | 2.59 ± 0.52 | 0.62 ± 0.14 |
| | Validation | 6.22 ± 0.10 | 4.96 ± 0.16 | 0.27 ± 0.02 |
| | Testing | 5.77 ± 0.11 | 4.65 ± 0.19 | -0.14 ± 0.04 |
| Total fat, % | Training | 2.93 ± 0.47 | 2.33 ± 0.40 | 0.38 ± 0.19 |
| | Validation | 3.44 ± 0.05 | 2.72 ± 0.06 | -0.003 ± 0.03 |
| | Testing | 4.19 ± 0.23 | 3.19 ± 0.21 | -0.20 ± 0.13 |
| Total lean, % | Training | 3.16 ± 0.09 | 2.45 ± 0.06 | 0.15 ± 0.06 |
| | Validation | 2.95 ± 0.17 | 2.23 ± 0.03 | 0.28 ± 0.02 |
| | Testing | 3.55 ± 0.04 | 2.81 ± 0.03 | 0.09 ± 0.02 |

*Measured with the Destron electronic
yTotal lean muscle and fat measured by using DEXA
RMSE=root mean square error; MAE=mean absolute error; os$R^2$=out of sample coefficient of determination.

### 4.4.4 Classification analysis

The performance of the CNN models trained for the classification analysis to segregate between a high and a low lean-grade index (> 109 scores) using DEXA and Destron lean methods is shown in Table 5. DEXA had moderate performance, with an average F1 score of 0.73 in the testing set. However, the F1 score for the lean-grade index based on the Destron leanness assessment was low (F1 score = 0.38) in the testing set, showing that the model misclassified many images. In addition, overfitting was also observed when training the CNN model based on the Destron leanness assessment, as indicated by a large difference between the model performance in the training set compared to the validation and testing sets, despite the different strategies employed to avoid overfitting (Table 5).

**Table 5. Model performance in classifying carcasses according to lean grade index using two methods of lean determination**

| Variable | Set | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|
| DEXA lean-grade index | Training | 0.69 ± 0.07 | 0.67 ± 0.06 | 0.93 ± 0.05 | 0.78 ± 0.03 |
| | Validation | 0.63 ± 0.05 | 0.63 ± 0.06 | 0.86 ± 0.13 | 0.72 ± 0.02 |
| | Test | 0.63 ± 0.04 | 0.62 ± 0.04 | 0.90 ± 0.11 | 0.73 ± 0.02 |
| Destron lean-grade index | Training | 0.92 ± 0.01 | 0.99 ± 0.01 | 0.82 ± 0.01 | 0.89 ± 0.01 |
| | Validation | 0.64 ± 0.03 | 0.69 ± 0.08 | 0.30 ± 0.10 | 0.41 ± 0.11 |
| | Test | 0.52 ± 0.02 | 0.45 ± 0.04 | 0.32 ± 0.05 | 0.38 ± 0.05 |

From 10-116 scores; segregating higher lean grade indexes (>109 scores; carcasses between 57.7-64.2% of leanness & 80-105kg of Hot carcass weight).

## 4.5 Discussion

### 4.5.1 Prediction of individual traits

Fat depth exhibited an out-of-sample R-squared (osR2) value of 0.04, which is notably low, indicating limited predictive capacity. This poor predictive power can be attributed to the inherent variability in fat tissue deposition, which presents significant challenges in accurate measurement and consequently introduces noise into the data (Wood et al. 2008). In the context of prediction model development, the data utilized often comprises two types of variables: replicable variables that demonstrate a genuine relationship with the outcome (referred to as "signal"), and non-replicable variables that exhibit only an idiosyncratic relationship with the outcome (termed "noise") (Sanchez-Pinto et al. 2018). This distinction highlights the complexity involved in developing robust predictive models for fat depth assessment.

Lean depth showed a relatively large performance decline from training to validation/testing, with $osR^2$ dropping from 0.62 to -0.14. This substantial decrease indicated a clear pattern of overfitting, where the model has memorized the training data, including its noise, but fails to generalize effectively to new data in the test set (Hawkins, 2004). Furthermore, the model's predictive accuracy for total fat (%) and total lean (%) also showed a decline from training to testing, indicating overfitting and poor generalization. Overfitting can occur when a model is more complex than necessary for the data. For example, while a neural network can capture complex, non-linear relationships, if the data mostly follows a linear pattern, using such a model adds unnecessary complexity. This extra flexibility does not improve performance and can lead to poorer predictions compared to a simpler model (Hawkins, 2004). Nonetheless, CNNs are well-suited for image data because they capture spatial hierarchies and local features effectively. In our study, the observed overfitting indicates that further measures are needed, such as increasing the number of augmentation strategies as well as adding regularization layers (L1, L2, and dropout) to avoid overfitting while training the models and improving their capacity to generalize.

Fernandes et al. (2020) developed a computer vision system (CVS) to predict muscle depth, and backfat thickness measured by ultrasound (Aloka SSD 500, 3.5-MHz, 12-cm linear probe) using top-view 3D images (Microsoft Kinect V2) of finishing pigs. A total of 12,000 images from 557 finishing pigs were obtained. This approach was likely aimed at capturing a comprehensive data set for each animal, which could potentially improve the accuracy of models. Their deep learning model achieved $R^2$ values of 0.50 for muscle depth, and 0.45 for back fat. Using 3D data also allowed the extraction of cross-sectional areas and volumes and the evaluation of features such as the squareness of back muscles, which are key indicators of lean muscle mass. Other researchers also have employed non-invasive methods for predicting carcass traits and reported moderate to high predictions based on the coefficient of determination reported. Masoumi et al. (2021) reported moderate predictability for the lean and fat content ($R^2$ = 0.77 and 0.73, respectively) of digital imaging developed from full 3D models of half carcass sides of pigs. Furthermore, using the images obtained from a fully automated VCS2000 camera (eþv® Technology GmbH, Oranienburg, Germany), Lohumi et al. (2018) found predictions with moderate accuracy for lean meat yield ($R^2$ = 0.77) in commercial pork carcasses. The current study employed multispectral 2D images and a smaller dataset, which may have influenced model performance.

Improving prediction performance could also be achieved by including additional predictor variables. Engel et al. (2004) noted a difference in predicted lean meat percentage between gilts and castrates in Dutch animals, going as high as 4% among certain Spanish breeds. For lean pigs, this difference was up to 3% between sexes and 6.5% between breeds. Therefore, including variables that distinguish between groups could be an alternative to improve model predictive performance. For instance, Doeschl-Wilson et al. (2005) reported $R^2$ of 0.31 and 0.19 for fat and 0.04 and 0.18 for the prediction of lean on the foreloin and hind loin regions, respectively, using the adjusted data from both the carcass and VIA measurements, which were created by excluding growth patterns In the same study, the predictive power of the models was about 70% as strong as the adjusted R2 values when other sources of information, such as sex, BW, and BF were included in the model.

In addition, Alsahaf et al. (2019) developed a system that extracted morphometric features from images of moving pigs and used them to predict muscle scores between 1 and 5, with 1 indicating pigs without any visible muscling and 5 indicating extremely muscled pigs. The gradient-boosted classifier achieved a cross-validation average MAE of 0.65. Obtaining and adding such morphometric features could also be an alternative to improve model predictive performance in future studies.

### 4.5.2 Carcass lean grade index classification

On the other hand, models trained for classification analysis had an improved performance; particularly by using DEXA. Studies evaluating the robustness of classification algorithms have been identified. Pei et al. (2023) examined the robustness of machine learning algorithms to predict the characteristics of optical micrographs. They found that while the classification model achieved a 90.79% accuracy, the regression model obtained an $R^2$ of 0.21. Furthermore, in a comparative study of classification and regression algorithms for modelling student academic performance, Strecht et al. (2015) found that classification algorithms successfully identified useful patterns, while regression models failed to outperform a simple baseline. The classification model demonstrated greater robustness, with a lower standard deviation (0.17 compared to 0.20). In contrast, all regression algorithms produced an error of approximately 5, which was considered very high on the 0 to 20 scale used in the study

In the current study, the classification model demonstrated a moderate performance in classifying the carcasses on high and low lean-grade indexes determined by DEXA. The DEXA device can assess the entire body to capture detailed information about tissue distribution and density, leading to accurate estimations of body composition. This may be the reason the classification model predictions from DEXA measurements demonstrated better performance than the model predictions based on the Destron that measures backfat thickness and muscle depth readings at one location on the carcass using light reflectance technology and then calculates the leanness of the whole carcass (Kipper et al. 2019). The model based on Destron variables demonstrated some level of overfitting despite the regularization procedures implemented, as it was seen to fit the training set and had an F1 score of 0.89, but for the test set, the F1 score was 0.38.

The data size could explain the moderate performance in classifying for lean grade index by DEXA. Gygi et al. (2023) noted that increasing the training dataset size often enhances prediction accuracy, adding that diverse data helps models generalize better to less-represented scenarios. Furthermore, Chen et al. (2022) mentioned that limited data sets will cause the trained models to overfit, stating the importance of developing models that identify consistent relationships, which is more effectively accomplished by incorporating diverse populations into the training data. Also, Chen et al. (2022) revealed that overfitting in convolutional neural networks arises from excessively large models, which are influenced by the size and number of convolutional kernels, a component learned during training and responsible for detecting patterns such as edges or textures. Larger kernels capture more information but increase parameters, complexity, and processing time. Smaller kernels reduce the visual range but enhance speed. Since kernel number (i.e., filters) and size were optimized in our study, the size of the data set was likely one of the main factors explaining the observed model performances.

The models predicting the lean grade index class based on the DEXA leanness values had a better performance than using the Destron leanness values (F1 score; 0.73 vs 0.38). Destron leanness values are obtained by determining loin depth and fat depth at a single point on the carcass, specifically the loin, to determine its commercial value. However, studies have highlighted the limitations of this approach, as relying on one site for grading may not accurately represent leanness or fatness across the entire carcass (Pomar & Marcoux, 2003). The device operates on the principle that white fat reflects more light than darker lean tissue (Berg et al. 1999), which may explain the lower prediction error for fat compared to lean observed in our study. Limitations of this technology include operator variability, random measurement errors, and the assumption that a single carcass site provides a reliable representation of the whole (Dorleku et al. 2023). Additionally, pigs exhibit considerable variation in body and carcass composition, particularly in the subcutaneous fat layer (Scholz et al. 2015). Arkfeld et al. (2017) investigated the factors and production practices contributing to variation in pork composition and attributes. Their findings revealed that pigs and other factors accounted for the principal sum of variation in carcass composition traits, with 51.2% for fat depth, 60.5% for loin depth, and 39.4% for lean percent.

In contrast, DEXA provides instant whole-body composition results by utilizing device-generated signals that interact with body or carcass tissues at the atomic or molecular level. These interactions produce attenuated signals, which are quantitatively analyzed by the instrument. The processed signals are used to determine tissue depths, areas, volumes, or distributions of fat, muscle, and bone minerals (Scholz et al., 2015). Kipper et al. (2019) assessed equations for predicting dissected composition using DEXA measurements and found strong coefficients of determination, especially for fat and lean masses. However, they emphasized that, methodologically, the choice of image acquisition and analysis techniques should be guided by the specific characteristics of the item being evaluated, such as the region of interest (ROI) being analyzed and the configuration mode of the software (total body and small animal modes) evaluated because different settings and regions of interest affect the accuracy and precision of the measurements, given the variations observed in their study.

### 4.6 Conclusions

The present study evaluated the potential application of multispectral imaging technology in conjunction with convolutional neural networks to predict carcass lean and fat content in growing-finishing pigs. The regression CNN models performed poorly when predicting individual traits. However, a moderate performance was found when a classification CNN model was trained to segregate animals based on the lean-grade index obtained using the DEXA leanness. In addition, Destron was less accurate in determining carcass leanness than DEXA (golden standard), which might explain the poor performance of the classification CNN models in segregating animals based on the lean-grade index obtained using the Destron. Multispectral imaging technology could support farmers in marketing their hogs based on the best grid-grade, but a larger and more diverse data set is needed to improve the predictive ability of the models, particularly when predicting individual traits.

# CHAPTER 5: GENERAL DISCUSSION

Efforts have focused on developing precise, non-invasive techniques for estimating body composition to support "value-based" marketing systems (Cross & Whittaker, 1992).

Conventional methods such as real-time ultrasonography and DEXA show promise for applications on live animals and carcasses, respectively, for carcass evaluation (Cross & Whittaker, 1992; Gresham et al. 1992). However, there remains a demand for a rapid, accurate, and cost-effective method to estimate composition that aligns with market pricing protocols, which emphasize carcass lean content (Gresham et al. 1994). Non-invasive and non-destructive imaging technologies, such as 2D and 3D digital imaging, have been used to determine live weight, body condition, and livestock welfare (Kim et al. 2013). This study addresses a gap in the literature by focusing on the use of multispectral imaging for live animal assessment, specifically for the real-time prediction of carcass traits. Doeschl-Wilson et al. (2005) reported low to moderate accuracy in predicting fat and lean weights in pigs. In contrast, in this study, prediction performance was low when models relied on individual traits, which may be attributed to the limited sample size (Doeschl-Wilson et al., 2005). However, combining two traits, hot carcass weight and lean yield to create labels for a classification model significantly improved prediction accuracy and achieved moderate performance.

Furthermore, comparing the performance of Destron to the DEXA, which is the gold standard, Destron may not serve as an alternative for the evaluation of leanness in growing-finishing pigs. Therefore, our study has demonstrated that multispectral imaging technology could be used to classify pigs based on their lean yield.

# CHAPTER 6: GENERAL CONCLUSION AND FUTURE DIRECTIONS

## 6.1. Conclusions

Previous studies have shown that computer vision system models exhibit varying levels of performance, from low to high, in predicting the carcass composition of pigs (Alsahaf et al. 2019; Bhoj et al. 2022; Fernandes et al. 2020). Chapter 4 of this research validates these findings, where our models also demonstrated a poor performance level in predicting individual carcass traits and composition. In contrast, the models effectively classified carcasses into a high and low lean-grade index. We therefore accept our hypothesis that multispectral imaging can be used to classify in-vivo animals based on lean grade index, but not to predict individual carcass traits and carcass leanness levels in growing pigs. This technology has potential applications in classifying pigs into higher and lower lean grade indexes within the grid grade index (based on carcass weight and estimated percent lean yield by DEXA) for a pork carcass. However, discrepancies with other studies may arise from differences in methodologies, dataset sizes, and the types of images used, such as 2D versus 3D images.

## 6.2 Future Recommendations

In Canada, Destron is the standard instrument used in the industry to predict lean yield, which was approved and used since 1994; however, our findings showed that the instrument could not match the level of leanness from the pork carcass cutout. Consequently, due to constant advances in genetics, nutrition and management applied in swine production since 1994, future studies should be carried out to recalibrate the predicted lean yield from Destron with the level of leanness from the current pork carcass population.

Future directions should focus on increasing sample size and incorporating more measurements like phenotypic data, representing one mode of data that measures physical traits (e.g., body weight, sex class, feed efficiency, age, average daily gain), and genetic data, (e.g. breed type, sire and dam line information) which represents another mode of data involving the genetic makeup of animals to form multimodal data. In addition to advancing from the use of 2D images that are void of depth to 3D images, which provide depth information and allow for a complete representation of the object being analyzed, could allow capturing the spatial relationships between different parts of the object and improving the models' ability to extract and learn useful features that improve their generalization power.

## CHAPTER 7: LIST OF REFERENCES


Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. In *2017 International Conference on Engineering and Technology (ICET)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICEngTechnol.2017.8308186

Alsahaf, A., Azzopardi, G., Ducro, B., Hanenberg, E. H. a. T., Veerkamp, R., & Petkov, N. (2019). Estimation of muscle scores of live pigs using a Kinect camera. *IEEE Access*, *7*, 52238–52245. https://doi.org/10.1109/access.2019.2910986

AMSA/NPPC. (2001). Pork Composition and Quality Assessment Procedures. American Meat Science Association & National Pork Producers Council. Retrieved from https://meatscience.org

Arkfeld, E. K., Mohrhauser, D. A., King, D. A., Wheeler, T. L., Dilger, A. C., Shackelford, S. D., & Boler, D. D. (2017). Characterization of variability in pork carcass composition and primal quality. *Journal of Animal Science*, 95(2), 697-708. https://doi.org/10.2527/jas.2016.1097

Balas, C. (2009). Review of biomedical optical imaging—a powerful, non-invasive, non-ionizing technology for improving in vivo diagnosis. *Measurement Science & Technology*, *20*(10), 104020. https://doi.org/10.1088/0957-0233/20/10/104020

Barducci, R. S., Zhou, Z., Wormsbecher, L., Roehrig, C., Tulpan, D., & Bohrer, B. M. (2020). The relationship of pork carcass weight and leanness parameters in the Ontario commercial pork industry. *Translational Animal Science*, *4*(1), 331–338. https://doi.org/10.1093/tas/txz169

Beens, L., Rajendiran, E., Derakhshani, H., Mejicanos, G., Yang, C., Nyachoti, M., Lei, H., Verschuren, L., Bergsma, R., & Rodas-Gonzalez, A. (2024). Selection for feed efficiency improves production traits and digestibility and its relationship to the fecal microbiota in both Large White dam and sire lines. *Canadian Journal of Animal Science*, 104(4), 477-487. https://doi.org/10.1139/cjas-2024-0009

Benjamin, M., & Yik, S. (2020). Precision livestock farming and technology in swine welfare. In *CABI eBooks* (pp. 376–384). https://doi.org/10.1079/9781789245219.0376

Benjamin, M., & Yik, S. (2019). Precision livestock farming in swine welfare: a review for swine practitioners. *Animals*, 9, 133-153. https://doi.org/10.3390/ani9040133

Beermann, D.H., Hafs, H.D., & Zimbleman, R.G. (1994). Carcass composition of animals given partitioning agents. *Low-Fat Meats: Design Strategies and Human Implications*, 203-232. https://doi.org/10.1007/978-1-4613-1125-6_8

Berg, E., Grams, D. W., Miller, R. K., Wise, J. W., Forrest, J. C., & Savell, J. W. (1999). Using current on-line carcass evaluation parameters to estimate boneless and bone-in pork carcass yield as influenced by trim level. *Journal of Animal Science*, 77(8), 1977-1984. https://doi.org/10.2527/1999.7781977x

Bergamaschi, M., Tiezzi, F., Huang, Y. J., Gray, K. A., Schillebeeckx, C., McNulty, N. P., & Maltecca, C. (2020). Gut microbiome composition differences among breeds impact feed efficiency in swine. Microbiome, 8(1), 1-14. https://doi.org/10.1186/s40168-020-00888-9

Bernau, M., Kremer, P. V., Lauterbach, E., Tholen, E., Petersen, B., Pappenberger, E., & Scholz, A. M. (2015). Evaluation of carcass composition of intact boars using linear measurements from performance testing, dissection, dual-energy X-ray absorptiometry (DXA) and magnetic resonance imaging (MRI). *Meat Science*, *104*, 58–66. https://doi.org/10.1016/j.meatsci.2015.01.011

Bezsonov, O., Lebediev, O., Lebediev, V., Megel, Y., Prochukhan, D., & Rudenko, O. (2021). Breed Recognition and Estimation of Live Weight of Cattle Based on Methods of Machine Learning and Computer Vision. *East. -Eur. J. Enterp. Technol.*, 6, 64–74. Retrieved from https://www.eastern-european-journal-of-enterprise-technologies.com

Bhoj, S., Tarafdar, A., Chauhan, A., Singh, M., & Gaur, G. K. (2022). Image processing strategies for pig live weight measurement: Updates and challenges. *Computers and Electronics in Agriculture*, 193, 106693. https://doi.org/10.1016/j.compag.2022.106693

Bohrer, B. M., & Boler, D. D. (2017). Subjective pork quality evaluation may not be indicative of instrumental pork quality measurements on a study-to-study basis. *The Professional Animal Scientist*, 33(5), 530-540. https://doi.org/10.15232/pas.2017-01644

Bohrer, B. M., Dorleku, J. B., Campbell, C. P., Duarte, M. S., & Mandell, I. B. (2023). A comparison of carcass characteristics, carcass cutting yields, and meat quality of barrows and gilts. *Translational Animal Science*, 7(1), txad079. https://doi.org/10.1093/tas/txad079

Boler, D. (2017). Projecting changes in pig growth, pork quality, eating experience, and muscle physiology due to increasing live and carcass weights. National Pork Board Report #17-090. University of Illinois.https://porkcheckoff.org/wpcontent/uploads/2021/02/16-115-BOLER-ABS.pdf

Brøndum, J., Egebo, M., Agerskov, C., & Busk, H. (1998). On-line pork carcass grading with the Autofom ultrasound system. *Journal of Animal Science*, *76*(7), 1859-1868. https://doi.org/10.2527/1998.7671859x

Burson, D., and Berg, E. (2001). Procedures for estimating pork carcass composition. Pork quality facts. Des Moines (IA): National Pork Producers Council. Available from https://alec.unl.edu/documents/ cde/2017/livestock-management/2017-procedures-for-estimating-pork-carcass-composition-2006.

Busk, H., Olsen, E. V., & Brøndum, J. (1999). Determination of lean meat in pig carcasses with the Autofom classification system. *Meat Science*, *52*(3), 307–314. https://doi.org/10.1016/s0309-1740(99)00007-8

Calvini, R., Ulrici, A., & Amigo, J. M. (2020). Growing applications of hyperspectral and multispectral imaging. *Data handling in science and technology*, 32, 605-629. https://doi.org/10.1016/B978-0-12-816355-7.00032-9

Canada Gazette. (1986). Hog Carcass Grading Regulations. *Canada Gazette, Part II*, 120(14), 2990-3002. Retrieved from https://laws.justice.gc.ca/eng/regulations/SOR-92-541/PITIndex.html

CPI, C. P. I. (1995). Canadian pork buyers manual. Ontario, Canada: Canadian Pork International. Retrieved from https://canadapork.com/?industry_tool=canadian-pork-buyers-guide

Carabús, A., Gispert, M., & Font-i-Furnols, M. (2016). Imaging technologies to study the composition of live pigs: A review. *Spanish Journal of Agricultural Research*, *14*(3), e06R01. https://doi.org/10.5424/sjar/2016143-8439

Carabús, A., Sainz, R. D., Oltjen, J. W., Gispert, M., & Font-I-Furnols, M. (2015). Predicting fat, lean and the weights of primal cuts for growing pigs of different genotypes and sexes using computed tomography. *Journal of Animal Science, 93*(3), 1388-1397. https://doi.org/10.2527/jas.2014-8697

Cavanagh, C. R., Jonas, E., Hobbs, M., Thomson, P. C., Tammen, I., & Raadsma, H. W. (2010). Mapping Quantitative Trait Loci (QTL) in sheep. III. QTL for carcass composition traits derived from CT scans and aligned with a meta-assembly for sheep and cattle carcass QTL. *Genetics Selection Evolution*, 42, 1-14. https://doi.org/10.1186/1297-9686-42-36

CCAC. (2009). Canadian Council on Animal Care. Guide to the Care and Use of Experimental Animals. Vol. 1. 2nd ed. Ottawa (ON), Canada: Canadian Council on Animal Care. Retrieved from https://ccac.ca

Chao, K., Chen, Y.-R., Hruschka, W. R., & Park, B. (2001). Chicken heart disease characterization by multi-spectral imaging. *Applied Engineering in Agriculture, 17(1), 99-106.* https://doi.org/10.13031/2013.6147

Chen, H., Geng, L., Zhao, H., Zhao, C., & Liu, A. (2022). Image recognition algorithm based on artificial intelligence. Neural Computing and Applications, 34(9), 6661-6672. https://doi.org/10.1007/s00521-021-06200-6

Chmiel, M., Słowiński, M., & Dasiewicz, K. (2011). Application of computer vision systems for estimation of fat content in poultry meat. *Food Control*, 22(8), 1424-1427. https://doi.org/10.1016/j.foodcont.2011.03.022

Chollet, F. (2022). Keras: The Python Deep Learning Library. Astrophysics source code library, ascl-1806. Retrieved from https://www.manning.com

Coffey, V. C. (2012). Multispectral imaging moves into the mainstream. *Optics and Photonics News*, 23(4), 18-24. https://doi.org/10.1364/OPN.23.4.000018

Council, C. P. (1994). National Pork Carcass Cutout Project (1992): A joint initiative of Agriculture and Agri-Food Canada, the Canadian Meat Council and the Canadian Pork Council. Ottawa: Canadian Pork Council.

Council, C. P. (1994). National Pork Carcass Cutout Project (1992): A joint initiative of Agriculture and Agri-Food Canada, the Canadian Meat Council and the Canadian Pork Council. Ottawa: Canadian Pork Council. Retrieved from https://www.betterfarming.com

Craigie, C., Navajas, E. A., Purchas, R. W., Maltin, C. A., Bünger, L., Hoskin, S. O., Ross, D. W., Morris, S. T., & Roehe, R. (2012). A review of the development and use of video image analysis (VIA) for beef carcass evaluation as an alternative to the current EUROP system and other subjective systems. *Meat Science*, *92*(4), 307–318. https://doi.org/10.1016/j.meatsci.2012.05.028

Cross, H. R., & Whittaker, A. D. (1992). The role of instrument grading in a beef value-based marketing system. *Journal of Animal Science*, 70(3), 984-989. Retrieved from https://www.animalsciencepublications.org

Dalla Bona, M., Schiavon, S., Carraro, L., & Gallo, L. (2016). Growth performance, carcass traits and meat quality of growing pigs on different feeding regimes slaughtered at 145 kg BW. *Italian Journal of Animal Science*, 15(3), 419-427. https://doi.org/10.1080/1828051X.2016.1192960

Daumas, G. (1999). *Classification of pig carcasses: Principles, results, and prospects*. *Inrae Productions Animales*, 36(4), 35-42. Retrieved from https://www.inrae.fr

Delgado-Pando, G., Allen, P., Troy, D. J., & McDonnell, C. K. (2021). Objective carcass measurement technologies: Latest developments and future trends. *Trends in Food Science & Technology*, 111, 771-782. https://doi.org/10.1016/j.tifs.2020.12.016

Doeschl-Wilson, A., Green, D. M., Fisher, A., Carroll, S., Schofield, C. P., & Whittemore, C. T. (2005). The relationship between body dimensions of living pigs and their carcass composition. *Meat Science*, *70*(2), 229–240. https://doi.org/10.1016/j.meatsci.2005.01.010

Dorleku, J. B., Wormsbecher, L., Christensen, M., Campbell, C. P., Mandell, I. B., & Bohrer, B. M. (2023). Comparison of an advanced automated ultrasonic scanner (AutoFom III) and a handheld optical probe (Destron PG-100) to determine lean yield in pork carcasses. *Journal of Animal Science, 101, 1-13*. https://doi.org/10.1093/jas/skad058

Edwards, D. B., Tempelman, R. J., & Bates, R. O. (2006). Evaluation of Duroc- vs. Pietrain-sired pigs for growth and composition. *Journal of Animal Science, 84*(2), 266–275. https://doi.org/10.2527/2006.842266x

Elbert, K., Matthews, N., Wassmuth, R., & Tetens, J. (2020). Effects of sire line, birth weight and sex on growth performance and carcass traits of crossbred pigs under standardized environmental conditions. Archives Animal Breeding, 63(2), 367–376. https://doi.org/10.5194/AAB-63-367-2020

Elgendy, M. (2019). *Deep learning for vision systems*. Manning Publications Co. Retrieved from https://www.manning.com

Engel, B., Buist, W. G., i Furnols, M. F., & Lambooij, E. (2004). *Subpopulations and accuracy of prediction in pig carcass classification*. *Animal Science*, 78(1), 37-52. Retrieved from https://www.cambridge.org/core/journals/animal-science

Engel, B., Lambooij, E., Buist, W., & Vereijken, P. (2012). Lean meat prediction with HGP, CGM and CSB-Image-Meater, with prediction accuracy evaluated for different proportions of gilts, boars, and castrated boars in the pig population. *Meat Science*, *90*(2), 338–344. https://doi.org/10.1016/j.meatsci.2011.07.020

Eriksson, D., & Poloczek, M. (2021, March). Scalable constrained Bayesian optimization. In *International Conference on Artificial Intelligence and Statistics* (pp. 730-738). PMLR. https://doi.org/10.48550/arXiv.2002.08526

Fernandes, A. F. A., Dórea, J. R. R., & Rosa, G. J. D. M. (2020). Image analysis and computer vision applications in animal sciences: an overview. *Frontiers in Veterinary Science*, 7, 551269. https://doi.org/10.3389/fvets.2020.551269

Fernandes, A. F. A., Dórea, J. R. R., Valente, B. D., Fitzgerald, R. L., Herring, W. O., & Rosa, G. J. M. (2019). Comparison of data analytics strategies in computer vision systems to predict pig body composition traits from 3D images. *Journal of Animal Science, 98*(8), 1-9 https://doi.org/10.1093/jas/skaa250

FAO. 2006. http://www.fao.org/fileadmin/user_upload/esag/docs/Interim_report_AT2050web

Font-i-Furnols, M., Carabús, A., Pomar, C., & Gispert, M. (2014). Estimation of carcass composition and cut composition from computed tomography images of live growing pigs of different genotypes. *Animal*, *9*(1), 166–178. https://doi.org/10.1017/s1751731114002237

Font-i-Furnols, M., & Gispert, M. (2009). Comparison of different devices for predicting the lean meat percentage of pig carcasses. *Meat Science*, *83*(3), 443–446. https://doi.org/10.1016/j.meatsci.2009.06.018

Forrest, J. C. (2020). New techniques for estimation of carcass composition. In *Quality and grading of carcasses of meat animals* (pp. 157-171). CRC Press. Retrieved from https://www.crcpress.com

Fortin, A., Jones, S. D. M., & Haworth, C. R. (1984). Pork carcass grading: a comparison of the New Zealand Hennessy grading probe and the Danish Fat-O-Meater. *Meat Science*, 10(2), 131-144. Retrieved from https://www.journalofmeatscience.com

Fortin, A., Tong, A. K. W., Robertson, W. M., Zawadski, S., Landry, S. J., Robinson, D., Liu, T., & Mockford, R. (2003). A novel approach to grading pork carcasses: computer vision and ultrasound. *Meat Science*, *63*(4), 451–462. https://doi.org/10.1016/s0309-1740(02)001043

Fortin, A., Wood, J. D., & Whelehan, O. P. (1987). Breed and sex effects on the development and proportions of muscle, fat and bone in pigs. *The Journal of Agricultural Science*, *108*(1), 39-45. https://doi.org/10.1017/S0021859600064121

Fredeen, H. T., & Bowman, G. H. (1968). Backfat thickness and carcass weight as predictors of the yield of hams and loins of pig carcasses. *Canadian Journal of Animal Science*, *48*(2), 117-129. Retrieved from https://cdnsciencepub.com/journal/cjas

Fredeen, H. T., Doornenbal, H., Berg, R. T., & Bowland, J. P. (1964). Prediction of yield and value of hog carcasses. *Canadian Journal of Animal Science*, *44*(3), 334-346. Retrieved from https://cdnsciencepub.com/journal/cjas

Furnols, M. F., & Gispert, M. (2009). Comparison of different devices for predicting the lean meat percentage of pig carcasses. *Meat Science*, *83*(3), 443-446. https://doi.org/10.1016/j.meatsci.2009.06.002

Galanopoulos, K., Aggelopoulos, S., Kamenidou, I., & Mattas, K. (2006). Assessing the effects of managerial and production practices on the efficiency of commercial pig farming. *Agricultural systems*, *88*(2-3), 125-141 https://doi.org/10.1016/j.agsy.2005.03.002

Gjerlaug-Enger, E., Kongsro, J., Ødegård, J., Aass, L., & Vangen, O. (2012). Genetic parameters between slaughter pig efficiency and growth rate of different body tissues estimated by computed tomography in live boars of Landrace and Duroc. *Animal*, *6*(1), 9–18. https://doi.org/10.1017/s1751731111001455

Goenaga, P., Lloveras, M. R., & Améndola, C. (2008). Prediction of lean meat content in pork carcasses using the Hennessy Grading Probe and the Fat-O-Meater in Argentina. Meat Science, 79(3), 611-613. https://doi.org/10.1016/j.meatsci.2007.12.004

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Regularization for deep learning. *Deep learning*, 216-261. MIT Press. Retrieved from https://www.deeplearningbook.org

Gresham, J. D., McPeake, S. R., Bernard, J. K., & Henderson, H. H. (1992). Commercial adaptation of ultrasonography to predict pork carcass composition from live animal and carcass measurements. *Journal of Animal Science*, 70(3), 631-639. https://doi.org/10.2527/1992.703631x

Gresham, J. D., McPeake, S. R., Bernard, J. K., Riemann, M. J., Wyatt, R. W., & Henderson, H. H. (1994). Prediction of live and carcass characteristics of market hogs by use of a single longitudinal ultrasonic scan. *Journal of Animal Science*, 72(6), 1409-1416. https://doi.org/10.2527/1994.7261409x

Gygi, J. P., Kleinstein, S. H., & Guan, L. (2023). Predictive overfitting in immunological applications: Pitfalls and solutions. *Human Vaccines & Immunotherapeutics*, 19(2), 2251830. https://doi.org/10.1080/21645515.2023.2251830

Hawinkel, S., Waegeman, W., & Maere, S. (2024). Out-of-sample R²: Estimation and inference. *The American Statistician*, 78(1), 15-25. https://doi.org/10.1080/00031305.2024.2251830

Hawkins, D. M. (2004). The problem of overfitting. *Journal of Chemical Information and Computer Sciences*, 44(1), 1-12. https://doi.org/10.1021/ci0342472

Hodnett, M., & Wiley, J. F. (2018). R Deep Learning Essentials: A step-by-step guide to building deep learning models using TensorFlow, Keras, and MXNet. Packt Publishing Ltd. Retrieved from https://www.packtpub.com

Hoque, M. A., Suzuki, K., Kadowaki, H., Shibata, T., & Oikawa, T. (2007). Genetic parameters for feed efficiency traits and their relationships with growth and carcass traits in Duroc pigs. Journal of Animal Breeding and Genetics, 124(3), 108–116. https://doi.org/10.1111/J.1439-0388.2007.00650.X

Hulsegge, I., Merkus, H., & van der Wal, P. (2010). Accuracy of different methods for predicting pork carcass composition. Journal of Animal Science, 88(8), 2685-2692. https://doi.org/10.2527/jas.2010-2515

Irshad, A., Kandeepan, G., Kumar, S., Kumar, A., Kumar, A., MR, V., & Shukla, V. (2013). Factors Influencing Carcass Composition of Livestock: a Review. *Journal of Animal Production Advances*, *3*(5), 177. https://doi.org/10.5455/japa.20130531093231

Jackson, A. R., Powell, S., Johnston, S. L., Matthews, J. O., Bidner, T. D., Valdez, F. R., & Southern, L. L. (2009). The effect of chromium as chromium propionate on growth performance, carcass traits, meat quality, and the fatty acid profile of fat from pigs fed no supplemented dietary fat, choice white grease, or tallow1. *Journal of Animal Science*, *87*(12), 4032–4041. https://doi.org/10.2527/jas.2009-2168

Jeon, R., Rykaczewski, C., Williams, T., Harrington, W., Kinder, J. E., & Trotter, M. (2025). Monitoring Pig Structural Soundness and Body Weight in Pork Production Systems Using Computer Vision Approaches. *Animals*, 15(5), 635. https://doi.org/10.3390/ani15050635

Johnson, R. K., Berg, E., Goodwin, R. N., Mabry, J. W., Miller, R. K., Robison, O. W., Sellers, H. J., & Tokach, M. D. (2004). Evaluation of procedures to predict fat-free lean in swine carcasses. *Journal of Animal Science*, *82*(8),2428–2441. https://doi.org/10.2527/2004.8282428x

Kipper, M. M. M. M., Marcoux, M., Andretta, I., & Pomar, C. (2019). Assessing the accuracy of measurements obtained by dual-energy X-ray absorptiometry on pig carcasses and primal cuts. *Meat Science*, 148, 79-87. https://doi.org/10.1016/j.meatsci.2018.10.005

Kim, B. G., Lindemann, M. D., & Cromwell, G. L. (2010). Effects of dietary chromium (III) picolinate on growth performance, respiratory rate, plasma variables, and carcass traits of pigs fed High-Fat diets. *Biological Trace Element Research*, *133*(2), 181–196. https://doi.org/10.1007/s12011-009-8417-7

Kim, J., Yu, S., Kim, I. J., & Lee, S. (2013). 3D multi-spectrum sensor system with face recognition. *Sensors*, 13(10), 12804-12829. https://doi.org/10.3390/s131012804

Klukkert, M., Wu, J. X., Rantanen, J., Rehder, S., Carstensen, J. M., Rades, T., & Leopold, C. S. (2016). Rapid assessment of tablet film coating quality by multispectral UV imaging. *AAPS PharmSciTech*, 17, 958-967. https://doi.org/10.1016/j.ejps.2015.12.004

Knecht, D., Duziński, K., & Lisiak, D. (2016). Accuracy of estimating the technological and economic value of pig carcass primal cuts with an optical-needle device. *Canadian Journal of Animal Science*, *96*(1), 37–44. https://doi.org/10.1139/cjas-2015-0048

Kremer, P. V., Fernández-Fígares, I., Förster, M., & Scholz, A. M. (2012). In vivo body composition in autochthonous and conventional pig breeding groups by dual-energy X-ray absorptiometry and magnetic resonance imaging under special consideration of Cerdo Ibérico. *Animal*, *6*(12), 2041–2047. https://doi.org/10.1017/s1751731112001267

Kremer, P. V., Förster, M., & Scholz, A. M. (2013). Use of magnetic resonance imaging to predict the body composition of pigs in vivo. *Animal*, *7*(6), 879–884. https://doi.org/10.1017/s1751731112002340

Lawrie, R. A., & Ledward, D. A. (1998). The conversion of muscle to meat. In *Lawrie's meat science* (6th ed., pp. 6). Woodhead Publishing. ISBN: 978-1-84569-159-2. https://doi.org/10.1016/j.meatsci.2007.03.005

Latorre, M. A., Iguácel, F., Sanjoaquín, L., & Revilla, R. (2009). Effect of sire breed on carcass characteristics and meat and fat quality of heavy pigs reared outdoor and intended for dry-cured meat production. *animal*, 3(3), 461-467. https://doi.org/10.1017/S1751731108003595

Lebret, B., et al. (2008). Effects of feeding and rearing systems on growth, carcass traits and meat quality in pigs. *Journal of Animal Science*, 86(4), 1012-1022. https://doi.org/10.2527/jas.2007-0676

Lei, X., Qin, J., Yao, T., Tang, X., Cui, D., Chen, L., Rao, L., Xiao, S., & Zhang, Z. (2022). Effects of carcass weight, sex and genotype on meat cuts and carcass traits in pigs. Research Square. https://doi.org/10.21203/rs.3.rs-27802/v1

Lohumi, S., Wakholi, C., Baek, J. H., Kim, B. D., Kang, S. J., Kim, H. S., Yun, Y. K., Lee, W. Y., Yoon, S. H., & Cho, B.-K. (2018). Nondestructive estimation of lean meat yield of South Korean pig carcasses using machine vision technique. *Korean Journal for Food Science of Animal Resources*, 38(5), 1109. Retrieved from https://www.kosfaj.org

Luiting, P., Kolstad, K., Enting, H., & Vangen, O. (1995). Pig breed comparison for body composition at maintenance: analysis of computerized tomography data by mixture distributions. *Livestock Production Science*, *43*(3), 225–234. https://doi.org/10.1016/0301-6226(95)00044-l

Magnusson, M., Carlsson, G. A., Sandborg, M., Tedgren, C., & Malusek, A. (2011). Optimal selection of base materials for accurate dual-energy computed tomography: Comparison between the Alvarez–Macovski method and DIRA. Journal of Medical Imaging and Radiation Sciences, 42(4), 309-318. https://doi.org/10.1016/j.jmirs.2011.09.002

Malgwi, I. H., Giannuzzi, D., Gallo, L., Halas, V., Carnier, P., & Schiavon, S. (2022). Influence of slaughter weight and sex on growth performance, carcass characteristics and Ham traits of Heavy pigs fed ad-libitum. *Animals*, 12(2), 215. https://doi.org/10.3390/ani12020215

Manchisi, K., et al. (2010). Comparison of carcass characteristics, carcass cutting yields, and meat quality of barrows and gilts. Translational Animal Science, 7(1), txad079. https://doi.org/10.1093/tas/txad079

Marcoux, M., Bernier, J., & Pomar, C. (2003). Estimation of Canadian and European lean yields and composition of pig carcasses by dual-energy X-ray absorptiometry. *Meat Science*, *63*(3), 359–365. https://doi.org/10.1016/s0309-1740(02)00094-3

Masoumi, M., Marcoux, M., Maignel, L., & Pomar, C. (2021). Weight prediction of pork cuts and tissue composition using spectral graph wavelet. *Journal of Food Engineering*, 299, 110501. https://doi.org/10.1016/j.jfoodeng.2021.110501

Miller, G. A., Hyslop, J. J., Barclay, D., Edwards, A., Thomson, W., & Duthie, C. A. (2019). Using 3D imaging and machine learning to predict live weight and carcass characteristics of live finishing beef cattle. *Frontiers in Sustainable Food Systems*, 3: 1-9. https://doi.org/10.3389/fsufs.2019.00030

Mitchell, A. D., Scholz, A., & Pursel, V. (2004). Prediction of the in vivo body composition of pigs based on cross-sectional region analysis of dual-energy X-ray absorptiometry (DXA) scans. *Arch Tierz, Dummerstorf*, 45, 535-545. https://doi.org/10.5194/aab-45-535-2002

Mitchell, A. D., Scholz, A. M., Pursel, V. G., & Evock-Clover, C. M. (1998). Composition analysis of pork carcasses by dual-energy x-ray absorptiometry. *Journal of Animal Science*, *76*(8), 2104-2114. https://doi.org/10.2527/1998.7682104x

Mitchell, S. C., Lelieveldt, B. P., Van Der Geest, R. J., Bosch, H. G., Reiver, J. H. C., & Sonka, M. (1996). Multistage hybrid active appearance model matching: segmentation of left and right ventricles in cardiac MR images. *IEEE Transactions on Medical Imaging*, 20(5), 415-423. https://doi.org/10.1109/42.925294

Mohammadi, V., Sodjinou, S. G., Katakpe, K. K., Rossé, M., & Gouton, P. (2022). Development of a Multi-spectral Camera for Computer vision applications. *Journal of WSCG*, 30(1-2). https://doi.org/10.24132/CSRN.3201.4

Mooney, K. W., & Cromwell, G. L. (1995). Effects of dietary chromium picolinate supplementation on growth, carcass characteristics, and accretion rates of carcass tissues in growing-finishing swine. *Journal of Animal Science*, 73(11), 3351-3357. https://doi.org/10.2527/1995.73113351x

Mörlein, D., Rosner, F., Brand, S., Jenderka, K., & Wicke, M. (2005). Non-destructive estimation of the intramuscular fat content of the longissimus muscle of pigs by means of spectral analysis of ultrasound echo signals. *Meat Science*, *69*(2), 187–199. https://doi.org/10.1016/j.meatsci.2004.06.011

National Research Council. (1988). Live animal and carcass composition measurement. In *Designing foods: Animal product options in the marketplace*. National Academies Press (US). https://doi.org/10.17226/1036

Newcom, D. W., Baas, T. J., & Lampe, J. F. (2002). Prediction of intramuscular fat percentage in live swine using real-time ultrasound. *Journal of Animal Science*, 80(12), 3046-3052. https://doi.org/10.2527/2002.80123046x

Newman, D. J. (2009). *An industry assessment of pork carcass composition*. North Dakota State University. Retrieved from https://www.ndsu.edu

Nguyen, V. (2019, June). Bayesian optimization for accelerating hyper-parameter tuning. In *2019* IEEE Second International Conference on Artificial Intelligence and Knowledge Engineering (AIKE*)* (pp. 302-305). IEEE. https://doi.org/10.1109/AIKE.2019.00056

NPPC. (2000). *Pork composition and quality assessment procedures*. National Pork Producers Council composition and quality assessment procedures manual. Retrieved from https://www.porkgateway.org

NPPC. (1991). *Procedures to Evaluate Market Hogs* (3rd ed.). National Pork Producers Council, Des Moines, IA. Retrieved from https://nppc.org

NRC. (1999). Nutrient Requirements of Swine: 10th Revised Edition. Nutrient Requirements of Swine. https://doi.org/10.17226/6016

Official United States standards for grades of slaughter swine. (1985). In USDA, Agricultural Marketing Service. Retrieved from https://www.ams.usda.gov/grades-standards/slaughter-swine-grades-and-standards

Olsen, E. V., Christensen, L. B., & Nielsen, D. B. (2017). A review of computed tomography and manual dissection for calibration of devices for pig carcass classification-Evaluation of uncertainty. *Meat Science*, 123, 35-44. https://doi.org/10.1016/j.meatsci.2016.09.001

O'quinn, P. R., Nelssen, J. L., Goodband, R. D., Unruh, J. A., Woodworth, J. C., Smith, J. S., & Tokach, M. D. (1998). Effects of modified tall oil versus a commercial source of conjugated linoleic acid and increasing levels of modified tall oil on growth performance and carcass characteristics of growing-finishing pigs. *Journal of Animal Science*, *78*(9), 2359-2368.

O'Shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. *Artificial Neural Networks*. https://doi.org/10.48550/arXiv.1511.08458

Pan, X., Zhu, J., Tai, W., & Fu, Y. (2021). An automated method to quantify the composition of live pigs based on computed tomography segmentation using deep neural networks.

*Computers and Electronics in Agriculture*, *183*, 105987. https://doi.org/10.1016/j.compag.2021.105987

Park, B., Kise, M., Lawrence, K. C., Windham, W. R., Smith, D. P., & Thai, C. N. (2007). Real-time multispectral imaging system for online poultry fecal inspection using unified modelling language. *Sensing and Instrumentation for Food Quality and Safety*, 1, 45-54. https://doi.org/10.1007/s11694-007-9007-5

Patience, J. F., Rossoni-Serão, M. C., & Gutiérrez, N. A. (2015). A review of feed efficiency in swine: Biology and application. *Journal of Animal Science and Biotechnology*, 6(1), 1–9. https://doi.org/10.1186/S40104-015-0031-2/TABLES/4

Pei, X., Hong Zhao, Y., Chen, L., Guo, Q., Duan, Z., Pan, Y., & Hou, H. (2023). Robustness of machine learning colour, size change, normalization, and image enhancement on micrograph datasets with large sample differences. *Materials & Design*, 232, 112086. https://doi.org/10.1016/j.matdes.2023.112086

Pomar, C., Marcoux, M., Gispert, M., Font-i-Furnols, M., & Daumas, G. (2009). Determining the lean content of pork carcasses. In *Improving the sensory and nutritional quality of fresh meat* (pp. 493-518). Retrieved from https://www.woodheadpublishing.com

Pomar, C., & Marcoux, M. (2003). Comparing the Canadian pork lean yields and grading indexes predicted from grading methods based on Destron and Hennessy probe measurements. *Canadian Journal of Animal Science*, 83(3), 451-458. https://doi.org/10.4141/A02-107

Pomar, C., & Marcoux, M. (2005). The accuracy of measuring backfat and loin muscle thicknesses on pork carcasses by the Hennessy HGP2, Destron PG-100, CGM and ultrasound CVT grading probes. *Canadian Journal of Animal Science*, *85*(4), 481–492. https://doi.org/10.4141/a05-041

Price, M. A. (2020). Development of carcass grading and classification systems. In *Quality and grading of carcasses of meat animals* (pp. 173-199). CRC Press. Retrieved from https://www.crcpress.com

Ravi, N., Gabeur, V., Hu, Y.-T., Hu, R., Ryali, C., Ma, T., Khedr, H., Rädle, R., Rolland, C., Gustafson, L., Mintun, E., Pan, J., Alwala, K. V., Carion, N., Wu, C.-Y., Girshick, R., Dollár, P., & Feichtenhofer, C. (2024). Sam 2: Segment anything in images and videos. *arXiv:2408.00714*. https://doi.org/10.48550/arXiv.2408.00714

R Core Team. (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing. Available at https://www.R-project.org/.

Rehfeldt, C., Te Pas, M. F. W., Wimmers, K., Brameld, J. M., Nissen, P. M., Berri, C., Valente, L. M. P., Power, D. M., Picard, B., Stickland, N. C., & Oksbjerg, N. (2011). Advances in research on the prenatal development of skeletal muscle in animals in relation to the quality of muscle-based food. I. Regulation of myogenesis and environmental impact. *Animal*, 5(5), 703–717. https://doi.org/10.1017/S1751731110002450

Saikia, A., Mejicanos, G., Rothy, J., Rajendiran, E., Yang, C., Nyachoti, M., Lei, H., Bergsma, R., Wu, Y., Jin, S., & Rodas-Gonzalez, A. (2024). Pork carcass composition, meat and belly qualities as influenced by feed efficiency selection in replacement boars from Large White sire and dam lines. *Meat Science*, 210, 109423. https://doi.org/10.1016/j.meatsci.2023.109423

Sakamoto, L. S., Mercadante, M. E. Z., Bonilha, S. F. M., Branco, R. H., Bonilha, E. F. M., & Magnani, E. (2014). Prediction of retail beef yield and fat content from live animal and carcass measurements in Nellore cattle. *Journal of Animal Science*, 92(11), 5230-5238. https://doi.org/10.2527/jas.2012-6065

Sanchez-Pinto, L. N., Venable, L. R., Fahrenbach, J., & Churpek, M. M. (2018). Comparison of variable selection methods for clinical predictive modelling. *International Journal of Medical Informatics*, 116, 10-17. https://doi.org/10.1016/j.ijmedinf.2018.05.006

Sather, A. P., Jones, S. D. M., Schaefer, A. L., Colyn, J., & Robertson, W. M. (1997). Feedlot performance, carcass composition and meat quality of free-range reared pigs. *Canadian Journal of Animal Science*, *77*(2), 225–232. https://doi.org/10.4141/a96-093

Schaefer, A. L., Ominski, K., Thompson, S., Crow, G., Bench, C., Colyn, J., Rodas-Gonzalez, A., Maharjan, D., Bollum, R., Cook, N. J., & Basarab, J. (2018). Energy utilization in cattle with steady state and non-steady state methods: The importance of thermal neutrality. *Heliyon*, 4, e00843. https://doi.org/10.1016/j.heliyon.2018.e00843

Schinckel, A. P., & Einstein, M. E. (1995). *Concepts of pig growth and composition*. Purdue Swine Day, 118. Retrieved from https://www.ansc.purdue.edu

Schinckel, A. P., Einstein, M. E., Jungst, S., Matthews, J. O., Fields, B., Booher, C., Dreadin, T., Fralick, C., Tabor, S., Sosnicki, A., & Wilson, E. (2012). The impact of feeding diets of high or low energy concentration on carcass measurements and the weight of primal and subprimal lean cuts. *Asian-Australasian Journal of Animal Sciences*, 25(4), 531. https://doi.org/10.5713/ajas.2012.12345

Scholz, A. M., Bünger, L., Kongsro, J., Baulain, U., & Mitchell, A. D. (2015). Non-invasive methods for the determination of body and carcass composition in livestock: dual-energy X-ray absorptiometry, computed tomography, magnetic resonance imaging and ultrasound: invited review. *Animal*, *9*(7), 1250–1264. https://doi.org/10.1017/s1751731115000336

Scholz, A. M., Nüske, S., & Förster, M. (2003). Body composition and bone mineralization measurement in calves of different genetic origin by using dual-energy X-ray absorptiometry. *Acta Diabetologica*, *40*(0), s91–s94. https://doi.org/10.1007/s00592-003-0037-7

Shurson, J., Whitney, M. H., Johnston, L., Burkey, T., & Frank, J. (2016). *Nutrition Guide*. Retrieved from https://www.umn.edu

Smeesters, L., Verbaenen, J., Schifano, L., Vervaeke, M., Thienpont, H., Teti, G., Forconi, A., & Lulli, F. (2023). Wide-Field-of-View multispectral camera design for continuous turfgrass monitoring. *Sensors*, 23(5), 2470. https://doi.org/10.3390/s23052470

Smit, M. N., Seneviratne, R. W., Young, M. J., Lanz, G., Zijlstra, R. T., & Beltranena, E. (2014). Feeding increasing inclusions of canola meal with distillers dried grains and solubles to growing-finishing barrows and gilts. *Animal Feed Science and Technology*, *189*, 107–116. https://doi.org/10.1016/j.anifeedsci.2013.12.012

Soladoye, O. P., Campos, Ó. L., Aalhus, J. L., Gariépy, C., Shand, P., & Juárez, M. (2016). Accuracy of dual-energy X-ray absorptiometry (DXA) in assessing carcass composition from different pig populations. *Meat Science*, 121, 310-316. https://doi.org/10.1016/j.meatsci.2016.06.001

Sosnicki, A., & Knap, P. W. (2024). Pig carcass composition and meat quality as delineated by breeding and genetics. In *Elsevier eBooks* (pp. 495–506). https://doi.org/10.1016/b978-0-323-85125-1.00088-0

Strecht, P., Cruz, L., Soares, C., Mendes-Moreira, J., & Abreu, R. (2015). *A Comparative Study of Classification and Regression Algorithms for Modelling Students' Academic Performance*. International Educational Data Mining Society. Retrieved from https://www.educationaldatamining.org

Sun, D. (Ed.). (2007). Computer vision technology for food quality evaluation (1st ed.). Elsevier Science & Technology. Retrieved from https://www.elsevier.com

Sun, D. W. (Ed.). (2017). Computer vision technology for food quality evaluation (2nd ed.). Academic Press. Retrieved from https://www.elsevier.com

Swatland, H. J., Ananthanarayanan, S. P., & Goldenberg, A. A. (1994). A Review of Probes and Robots: Implementing New Technologies in Meat Evaluation. *Journal of Meat Science*, 72, 1475-1486. Retrieved from https://www.journalofmeatscience.com

Swennen, Q., Janssens, G., Geers, R., Decuypere, E., & Buyse, J. (2004). Validation of dual-energy x-ray absorptiometry for determining in vivo body composition of chickens. *Poultry Science*, *83*(8), 1348–1357. https://doi.org/10.1093/ps/83.8.1348

Szeliski, R. (2011). Computer Vision. In *Texts in computer science*. https://doi.org/10.1007/978-1-84882-935-0

Taylor, W. E., Humphrey, D. C., Peyer, B. D., Cassady, C. J., Lonergan, S. M. & Stalder, K. J., (2023) "Thermal Imaging Efficacy in Predicting Trim Loss from Cull Sow Carcasses", *Meat and Muscle Biology* 7(1): 16758, 1-10. doi: https://doi.org/10.22175/mmb.16758

Torres, G. F., & Kämäräinen, J. (2023). Depth-aware image compositing model for parallax camera motion blur. In Scandinavian Conference on Image Analysis (pp. 279-296). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-31435-3_19

Van Der Peet-Schwering, C. M. C., Verschuren, L. M. G., Bergsma, R., Hedemann, M. S., Binnendijk, G. P., & Jansman, A. J. M. (2021). The effects of birth weight and estimated breeding value for protein deposition on nitrogen efficiency in growing pigs. Journal of Animal Science, 99(6), 1–13. https://doi.org/10.1093/JAS/SKAB101

Van Milgen, J., & Dourmad, J. Y. (2015). Concept and application of ideal protein for pigs. *Journal of Animal Science and Biotechnology*, *6*(1), 15. https://doi.org/10.1186/s40104-015-0016-1

Vollmer, M. (2022). Infrared cameras as smartphone accessory: Qualitative visualization or quantitative measurement? In *Thermal Cameras in Science Education* (pp. 129-145). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-97851-3_8

Wang, M. Q., & Xu, Z. R. (2004). Effect of chromium nanoparticle on growth performance, carcass characteristics, pork quality and tissue chromium in finishing pigs. *Asian-Australasian Journal of Animal Sciences*, 17(8), 1118-1122. https://doi.org/10.5713/ajas.2004.1118

Wells, J. C. K. (2009). The limitations of DXA for body composition assessment. *Endocrine Abstracts*, 19, S78. https://doi.org/10.1530/endoabs.19.S78

Wood, J. D., Richardson, R. I., Nute, G. R., Fisher, A. V., Campo, M. M., Kasapidou, E., Sheard, P. R., & Enser, M. (2008). Fat deposition, fatty acid composition, and meat quality: A review. *Meat Science*, 78(4), 343–358. https://doi.org/10.1016/j.meatsci.2007.07.019

Wu, J. X., Rehder, S., van den Berg, F., Amigo, J. M., Carstensen, J. M., Rades, T., Leopold, C. S., & Rantanen, J. (2014). Chemical imaging and solid-state analysis at compact surfaces using UV imaging. *International Journal of Pharmaceutics*, 477(1-2), 527-535. https://doi.org/10.1016/j.ijpharm.2014.10.001

Zhao, Y., Ramirez, B. C., Siegford, J. M., Gan, H., Wang-Li, L., Berckmans, D., & Burns, R. T. (2024). Field Implementation of Precision Livestock Farming: Selected Proceedings from the 2nd US Precision Livestock Farming Conference. *Animals*, 14(7), 1128. https://doi.org/10.3390/ani14071128

Zheng, S., Cheng, M. M., Warrell, J., Sturgess, P., Vineet, V., Rother, C., & Torr, P. H. (2014). Dense semantic image segmentation with objects and attributes. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3214-3221). https://doi.org/10.1109/CVPR.2014.410.

Zhou, Z. Y., & Bohrer, B. M. (2019). Defining pig sort loss with a simulation of various marketing options of pigs with the assumption that marketing cuts improve variation in carcass weight and leanness. *Canadian Journal of Animal Science*, 99(3), 542-552. https://doi.org/10.1139/cjas-2019-0052