UNIVERSIDADE FEDERAL DE VIÇOSA

A preliminary comparison using 2D and 3D images to predict hot carcass weight and saleable meat yield in pigs

Isabelle Pinheiro Siqueira
Magister Scientiae

VIÇOSA - MINAS GERAIS
2025

ISABELLE PINHEIRO SIQUEIRA

A preliminary comparison using 2D and 3D images to predict hot carcass weight and saleable meat yield in pigs

Dissertation submitted to the Animal Science Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Magister Scientiae*.

Adviser: Mario Luiz Chizzotti

Co-adviser: Erica Beatriz Schultz

VIÇOSA - MINAS GERAIS
2025

Ficha catalográfica elaborada pela Biblioteca Central da Universidade Federal de Viçosa - Campus Viçosa

T

S618p
2025

Siqueira, Isabelle Pinheiro, 1998-
A preliminary comparison using 2D and 3D images to predict hot carcass weight and saleable meat yield in pigs / Isabelle Pinheiro Siqueira. – Viçosa, MG, 2025.
1 dissertação eletrônica (24 f.): il. (algumas color.).

Orientador: Mário Luiz Chizzotti.
Dissertação (mestrado) - Universidade Federal de Viçosa, Departamento de Zootecnia, 2025.
Referências bibliográficas: f. 22-24.
DOI: https://doi.org/10.47328/ufvbbt.2025.492
Modo de acesso: World Wide Web.

1. Suínos - Carcaças - Medição. 2. Suínos - Registros de desempenho. I. Chizzotti, Mário Luiz, 1980-. II. Universidade Federal de Viçosa. Departamento de Zootecnia. Programa de Pós-Graduação em Zootecnia. III. Título.

CDD 22. ed. 636.40883

Bibliotecário(a) responsável: Euzébio Luiz Pinto CRB-6/3317

ISABELLE PINHEIRO SIQUEIRA

A preliminary comparison using 2D and 3D images to predict hot carcass weight and saleable meat yield in pigs

Dissertation submitted to the Animal Science Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Magister Scientiae*.

APPROVED: June 16, 2025.

Assent:

Isabelle Pinheiro Siqueira
Author

Mario Luiz Chizzotti
Adviser

ACKNOWLEDGMENTS

Agradeço a Deus por ter guiado meus passos e me sustentado até aqui.

À minha mãe, Denise Pinheiro, por me dar forças, impulso, carinho e sempre me mostrar que tudo tem um tempo certo.

Ao meu pai, Alexandre Roberto da Silva, por ser o maior fã que eu poderia, sempre sorrir minhas conquistas e me abraçar nas minhas derrotas.

Aos meus tios, Ligia Pinheiro Carvalho e Célio da Silva Carvalho, por me escutarem, me abraçarem, sempre torcerem e darem tudo e mais um pouco para que eu sempre seja feliz.

Aos meus irmãos, Emanuelle Pinheiro Silva, João Pedra da Silva e Leonardo Pinheiro Siqueira, por dividirem sonhos, conquistas, simples risadas e serem meu lar.

Ao profº Dr. Mário Luiz Chizzotti pela orientação, paciência, trocas de conhecimento e apoio ao longo do meu caminho dentro da pós-graduação na zootecnia. Foi um prazer conviver com uma mente brilhante.

À profª Dr. Érica Beatriz Schultz minha coorientadora durante esta jornada, que além de guia acadêmica e mentora das estatísticas se tornou uma grande amiga nos momentos de dúvida e desespero, obrigada por sempre manter a porta da sua sala aberta para mim.

Aos meus colegas do Laboratório de Ciência e Qualidade da Carne e do Laboratório de Zootecnia de Precisão do Departamento de Zootecnia - UFV, que me receberam e compartilharam muito dessa jornada comigo, principalmente à Nathália, Pâmela, Cris, Jenifer, Rizielly e Mariana, pelos cafés, almoços e lanches na cantina compartilhados, assim como pelos incontáveis dias de trabalho.

À Nathália Farias e a Cris Luana por todo tempo e atenção ao meu trabalho, à prontidão de sempre estender a mão, seja para me ajudar na estatística ou para ler cada linha do meu trabalho.

Às minhas irmãs da Rep. Pompeia e à Pâmela Gracioli, por fazerem de uma casa um lar, por estarem por perto nas alegrias e nas frustrações, por tornarem tudo mais leve, e por sempre me fazerem enxergar que era possível.

Aos demais mestrandos e doutorandos, professores e funcionários do Departamento de Zootecnia que de alguma forma me ajudaram e compartilharam seus conhecimentos comigo.

Ao Departamento de Zootecnia – UFV, especialmente ao Programa de Pós-Graduação em Zootecnia pela excelência no que fazem, e por terem os melhores profissionais envolvidos nisto.

À todos os órgãos de fomento que financiam pesquisa no nosso país, CNPq, FAPEMIG e em especial a CAPES, uma vez que o presente trabalho foi realizado com apoio da Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Código de Financiamento 001

À Rede de pesquisa em Inteligência Artificial aplicada à pecuária digital - Rede IAPD FAPEMIG Processo: RED-00172-22.

Ao Instituto de Inteligência Artificial e Computacional (Idata) da Universidade Federal de Viçosa (UFV)

Ao Instituto Nacional de Ciência e Tecnologia em Ciência Animal (INCT-CA)

À Universidade Federal de Viçosa que foi minha casa durante tantos anos, onde pude crescer, me desenvolver e conhecer pessoas incríveis.

À banca examinadora, Dr. Mário Luiz Chizzotti, Drª Érica Beatriz Schultz e Dr. Rodrigo Vidal Oliveira por aceitarem avaliar este trabalho.

Por fim, aos animais de produção que foram os instrumentos dessa pesquisa do começo ao fim da vida, agradeço a vida de cada um.

This work has been sponsored by the following Brazilian research agencies: Coordination for the Improvement of Higher Education Personnel (CAPES; Financing code 001), Minas Gerais State Foundation for Research Aid (FAPEMIG) and National Council of Scientific and Technological Development (CNPq).

"A mente que se abre a uma nova ideia jamais voltará ao seu tamanho original."

— Albert Einstein

ABSTRACT

SIQUEIRA, Isabelle Pinheiro, M.Sc., Universidade Federal de Viçosa, June, 2025. **A preliminary comparison using 2D and 3D images to predict hot carcass weight and saleable meat yield in pigs**. Adviser: Mario Luiz Chizzotti. Co-adviser: Erica Beatriz Schultz.

This study aimed to evaluate the predictive accuracy of the Artec LEO® scanner in estimating pork hot carcass weight (HCW) and saleable meat yield (SMy), compared to traditional 2D imaging methods. Thirty-nine half pig carcasses were used. HCW and 3D images were obtained before the chilling process, after 24h chilling the cuts shoulder, top loin, loin, belly, ribs, and ham were made and the sum of all cuts was defined as SMy. To obtain 3D images, carcasses were suspended in a fixed position and manually scanned using the Artec Leo®, which features automatic light adjustment. The digitized images were imported into Artec Studio 18 to generate the 3D models, from which total carcass volume (TCV, mm^3) was extracted. Standardized 2D images were created from dorsal and lateral views by capturing screenshots within the 3D modeling environment. These views were consistently applied to all carcasses. ImageJ software was used to extract dorsal plane area (DPA, cm^2) and lateral plane area (LPA, cm^2) from these images. Descriptive statistics and Pearson's correlation were used to explore associations between HCW, SMy, and image-derived features. Simple and multiple linear regressions optimized by leave-one-out cross-validation assessed the predictive power of 3D and 2D features for HCW and SMy. Model performance was evaluated using the determination coefficient (R^2), root mean square error (RMSE) and mean absolute error (MAE), Mean Absolute Percentage Error (MAPE). TCV showed a strong, significant correlation with HCW ($r = 0.9659$, $P < 0.001$) and a moderate, significant correlation with SMy ($r = 0.6272$, $P < 0.001$). In contrast, 2D features had weaker and non-significant correlations. Among simple regression models, TCV had the best performance for HCW prediction ($R^2 = 0.9329$; RMSE = 0.4312 kg) DPA and other 2D features performed poorly ($R^2 = 0.0488$, RMSE = 1.6231). In multiple regression, using predictors from 2D combined to 3D images, there was similar performance. ($R^2 = 0.9413$; RMSE = 0.4033 kg). For SMy, TCV also showed the best predictive performance among simple models ($R^2 = 0.4773$; RMSE = 1.1795 kg) and adding 2D features offered little improvement. Model 7 again had the best result ($R^2 = 0.5117$; RMSE = 1.1401 kg). It is concluded that the use of 3D image variables is better than 2D images for predicting pig carcass weight and yield.

Keywords: computer vision; pig farming; precision

RESUMO

SIQUEIRA, Isabelle Pinheiro, M.Sc., Universidade Federal de Viçosa, junho de 2025. **Comparação preliminar utilizando imagens 2D e 3D para predição do peso de carcaça quente e rendimento de carne comercializável em suínos**. Orientador: Mario Luiz Chizzotti. Coorientadora: Erica Beatriz Schultz.

Objetivou-se com o presente estudo avaliar o uso de imagens 3D em comparação a 2D na estimativa do peso de carcaça quente (PCQ) e do total de carne vendável (TCv) de suínos. Foram analisadas 39 meias carcaças. O PCQ e as imagens 3D foram obtidos antes do resfriamento. Após 24 horas de refrigeração, realizaram-se os cortes paleta, copa lombo, lombo, barriga, costela e pernil, sendo a soma desses cortes comerciais definida como TCv. Para obter as imagens 3D, as carcaças foram suspensas em posição fixa e digitalizadas com o scanner portátil Artec Leo®, que possui ajuste automático de luz. As imagens foram importadas para o software Artec Studio 18 para gerar os modelos 3D, dos quais se extraiu o volume total da carcaça (VTC, mm^3) e comprimento de carcaça (CC, cm). A partir dos modelos 3D, imagens 2D padronizadas foram capturadas das vistas dorsal e lateral. Essas imagens foram processadas no software ImageJ, onde foram obtidas a área do plano lateral (APL, cm^2) e a área do plano dorsal (APD, cm^2). Análise descritiva e correlação de Pearson foram utilizadas para explorar associações entre PCQ, TCv e as variáveis extraídas. Modelos de regressão linear simples e múltipla otimizados pela validação cruzada leave-one-out foram utilizados para predição do PCQ e TCv com as variáveis da imagem 2D e 3D. O desempenho dos modelos foi analisado com base no coeficiente de determinação (R^2), raiz do erro quadrático médio (RMSE) e erro absoluto médio (MAE), Erro percentual absoluto médio (MAPE). O VTC apresentou forte correlação com o PCQ ($r = 0,9659$; $P < 0,001$) e moderada com o TCv ($r = 0,6272$; $P < 0,001$). As variáveis 2D apresentaram correlações fracas e não significativas (0,2210 $P > 0,05$). O modelo linear simples com a variável VTC teve o melhor desempenho para predição do PCQ ($R^2 = 0,9329$; RMSE = 0,4312 kg), enquanto o APD teve baixo desempenho ($R^2 = 0,0488$, RMSE = 1,6231). Na regressão múltipla, utilizando preditores da imagem 2D e 3D, houve desempenho similiar ($R^2 = 0,9413$; RMSE = 0,4033 kg). Para o TCv, o VTC também foi o melhor preditor ($R^2 = 0,4773$; RMSE = 1,1795 kg). Conclui-se que uso de variáveis da imagem 3D é melhor do que de imagens 2D para predição de peso e rendimento da carcaça suína, podendo ser utilizada para predizer o peso de carcaça quente de suínos.

Palavras-chave: precisão; suinocultura; visão computacional

Summary

1. Introduction

Pork plays a significant role in the global meat industry. According to the USDA report, pork is expected to be the most produced and consumed meat worldwide by 2025. Production is expected to continue growing in countries such as the United States and Brazil (USDA, Foreign Agricultural Service, 2024). This positive scenario has driven the production sector to seek improvements and encouraged producers to aim for higher market values for their carcasses. The overall market value of a carcass is defined by the value of its primary, commercial, and retail cuts, which are largely affected by its weight and composition (Masoumi et al., 2021). However, challenges such as the timing and speed of carcass weighing, as well as variability in butchering techniques, can lead to inconsistencies in carcass pricing. Nissen et al. (2006) demonstrated that the butcher has a significant influence on meat yield estimates. This variability not only affects the commercial value of the carcass but also impacts producers' income, who often lack objective data to dispute yield assessments.

With advancements in new technologies, the use of image analyses is increasing worldwide (Masoumi et al., 2021; Matthews et al., 2022; Wakholi et al., 2022; Nisbet et al., 2024; Candek-Potokar et al., 2024). The images can be two- or three-dimensional functions and have emerged as promising alternatives for carcass weight and saleable meat yield prediction. 2D images offer an accessible and easy-to-implement approach, enabling the efficient and cost-effective acquisition of superficial carcass measurements. In contrast, three-dimensional (3D) images allow for a more detailed analysis of the carcass, providing volume and texture, potentially increasing prediction accuracy by capturing more comprehensive three-dimensional information.

The development of automated systems based on video image analysis (VIA) technology began in the early 1980s (Allen, 2009). These systems, which may consist of multiple cameras integrated into a single model, have been widely adopted to assist in predicting grading, classification, and saleable meat yield in beef carcasses (Allen and Finnerty, 2000; Craige et al., 2012). Recent research has also demonstrated the application of VIA systems in predicting carcass conformation in sheep (Araújo et al., 2020) and lambs, as well as estimating cold carcass weight, using dorsal and lateral images (Afonso et al., 2024). Despite their practicality, 2D systems face notable limitations due to the complexity of animal morphology. Therefore, the models often rely on many extracted features, which results in extensive mathematical equations.

On the other hand, 3D imaging stands out for providing a comprehensive dataset within a single model, including morphological information from linear measurements, biometric parameters such as area, volume, perimeter, spatial coordinates, and vectors, as well as color and texture features. Also, 3D images are relatively easier to process when it comes to cutting out the background, without the necessity of a specific background during the image acquisition, removing artifacts, joining the features mesh, and lighting conditions (Fernandes et al., 2020). The use of 3D images has been applied to obtain precise cuts in the meat industry for different species, such as lambs (Bao et al., 2022), predict carcass conformation (Nisbet et al., 2024) and lean meat yield of beef cattle (Alempijevic et al., 2021), and pork (Masoumi et al., 2021). While the studies have yielded encouraging outcomes, the availability of a straightforward, user-friendly instrument would simplify the implementation of this technology in the meat industry.

The advent of new sensors, such as handheld scanners, facilitates a more practical approach using 3D images in pig carcass evaluation. The Artec LEO, a handheld scanner, allows for quick capture of high-quality 3D images, however, this is the first time it has been used on pork carcasses along the slaughter line. Therefore, this study aimed to evaluate the predictive accuracy of the 3D Artec LEO scanner features compared to traditional 2D imaging methods to predict carcass weight and saleable meat yield in pork.

2. Material and Methods

2.1 Carcass sampling

Thirty-nine carcasses of immunocastrated male swine, Camborough x AGPIC337 (PIC Agroceres), slaughtered at 5 months of age, were used in this study. Following slaughterhouse processing, each carcass was divided lengthwise into two identical portions. The right side of the carcasses was weighed to obtain the hot carcass weight (HCW). After 24h of cooling at 4ºC, the right half-carcasses were sent to the deboning room where the cuts: shoulder, top loin, loin, belly, ribs, and ham were made. Each cut was individually weighed, and saleable meat yield (SMy) was defined as the sum of all cuts.

2.2 Carcass digitalization

All the right half-carcasses were scanned with the portable 3D scanner, Artec Leo (Artec 3D, Luxembourg). The Artec Leo features automatic light adjustment, eliminating the need for additional lighting in the environment. Artec Leo uses structured light technology, allowing the object to be scanned from different angles. In this study, a capture rate of 30 fps (frames/second) was used, aiming for a balance between detail and storage capacity, creating a high-quality 3D scan. For the scanning procedure, the right half-carcasses were hooked at a constant height.

Two team members conducted manual scanning of the carcasses to minimize variability in the scanning process. The scanner itself indicates when additional scanning of a particular area is necessary, or when the scanning speed or distance from the object is insufficient. The average time required to scan each half-carcass was approximately seven minutes.

2.3 Image processing and data extraction

The raw digitized images were imported into Artec Studio 18 software to generate the 3D models. In the software, the first step was to remove the outliers found with *Eraser* tool inside the *Editor* panel to facilitate processing avoiding unwanted parts. After removing the outliers, the second step was aligning the frames through *Auto-alignment* command from the *Align* panel selecting the *Best fit* along the type options. If any frame was left out of the image, it could be deleted without damage, using the *Eraser* tool. After all the image alignment, we ran the *Global Registration* algorithm within the *Tools* panel between the registration options, which turned all the frames into a single coordinate system, joining corresponding geometric points between different frames. After that, the fourth step was using the *Fusion* command from the *Tools* panel was used to merge the processed frames, creating a polygonal 3D model. The algorithm chosen to do the fusion was *Sharp Fusion*, which is suitable for both industrial objects and human bodies, as well as animals. Despite the team's careful handling during the half-carcass scanning process, occasional flaws in the images may occur, which were corrected using Artec Studio 18 software. If any gaps remained in the model, the *Fix Holes* tool, which recognizes holes and can fill them in a flat or smooth way, was used in *smooth* mode. Since Artec Leo is equipped with a color camera, the final step was run the texturing algorithm on the final model, which applies colors to the 3D model, making it look like a real half-carcass. For that we use the *Texture* panel, selected the fusion created, selected preview, and ran the task (Figure 1). The whole process described above took about 30 minutes per half-carcass. To obtain measurements of the generated 3D model, the *Measure* panel was utilized within the *Sections and Volume* tool. The option *Measure entire model* was selected, from which the total carcass volume in mm^3 (TCV) was obtained (Figure 2). The same tool was also used to measure the carcass total length (CL) in the Distance panel. To perform CL measurement, two points were manually placed on the model: one at the cranial edge of the symphysis pubis and the other at the cranial edge of the first rib (Bridi and Silva, 2009) (Figure 2).

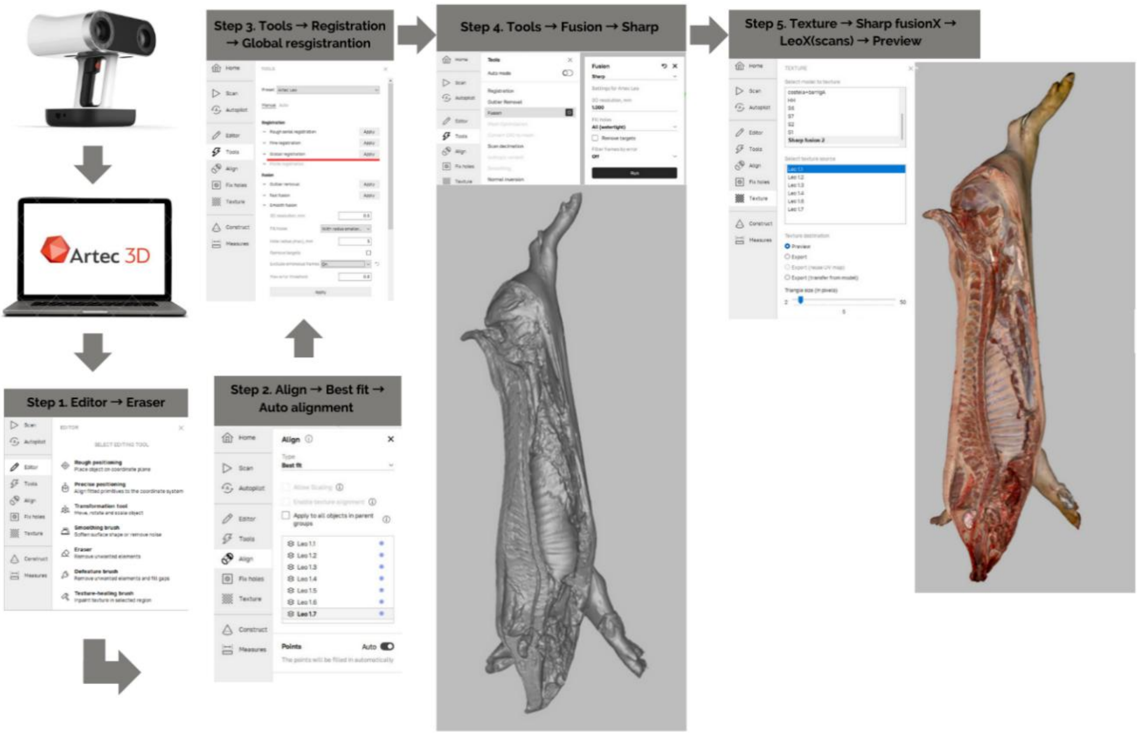

Figure 1. Schematic overview of 3D Model processing steps within Artec Studio 18.

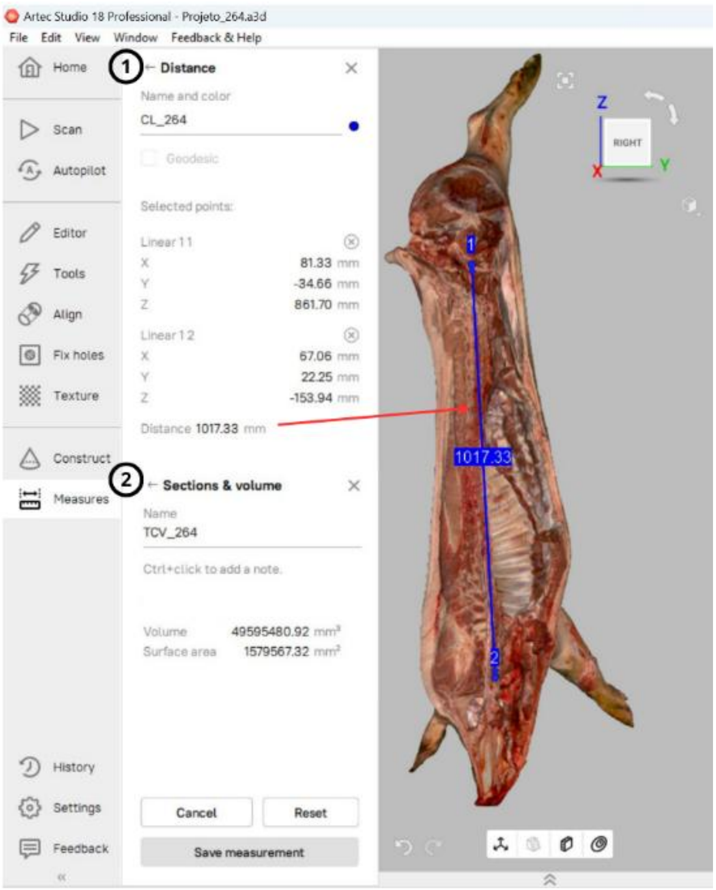

Figure 2. 3D model of half pig carcass. (1) Red arrow indicating the linear distance between two points used to determine carcass length (CL), and (2) the volume of the entire model (TCV).

2.4 Acquisition of two-dimensional images and measurements

Once the 3D models of the carcasses were generated, standardized 2D images were obtained by capturing screenshots of the dorsal and lateral views. These views were consistently applied for all carcasses based on the coordinate plane orientation within the 3D modeling environment. The coordinates were defined from the first model using the Measure tool from status bar, setting the coordinates for the dorsal views, X=101.7, Y=19.73, and Z=-147.84 and X=128.26, Y=-164.52, and 50.98 for lateral views. These coordinates were applied for all carcasses through the Transform tool from the left tool bar. Once the desired orientation and positioning were achieved, it was selected to fix the model's position. After image acquisition, the dorsal and lateral images were processed using ImageJ software (version 1.51, National Institutes of Health, Bethesda, MD, USA) to determine the respective areas. The polygon selection tool was used to select the lateral plane area (LPA) and dorsal plane area (DPA) of each carcass and extract the corresponding measurements (Figure 3.). To calibrate the measurements in ImageJ, a known reference previously measured directly on the 3D model within Artec Studio 18 software was used, resulting in a scale of 5.8245 pixels/cm ± 0.2312.

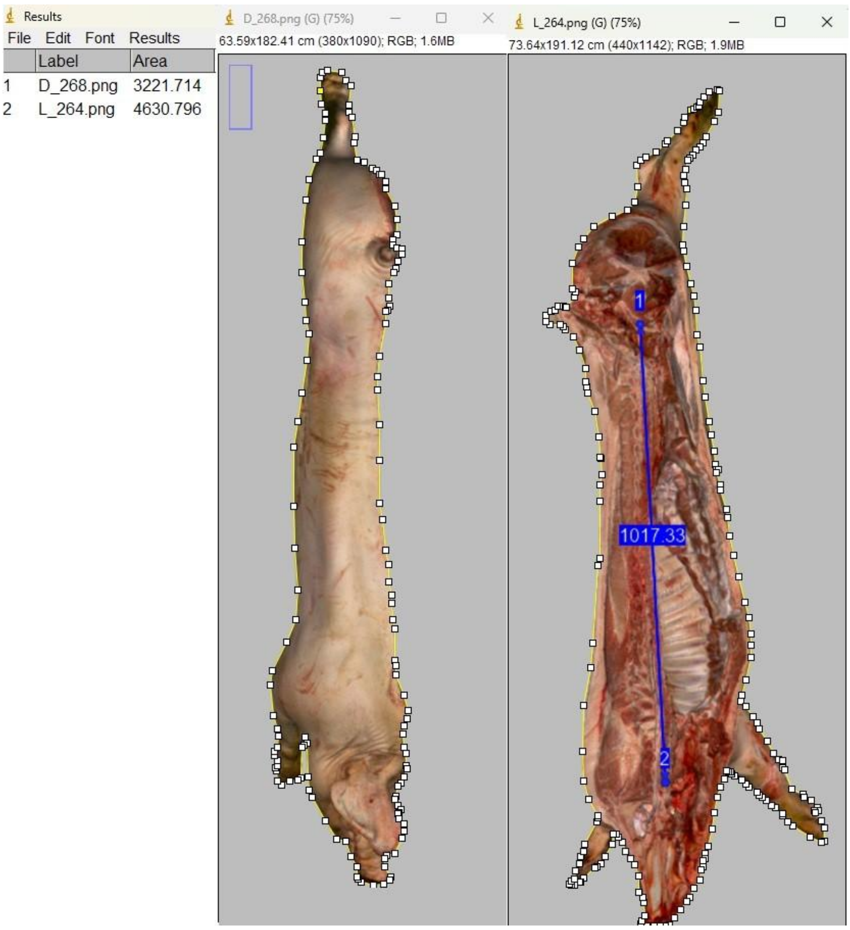

Figure 3. Carcass views in ImageJ software: on the left, a dorsal view with the corresponding measurement (1) DPA; on the right, a lateral view with the corresponding measurement (2) LPA.

2.5 Statistical analysis

A descriptive analysis was performed to show the data distribution of HCW, SMy, TCV, CL, DPA, and LPA.

Pearson's correlation analysis was used to explore the relationships between HCW, SMy, and the features obtained from the 3D and 2D images. Correlation coefficients range from -1 to 1, being positive or negative, and were classified as low (0.00 ± 0.30), moderate (0.30 ± 0.70), or strong (0.70 ± 1.0) (Ratner et al., 2009).

Simple and multiple linear regression analyses were performed using the leave-one-out cross-validation technique to predict hot carcass weight (HCW) and saleable meat yield (SMY) based on 3D and 2D features. Models' performances were evaluated using the determination coefficient (R^2), root mean square error (RMSE), mean absolute error (MAE) and Mean Absolute Percentage Error (MAPE). The analysis was performed using RStudio (version 4.3.1).

3. Results

The HCW and SMy average were 53.22 ± 1.69 kg and 44.14 ± 1.65 kg (Table 1), respectively, which shows low variability between the carcasses used in the study. A similar pattern is observed for TCV and CL, with a standard deviation of 1771.0 cm^3 and 2.43 cm in mean values of 52603.0 cm^3 and 102.0 cm, respectively.

Table 1. Summary of carcass traits and image-based feature measurements

	Mean	SD	Max.	Min.
HCW (kg)	53.22	1.69	56.8	48.8
SMy (kg)	44.14	1.65	48.0	39.8
TCV (cm^3)	52603	1771.0	56522	48154
CL (cm)	102.0	2.43	107.1	96.17
DPA (cm^2)	3230.0	297.55	3849.0	2738.0
LPA (cm^2)	4967.0	388.99	6036.0	4288.0

HCW: hot carcass weight (kg); SMy: saleable meat yield (kg); TCV: total carcass volume (cm3); CL: carcass length (cm); DPA: dorsal plane area (cm2); LPA: lateral plane area (cm2).

TCV exhibited a strong and significant correlation with HCW (0.9659, $P < 0.001$). Similarly, SMy showed a moderate, but significant correlation with HCW (0.6272, $P < 0.001$). However, CL, DPA, and LPA variables demonstrated weak to moderate and non-significant correlations with the main response variables, suggesting they may be less predictive (Table 2).

Table 2. Pearson's correlation coefficients between hot carcass weight, saleable meat yield, and 2D/3D image features.

	HCW					
SMy	0.6272*	SMy				
TCV	0.9659*	0.6909*	TCV			
CL	0.0747	-0.0065	0.0636	CL		
DPA	0.2210	0.3544	0.2645	-0.2354	DPA	
LPA	0.0591	0.1753	0.1499	0.1119	0.1601	LPA

HCW: hot carcass weight (kg); TCV: total carcass volume (cm^3); SMy: saleable meat yield (kg); CL: carcass length (cm); DPA: dorsal plane area (cm^2); LPA: lateral plane area (cm^2); *P<0.001; correlation values without asterisk are non-significant p>0.05.

3.1 Prediction of hot carcass weight

In simple linear regression models CL, DPA, and TCV were each evaluated individually. Among features from 2D images, CL (Model 1) performed the worst, with an R^2 of 0.0056 and RMSE of 1.6596 kg, DPA (Model 2) showed weak predictive performance, with an R^2 of 0.0488 and RMSE of 1.6231 kg. Among these, TCV (Model 5), extract from 3D image, presented the highest predictive power (R^2 = 0.9329; RMSE = 0.4312 kg) (Figure 3) (Table 3).

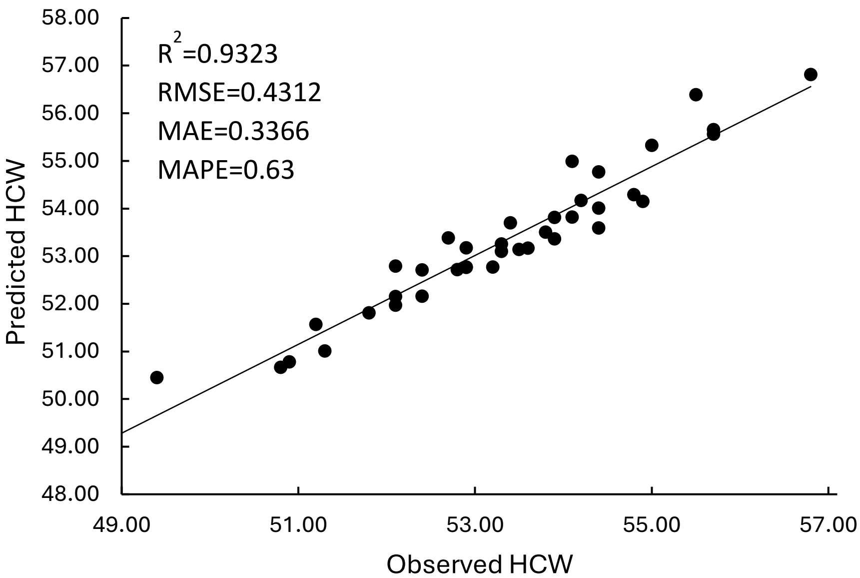

Figure 3. Observed HCW versus HCW predicted by the best model (model 5).

For the multiple linear regression models, different sets of variables were combined. Model 3 and Model 4, using only 2D predictors, did not outperform the individual 2D models, achieving an R^2 of 0.0494, 0.0658 and RMSE of 1.6226, 1.6086 kg, respectively. Statistically significant results (P < 0.001) were found for models 5, 6, and 7, showing the relevance of models incorporating 3D data (TCV). Model 6 (R^2 = 0.9342; RMSE = 0.4270 kg) and Model 7 (R^2 = 0.9413; RMSE = 0.4033 kg) outperformed all other models. The best-performing model, Model 7, which included all predictors, achieved the highest R^2 and lowest RMSE (Table 3).

However, its performance was only marginally better than that of Model 5, which relied on a single predictor. This suggests that including additional variables did not significantly enhance prediction accuracy.

Table 3. Predictive performance of simple and multiple linear models for hot carcass weight.

HCW (Y)	R^2	p-value	RMSE	MAE	MAPE
Model 1 Y=4.5851-0.0044CL	0.0056	0.6514	1.6596	1.2936	2.43
Model 2 Y=37.7759+0.0020DPA	0.0488	0.1764	1.6231	1.2269	3.05
Model 3 Y=35.5576+0.0018DPA+0.0005LPA	0.0494	0.4017	1.6226	1.2273	2.30
Model 4 Y=31.0371+0.0434CL+0.0020DPA+0.0005LPA	0.0658	0.4909	1.6086	1.1981	2.25
Model 5 Y=10.2294+0.0006TCV	0.9329	<0.001	0.4312	0.3366	0.63
Model 6 Y=9.3133+0.0006TCV+0.0010DPA	0.9342	<0.001	0.4270	0.3334	0.62
Model 7 Y=9.4199+0.0006TCV-0.0081CL+0.0010DPA+0.0002LPA	0.9413	<0.001	0.4033	0.3154	0.59

3.2 Prediction of saleable meat yield

The simple models 8, 9 and 12, using individual measurements, showed varying degrees of predictive ability. Among these, the model using TCV alone (Model 12) achieved an R^2 of 0.4773 and an RMSE of 1.1795 kg, the best result among the simple models, highlighting the importance of volumetric information (Figure 4) (Table 4).

Model 10, including DPA and LPA, achieved an R^2 of 0.14 and an RMSE of 1.5129 kg. Adding CL to these predictors in Model 11, the R^2 was almost the same (R^2 = 0.1438), showing the low importance of this variable. Combining TCV and DPA (Model 13) did not improve the prediction (R^2 = 0.509; RMSE = 1.1432 kg) compared to Model 12. The most complex model, Model 14, which included all extracted features, achieved an R^2 of 0.5117 and an RMSE of 1.1401 kg (Table 4). Although Model 14 exhibited a superior R^2 value, it demonstrated a higher prediction error as measured by MAPE (MAPE=2.11), with its MAPE exceeding that of Model 12 (MAPE=2.06). This suggests that despite the improved explained variance, Model 14 predictive accuracy in terms of percentage error did not improve correspondingly. Overall, the findings emphasize the greater predictive power of 3D volumetric measurement compared to 2D features.

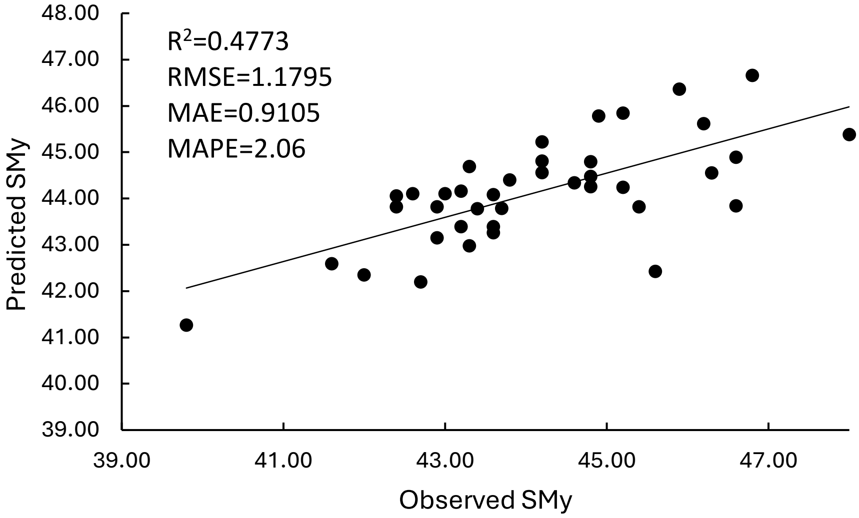

Figure 4. Observed SMy versus SMy predicted by the best model (model 12).

Table 4. Predictive performance of simple and multiple linear models for saleable meat yield.

SMy (Y)	R^2	p-value	RMSE	MAE	MAPE
Model 8 Y=4.5851-0.0044CL	<0.0001	0.9688	1.6315	1.3179	2.98
Model 9 Y=37.7759+0.0020DPA	0.1256	0.0268	1.5256	1.2079	2.73
Model 10 Y=35.5576+0.0018DPA+0.0005LPA	0.14	0.0662	1.5129	1.1937	2.70
Model 11 Y=31.0371+0.0434CL+0.0020DPA+0.0005LPA	0.1438	0.1381	1.5096	1.1892	2.70
Model 12 Y=10.2294+0.0006TCV	0.4773	<0.001	1.1795	0.9105	2.06
Model 13 Y=9.3133+0.0006TCV+0.0010DPA	0.509	<0.001	1.1432	0.9273	2.10
Model 14 Y=9.4199+0.0006TCV-0.0081CL+0.0010DPA+0.0002LPA	0.5117	<0.001	1.1401	0.9317	2.11

4. Discussion

The data set used in this study exhibited low variability, as evidenced by the small standard deviations observed for hot carcass weight and saleable meat yield. The observed homogeneity is mainly due to the uniform genetic background of the animals. As well as a controlled sampling strategy and standardized slaughtering procedures. Future studies should aim to include more heterogeneous samples to assess the robustness and scalability of predictive models (Pabiou et al., 2011; Matthews et al., 2022).

This study demonstrated the superior performance of 3D imaging, particularly carcass volume, over 2D image features in predicting both HCW and SMy. The strong correlation between TCV and HCW, coupled with the high R^2 value and low RMSE in the regression model, highlights the reliability of volumetric data obtained via 3D scanning.

These results are in line with prior research emphasizing the advantages of 3D imaging in livestock (Delgado-Pando et al., 2021). In contrast, 2D features showed weak predictive power and contributed minimally to multiple regression models. Although we selected 2D traits that have historically been used to predict carcass characteristics, Bozkurt et al. (2008) used the same traits to predict HCW in beef carcasses and obtained good results, R2=86.4% using carcass area, length, and deep.

Interestingly, the inclusion of 2D features in multiple regression models did not markedly improve prediction performance. A similar finding was reported by Wakholi et al. (2022), who observed that their model for predicting HCW in beef carcasses using 1,400 variables ($R^2 = 0.91$, RMSE = 29.1) performed nearly as well as a model using only 8 selected variables ($R^2 = 0.92$, RMSE = 23.43). This highlights that the essential variation can be effectively captured with a smaller set of well-chosen features, supporting the idea that the dimensional and structural richness of 3D models may render additional 2D measurements unnecessary.

For SMy prediction, the overall model performance was lower than for HCW, likely due to variability and subjective trimming practices during deboning (Zappaterra et al., 2022; Nissen et al., 2006). Nonetheless, 3D-based models still outperformed those using only 2D features. This finding contrasts with Fortin et al. (2003), where adding 3D data to ultrasound models initially improved prediction of saleable meat yield for pig carcass, but was later replaced by 2D-only models, likely due to the cost and complexity of early 3D systems. At that time, 3D imaging equipment was often large, expensive, and difficult to implement, making 2D alternatives more practical despite their limitations. A similar observation was reported in a study aiming to predict carcass cut yields in beef, where the removal of conformation and fat scores from the model was compensated by incorporating carcass measurements extracted from 2D and 3D images (Matthews et al., 2022), but they have not made any selections. McClure (2003) achieved satisfactory results ($R^2 = 0.77$) when predicting saleable product weight in pork carcasses using 2D features; however, the inclusion of HCW in the models may have artificially inflated performance metrics, as we observed that HCW can misleadingly improve predictions.

In our study, the best-performing models without overwhelming, achieved an R^2 of 0.9329 for HCW and 0.4773 for SMy, again highlighting the predictive value of 3D features, particularly TCV, on both predictions. From a practical standpoint, integrating 3D imaging, the Artec Leo scanner can help to predict several carcass characteristics, such as classification, composition, and support yield-based pricing systems. These are subjects that still need to be explored. The scanner's portability, speed, and ease of use make it suitable for implementation in industrial slaughter lines without requiring structural changes.

The cited studies used different cameras and imaging setups, many requiring controlled backgrounds, and additional lighting to ensure image quality. Fortin et al. (2003), although using a computer vision system developed for the Lacombe Research Centre, did not specify the devices that composed the system. However, they described a controlled imaging environment that included halogen lighting and a blue backdrop, likely aimed at enhancing image contrast and segmentation accuracy. In contrast, McClure et al. (2003) utilized the VCS2001 system, which combines color imaging and structured light and requires a controlled background to ensure image consistency. Bozkurt et al. (2008) employed a simpler setup, using a consumer-grade Canon MV850i digital camera under standard illumination. Although this approach is accessible, it may limit reproducibility and the extraction of 3D information. The camera was fixed in position, and two sequential images of each carcass were captured. A big structure was built for Alempijevic et al. (2021) to reconstruct a 3D model for a beef carcass. The data acquisition system uses three cameras that capture color (red, green, blue) and depth information, mounted on a circular structure composed of three vertical beams positioned around a rotating base. During scanning, the carcass is manually positioned in the center of the structure. The cameras move up and down while the base rotates 180 degrees. Pabiou et al. (2011) and Matthews et al. (2022) adopted the VBS2000 system, developed by the same company as the VCS2001. This system uses a color camera and an external structured light source to generate both 2D and 3D representations and offers a standardized platform designed specifically for carcass grading. Wakholi et al. (2022) implemented a more elaborate setup, employing a wide-angle camera, LED lamps, and a motorized system to rotate the carcass, enabling image capture from both medial (0°) and dorsal (90°) views. While this approach provides high quality images, it is not particularly user-friendly due to its structure complexity. In a more recent study, Masoumi et al. (2021) used a portable scanner to acquire 3D images of half pig carcasses under which eliminate some environmental constraints but involves computationally intensive processing to extract shape descriptors from 3D meshes using spectral graph theory. Collectively, these studies highlight how differences in hardware specifications, lighting conditions, image angles, and post-processing approaches can influence the comparability of imaging data, underscoring the need for standardized imaging protocols in carcass evaluation research. Although VCS2000 system is a well-established technology for predicting carcass traits, the access to such a complex system remains limited for many segments. Despite its proven long-term economic viability, with an internal rate of return of 13.52% and a break-even point after seven years (Kim et al., 2021), the initial investment may be unaffordable for smaller and medium operations. Therefore, exploring alternative tools, such as portable 3D scanners, becomes essential to democratize access to carcass evaluation technologies.

The ability of simple 3D models to predict key carcass traits highlights their potential to enhance transparency, efficiency, and objectivity in carcass evaluation within the pork industry. Nonetheless, further research is needed using more variable datasets to ensure the robustness and applicability of these models under commercial conditions.

5. Conclusion

The preliminary data shown in this study demonstrated that 3D imaging features obtained from the Artec LEO scanner, particularly volumetric measurements, offer greater predictive accuracy for carcass weight (HCW) and saleable meat yield (SMY) in pork when compared to traditional 2D imaging methods.

6. References

Afonso, J. J., Almeida, M., Batista, A. C., Guedes, C., Teixeira, A., Silva, S., & Santos, V. (2024). Using Image Analysis Technique for Predicting Light Lamb Carcass Composition. *Animals*, *14*(11), 1593.

Alempijevic, A., Vidal-Calleja, T., Falque, R., Quin, P., Toohey, E., Walmsley, B., & McPhee, M. (2021). Lean meat yield estimation using a prototype 3D imaging approach. *Meat science*, *181*, 108470.

Allen, P. (2009). Automated grading of beef carcasses. Improving the sensory and nutritional quality of fresh meat, Woodhead Publishing (2009), pp. 479-492

Allen, P. and Finnerty, N. (2000). Objective beef carcass classification. A report of a trial of three VIA classification systems. *The National Food Centre, Dublin*, *15*.

Araújo, J. C., Lima, A. C. S., Nunes, M. P. M., Sousa, M. A. P., Serrão, G. X., Morais, E. C., & Silva, A. G. M. (2020). Relationships among carcass shape, tissue composition, primal cuts and meat quality traits in lambs: A PLS path modeling approach. *Small Ruminant Research*, *182*, 52-66.

Bridi, A. M., & Silva, C. D. (2009). Avaliação da carcaça. *Londrina: Midiograf*, 1-15.

Čandek-Potokar, M., Lebret, B., Gispert, M., & Font-i-Furnols, M. (2024). Challenges and future perspectives for the European grading of pig carcasses–A quality view. *Meat Science*, *208*, 109390.

Craigie, C. R., Navajas, E. A., Purchas, R. W., Maltin, C. A., Bünger, L., Hoskin, S. O., & 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.

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.

Fernandes, A. F., Dórea, J. R., Valente, B. D., Fitzgerald, R., Herring, W., & Rosa, G. J. (2020). Comparison of data analytics strategies in computer vision systems to predict pig body composition traits from 3D images. *Journal of Animal Science*, *98*(8), skaa250.

Fortin, A., Tong, A. K. W., Robertson, W. M., Zawadski, S. M., Landry, S. J., Robinson, D. J., & Mockford, R. J. (2003). A novel approach to grading pork carcasses: computer vision and ultrasound. *Meat Science*, *63*(4), 451-462.

Kim, J., Han, H. D., Lee, W. Y., Wakholi, C., Lee, J., Jeong, Y. B., & Cho, B. K. (2021). Economic analysis of the use of vcs2000 for pork carcass meat yield grading in Korea. *Animals*, *11*(5), 1297.

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.

Matthews, D., Pabiou, T., Evans, R. D., Beder, C., & Daly, A. (2022). Predicting carcass cut yields in cattle from digital images using artificial intelligence. *Meat Science*, *184*, 108671.

McClure, E. K., Scanga, J. A., Belk, K. E., & Smith, G. C. (2003). Evaluation of the E+ V video image analysis system as a predictor of pork carcass meat yield. *Journal of animal science*, *81*(5), 1193-1201.

Nisbet, H., Lambe, N., Miller, G., Doeschl-Wilson, A., Barclay, D., Wheaton, A., & Duthie, C. A. (2024). Using in-abattoir 3-dimensional measurements from images of beef carcasses for the prediction of EUROP classification grade and carcass weight. *Meat science*, *209*, 109391.

Nissen, P. M., Busk, H., Oksama, M., Seynaeve, M., Gispert, M., Walstra, P., & Olsen, E. (2006). The estimated accuracy of the EU reference dissection method for pig carcass classification. *Meat Science*, *73*(1), 22-28.

Pabiou, T., Fikse, W. F., Cromie, A. R., Keane, M. G., Näsholm, A., & Berry, D. P. (2011). Use of digital images to predict carcass cut yields in cattle. *Livestock Science*, *137*(1-3), 130-140.

Ratner, B. (2009). The correlation coefficient: Its values range between+ 1/− 1, or do they?. *Journal of targeting, measurement and analysis for marketing*, *17*(2), 139-142.

United States Department of Agriculture. (2024). *Livestock and Poultry: World Markets and Trade*. USDA. https://apps.fas.usda.gov/psdonline/app/index.html#/app/downloads

Wakholi, C., Kim, J., Kwon, K. D., Mo, C., Seo, Y., Cho, S., & Cho, B. K. (2022). Nondestructive estimation of beef carcass yield using digital image analysis. *Computers and Electronics in Agriculture*, *194*, 106769.

Zappaterra, M., Padalino, B., Menchetti, L., Arduini, A., Pace, V., & Nanni Costa, L. (2022). Carcass lesion severity and pre-slaughter conditions in heavy pigs: a prospective study at a commercial abattoir in northern Italy. *Applied Sciences*, *12*(3), 1078.