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On-farm 3D images of beef cattle for the prediction of carcass classification traits and cold carcass weight

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A B S T R A C T

For beef cattle, subjective methods tend to be used on-farm for assessing readiness for slaughter. This means that the target classification grades cannot be accurately estimated, leading to over– and under-finished animals being sent to slaughter. This leads to financial losses and potentially to increased greenhouse gas emissions. To counteract this, objective technologies are needed to select slaughter cattle at the optimal point. Video image analysis systems have proven their suitability for the estimation of carcass traits postslaughter. There is potential for this technology to support on-farm assessment of the live animal. This study explored 3D measurements extracted from images of live beef animals and their ability to predict key carcass traits when coupled with additional animal or carcass details. The images were captured from four commercial beef finishing farms across the UK and the cattle were processed at commercial abattoirs. Data for 762 animals were used to build models for the prediction of EUROP conformation and fat class, and cold carcass weight (**CCW**), using either traditional statistics (multiple linear regression using stepwise feature selection) or machine learning techniques (random forest models). Various model inputs were combined and tested, including breed, sex, the camera unit that the images were captured on, the number of days before slaughter the images were captured, and the month of image capture as fixed effects, the 34 3D measurements, and CCW. The best linear models predicted EUROP conformation class with moderate accuracy (R^2 = 0.37), EUROP fat class with low accuracy (R^2 = 0.24) and CCW with moderate accuracy (R^2 = 0.38). Moderate accuracies were also found when using the machine learning methods, with the best random forest models predicting EUROP conformation and fat classes with moderate accuracy (58 and 45% of classes, respectively, predicted correctly) and CCW with moderate accuracy (R^2 = 0.41). The results indicate that there is potential for imaging systems on farm to predict key carcass traits currently assessed in the abattoir, providing a tool for farmers to objectively select cattle at the optimum conditions for slaughter.

Implications

Objective on-farm estimation of optimum slaughter date to replace current subjective estimates would provide new opportunities to reduce beef production emissions while improving profitability. Incorporating precision livestock farming technologies into beef production systems that are capable of objectively estimating key carcass traits has the potential to help select cattle at the optimum slaughter condition, reducing emissions and increasing profitability. The current study found that 3D measurements, extracted from on-farm images of beef cattle, could be used to predict slaughter traits currently used for valuing carcasses with low-moderate accuracy, when combined with additional animal details.

Introduction

Within the agricultural industry, livestock production plays a large role in greenhouse gas emissions, with the sector estimated to produce at least 16.5% of greenhouse gas emissions globally (Twine, 2021). Over the past few decades, there has been increased pressure on livestock producers to reduce emissions to mitigate global warming and climate change. Not only must emissions be reduced, but output must be increased to maintain food security for the growing global population. Improved efficiency must therefore be at central to changes in practices to achieve this. Incorpo-

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rating precision livestock farming (**PLF**) technologies into current systems has the potential to support producers in reaching efficiency goals by automating practices and gathering robust data (Banhazi et al., 2012). As technology advances, not only are there more options available for farmers, but they also are becoming increasingly more affordable. The resources needed for storing large volumes of data are also improving and this, alongside advancements in data processing, is allowing for real-time analysis of big data (Gandomi and Haider, 2015), providing further opportunities and incentives for the uptake of PLF technologies.

A key area where PLF technology could assist producers in reducing emissions would be through an objective assessment of the optimum slaughter date of beef cattle. Currently, many factors influence a producer's decision on which cattle to send to slaughter, with one of the main factors being price. In the United Kingdom, cattle carcasses are valued on pence per kilogram (p/kg), with different carcass classification grades determining the price paid, with the given prices often fluctuating weekly. The grades are based on the EUROP carcass classification grid (Fisher, 2007), which assesses both conformation (shape) of a carcass and its fat coverage. The letters of EUROP represent conformation classes, ranging from carcasses of excellent shape (E) to carcasses of poor shape (P). Classes U, O and P are further classified into plus (+) or minus (−) subclasses. The fat coverage class categorise carcasses as either very lean (1) or too fat (5). High (H) and low (L) subclasses are used for classes 4 and 5. Target classifications (E-R conformation classes, 1-4L fat classes), which represent carcasses that most closely match the market specifications, yield higher prices. Therefore, not only should producers aim to achieve these grades for economic reasons but also to reduce environmental impacts. The environmental impacts come in the form of excess emissions (Gerber et al., 2013) and are often associated with over-fat cattle in particular. Excess emissions result from the production, processing and transport of inputs (i.e feed and bedding) as well as enteric methane produced through the increased lifetime of the animal (Sabia et al., 2024). There is also increased wastage post slaughter, for example with fat trim, where an increase in fat class from R4L to R4H is estimated to result in a1.7% increase in fat trim (Roehe et al., 2013), meaning energy is converted to producing lower-value produce that may end up being discarded. This indicates the need for objective and accurate methods for estimating the optimum slaughter date. Although there are technologies available to aid on-farm and post-slaughter assessment (Delgado-Pando et al., 2021), producers and processors tend to rely on subjective techniques for assessing carcass value. This may be due to the expenses associated with potential technology, or the impracticality of available systems (e.g computed tomography). Therefore, producers continue to rely on subjective methods to select the cattle they send to slaughter, with visual assessment and assumptions on how the animal's shape and weight will translate into these desired carcass classification traits being utilised. Published industry data, however, indicate that this subjective method is not sufficient for estimating the optimum date of slaughter, with over half of cattle sent to slaughter in 2022 (50.67%) achieving sub-optimal grades (Agriculture and Horticulture Development Board, AHDB, 2023). Within the beef industry, improved efficiency has the potential to be achieved through objectively assessing the optimum slaughter date of cattle, which has the potential to be achieved through the use of video image analysis (**VIA**) technology. Previous studies have explored the ability of on-farm 3D VIA systems to identify live animal traits of cattle, such as morphological measurements or body condition scores (Le Cozler et al., 2019; Fischer et al., 2015). On-farm data collected using imaging systems have also been used to predict carcass traits in sheep (Lambe et al., 2008), pigs (Carabús et al., 2016) and cattle (Lambe et al., 2010). With systems such as ultrasound or computed tomography scanning, however, the practicality of these commercially is limited. Less-invasive VIA systems therefore have the potential to be more suited to commercial use and studies have already explored systems requiring limited infrastructure and their ability to predict carcass traits, specifically those used for valuing carcasses (i.e EUROP classes and cold carcass weight, **CCW**) (Miller et al., 2019).

This study aimed to develop a method for prediction of EUROP conformation class, fat class, and the cold carcass weight of beef carcasses, using 3D measurements extracted from images of the live animal on farm. The images were captured during the finishing phase using time-of-flight cameras, which require limited infrastructure. The 3D measurements were used, along with other information relating to the category of animal and when and where they were measured, and predictions were made using different analysis techniques, including machine learning algorithms.

Material and methods

Live animal data were initially collected from 1 861 finishing beef cattle, across four Scottish farms (three commercial farms and one research farm). The farms were selected based on the type of finishing system (indoor finishing) and finished similar numbers of animals per year. Data from 41 different breeds were recorded, across 521 days between 12 January 2021 and 7 July 2023. Cattle were on the system for an average of 72 days prior to slaughter. Slaughter data for these animals were collected from five Scottish abattoirs on 122 selected days between 13 January 2021 and 8 August 2023. Slaughter data included the CCW which was recorded post-slaughter, and the EUROP fat and conformation classes, assessed manually by a trained accredited assessor employed by the abattoir.

Study design

Image capture

A total of seven automatic cattle weigh systems (Beef Monitor Units; **BMU**, Ritchie Ltd., Angus, Scotland) were each adapted to suspend a Basler Blaze (Basler Inc., Exton, PA, USA) time-of-flight near infra-red camera (housing size $100 \times 81 \times 64$ mm) at 3 m from the ground, using a custom frame (Fig. S1a). The BMUs were the sole water source for up to 50 cattle in grouped pens, ensuring each animal visited the camera system. The individual animals in the pens with each BMU were selected based on animal weight and visual assessment of condition by the farmers. When an animal entered the BMU (Fig. S1b), its electrical identification (EID) tag was scanned, triggering both the weigh cells on the unit and image capture. The camera illuminates the animal multiple times per second with an IR pulse. The pulse was modulated to distinguish it from background IR radiation and reflected off the animal to a sensor on the camera, which then computes from the elapsed time and the speed of light in air the distance from the plane of the camera to each point within its field of view. This allowed for a 3D point cloud of the animal to be generated (e.g. Fig. S2a and b), from which a series of measurements could be extracted. A total of five frames were captured per second, and the total number of frames per visit varied depending on the duration of the visit. Each camera unit was assigned a number, allowing easy identification of which unit the images had been captured on.

Image processing and dimensional measurement calculation

The point cloud image frames were processed by Innovent technology Ltd., using algorithms developed in Halcon Processing Library (MVTech Software, GmbH, Munich, Germany). From each frame, a series of 34 3D measurements (Table 1; Fig. 1) were extracted from within a 3D area defined by a single edge contour (outline) of the animal. A total of 34 3D measurements were extracted (five widths, six lengths, five heights, four diagonals (Fig. 1) seven areas and seven volumes). Key areas of the animal were identified (shoulder, middle, and rear) with widths being measured at the widest part of each section. Two widths were also recorded at the narrowest point between the widest points of each section. A total length of the animal is measured from the tail to the mid-point of the line drawn across the widest point of the shoulder. Diagonal measurements were also recorded from the left-hand edge of width of the rear to the right-hand edge of the width of the middle, and from the left-hand edge of the middle width to the right-hand edge of the shoulder width. At points where these diagonal measurements crossed the line measuring the total length of the animal, height measurements were recorded and additional heights were recorded at the midpoint of the widest point of the shoulder, middle and rear. The calibrated floor distance from the camera was set as 3 m, and thus, the distance from the camera to the animal at these points was subtracted from 3 m to give the height. A series of different areas and volumes were calculated for different regions of the animal using the intersection between length and widths to define these regions (Fig. 1). Area measurements represented the surface area of the animal within each section (separated by the width and length lines). This was similar for the volumes, however, they also accounted for depth,

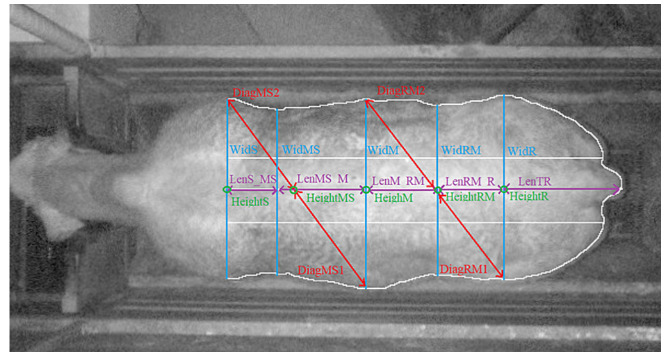

Fig. 1. Scan of live beef cattle on farm and the 3D measurements (widths, lengths, heights and diagonals, see Table 1 for abbreviations) extracted.

Table 1
List of the 34 3D measurements extracted from the image frames of the live beef animals and their description.

Measurements	Description
Widths	
WidS	Widest measurement of the shoulder section of the animal
WidMS	Width measurement between WidS and WidM
WidM	Widest measurement of the middle section of the animal
WidRM	Width measurement between WidR and WidM
WidR	Widest measurement of the rear section of the animal
Lengths	
LenTOT	Total length, measuring from the tail to the mid-point of the WidS measurement
LenTR	Length between the tail and the mid-point of the WidR measurement
LenRM_R	Length between the mid-point of WidR and the mid-point of WidRM.
LenM_RM	Length between the midpoint of WidM and the midpoint of WidRM
LenMS_M	Length between the midpoint of WidMS and the midpoint of WidM
LenS_MS	Length between the midpoint of WidMS and the midpoint of WidS
Heights	
HeightS	Height at the midpoint of WidS
HeightMS	Height at the midpoint of WidMS
HeightM	Height at the midpoint of WidM
HeightRM	Height at the midpoint of WidRM
HeightR	Height at the midpoint of WidR
Areas	
AreaRM1	Area to the left-hand side of LenTOT between WidR and WidM
AreaRM2	Area to the right-hand side of LenTOT between WidR and WidM
AreaMS1	Area to the left-hand side of LenTOT between WidM and WidS
AreaMS2	Area to the right-hand side of LenTOT between WidM and WidS
AreaTR	Area of animal between the tail and WidR
AreaB	Area of the middle third of the animal (largest width divided by three, and from WidS to the outline at the rear of the animal)
AreaTOT	Total area of the animal within the single edge contour outline
Volumes	
VolMS1	Volume for animal below AreaMS1
VolMS2	Volume for animal below AreaMS2
VolRM1	Volume for animal below AreaRM1
VolRM2	Volume for animal below AreaRM2
VolTR	Volume for animal below AreaTR
VolB	Volume of the middle third of the animal (largest width divided by three, and from WidS to the outline at the rear of the animal)
VolTOT	Total volume of the animal within the single edge contour outline
Diagonals	
DiagMS1	Measurement from the left-hand edge of WidM to the right-hand edge of WidS, to the left of LenTOT
DiagMS2	Measurement from the left-hand edge of WidM to the right-hand edge of WidS, to the right of LenTOT
DiagRM1	Measurement from the left-hand edge of WidR to the right-hand edge of WidM, to the left of LenTOT
DiagRM2	Measurement from the left-hand edge of WidR to the right-hand edge of WidM, to the right of LenTOT

which ran to a distance 20 cm below the lowest point of the surface of the animal scanned.

Validation and quality assurance

The measurements extracted from the images of the live animals were imported into RStudio V4.2.3 (Rstudio, Boston, MA, USA). Image data were collected from 1 861 animals. Slaughter data were collected for 1 453 of these animals. Data on only steers and heifers were retained for further analysis, leaving 1 348 animals. Measurements from each image for all animals were plotted to identify dates when issues had occurred with the image capture/processing, and data for these dates were removed, leaving data for 1 268 animals. Data were then removed for any animals where their final image was > 10 days before slaughter. This may have been caused by a number of reasons, for example, the animal being removed from the pen, the electronic tags not being read by the system, or the BMU not working. Thresholds based on five SDs above or below the mean of each 3D measurement were set, removing any extreme outliers and leaving clean data for 726 animals that had an image within 10 days of slaughter. A total of 6 434 images were recorded for the 726 animals on the day of their final image capture. Measurements for only the last visit to the BMU were retained, and the CV was calculated across animal to check for repeatability across the images captured during this last visit (average n = 8.86. Generally, the CV was low for all animals, with the average CV for each measurement being < 0.3. For this reason, the measurements from all images of the final visit BMU were averaged, leaving one row of data per animal for further analysis. Weight data recorded by the BMU were not included in the analyses as the system was under development and suitable weight data were not obtained for the purposes of this study.

Statistical analysis of data

The final dataset (Table 2, Table 3) was separated into training and validation datasets (Table 3), stratified randomly using a 70:30 split based on conformation class, fat class, breed type (cattle of continental or British decent), sex (steer or heifer), farm (n = 4), and place of slaughter (abattoir; n = 5). The split of data remained the same for all models. The number of animals of each breed type, sex and number of animals slaughtered at each abattoir for each farm are listed in Supplementary Table S1 for the full dataset, Supplementary Table S2 for the training dataset, and Supplementary Table S3 for the validation dataset. Multiple linear regression (**MLR**) models and random forest (**RF**) models were built. Previous studies (Nisbet et al., 2024b) identified RF techniques to be superior to alternative machine learning techniques (artificial neural networks) for the prediction of carcass traits, so RF models were the only machine learning techniques tested in the current study. For the MLR models, the conformation and fat classes were converted to a numeric class in line with the 15-point numeric EUROP carcass classification grid (Fisher, 2007). For the RF models, these traits remained as their categorical class, as the RF algorithm allows for the prediction of categorical traits.

Linear modelling

The training dataset was used to build a series of MLR models, using the "lm" function in base R (R Core Team, 2023) and the "stepAIC" function from the "MASS" package (Venables et al., 2002), for the prediction of conformation class, fat class and cold carcass weight. The forwards and backwards stepwise selection process resulted in variables being added individually to the models, with any non-significant variables being dropped. This process was repeated until the simplest model with the lowest Akaike information criterion (**AIC**) value (Cavanaugh and Neath, 2011) resulted.

Initially, models were built fitting fixed effects of breed type (British or Continental), sex (steer or heifer), camera number (7 categorical numbers), month (Jan-Dec; to account for seasonal variation) and the number of days before slaughter that the final measured images were captured (range from 1 to 10 days). Models were then built using the 34 3D measurements only, or both the 3D measurements and the fixed effects, indicating how much variation the on-farm data explained alone. Previous studies have indicated a strong relationship between liveweight and carcass traits (Coyne et al., 2019; Miller et al., 2019). As liveweight could not be used in the current study, additional models were built including the CCW collected at the abattoir as a proxy for liveweight.

Random forests

The training dataset was used to build RF models, and only for model input combinations that included the 3D measurements. Machine learning models were not built using only fixed effects due to the limited number of inputs. The "train" function from the "caret" package (Kuhn, 2008) was used to build the RF models, with the method set to "randomForest" from the "randomForest" package (Liaw and Wiener, 2002). Parameters tuned in the RF models were ntree (number of trees in the forest), which ranged from 100:1 000 at each 100 increment, and mtry (number of variables subset at each split), which ranged from 1:maximum number of inputs.

Model validation

All models were validated using the unseen data (validation dataset). The "predict" function from base R (R Core Team, 2023)

Table 2
Number of beef cattle of each EUROP carcass classification grade in the final averaged dataset.

	Fat Class[a]							
Conformation class[b]	1	2	3	4L	4H	5L	5H	Total
E	1		2					3
U+	2	6	18	13	2			41
U-	1	9	75	116	45	3		249
R		14	97	166	86	4	1	368
O+	1	4	24	26	27	1		83
O-			10	7				17
P+			1					1
P-								0
Total	5	33	227	328	160	8	1	762

[a] Fat classes range from 1 (very lean) to 5 (too fat) with low (L) and high (H) subclasses for 4 and 5.
[b] Conformation classes range from E (excellent conformation) to P (poor conformation) with high (+) and low (−) subdivisions for classes for U, O and P.

Table 3
Number of beef cattle in the training and validation datasets, and the split of breed types and sexes.

		Sex		Breed	
Dataset	Total	Steer	Heifer	British	Continental
Training	547	343	204	272	275
Validation	215	139	76	108	107
Total	762	482	280	380	382

was used to predict the dependent variable using the previously built models. For the MLR models, the R^2, RMSE and mean absolute error (**MAE**) were calculated using base R (R Core Team, 2023) and the "Metrics" package (Hamner and Frasco, 2018). These metrics were also calculated for the RF model built for the prediction of CCW, as this trait was continuous. For the predicted fat and conformation classes, confusion matrices were built indicating the percentage of correctly classified cases. For the MLR models, the predicted numeric fat and conformation class were converted back to the corresponding EUROP class from the traditional EUROP grid used within the UK. The area under the receiver operator curve (**AUC**) was calculated for the conformation and fat classes predicted using the RF models, with the probability of each grade being calculated and the multiclass receiver operating characteristic (ROC curve) being calculated using the "multiclass.roc" function (Robin et al., 2011). This plotted the true positive and false positive rate, with a value between 0 and 1. The greater the value, the better the model is at predicting the correct class, thus providing an additional metric for assessing the accuracy of the machine learning models. The importance of variables in the best MLR model and best RF models were calculated using the "varimp" function from the "Caret" package (Kuhn, 2008). The importance was scaled from 0 to 100, with 100 being of the highest importance. For the RF model built for the prediction of CCW, as this trait was continuous, the RF importance was displayed as the mean decrease in gini, indicating how the variable contributes to the node purity of the model, with the higher the value, the higher the importance.

Results

Conformation class results

Multiple linear regression models

The MLR models built for the estimation of conformation class resulted in low-moderate goodness of fit (Table 4). The model built using only fixed effects (ConfMLR1; breed type, sex and camera number) as predictors resulted in the lowest goodness of fit (adjusted R^2 = 0.19, RMSE = 1.53, AIC = 484.60). The goodness of fit was higher for the MLR model built using only the 3D measurements (ConfMLR2, adjusted R^2 = 0.27, RMSE = 1.43, AIC = 435.33). The amount of variation explained by the model increased when combining both the fixed effects and 3D measurements as predictors (ConfMLR3, adjusted R^2 = 0.35, RMSE = 1.35, AIC = 382.78). Further expanding the equation to include CCW (ConfMLR4) again improved goodness of fit (adjusted R^2 = 0.52, RMSE = 1.17, AIC = 211.35). Importance of variables in the best MLR model (ConfMLR4) are listed in Supplementary Table S4. The CCW was identified as the most important predictor. The other variables were all of similar importance, with no other variables clearly being of superior importance in the model.

For model validation, the model built using only the 3D measurements (ConfMLR2) resulted in the lowest prediction accuracy (R^2 = 0.13, RMSE = 1.51, MAE = 1.19), lower than ConfMLR1, which was built using only the fixed effects (R^2 = 0.25, RMSE = 1.36, MAE = 1.06). When combining the fixed effects with the 3D measurements (ConfMLR3), negligible improvements in prediction accuracy (R^2 = 0.25, RMSE = 1.39, MAE = 1.11) were seen compared to that of the model using only fixed effects, however, when including CCW (ConfMLR4), prediction accuracy increased (ConfMLR4; R^2 = 0.37, RMSE = 1.27, MAE = 1.01). When the predicted classes were mapped back to the traditional grid, the confusion matrix (Table 5) showed that 59% of classes were predicted correctly and a further 40% were predicted as a neighbouring class.

Random forest models

Random forest models were built using 3D measurements only, 3D measurements and fixed effects, or 3D measurements, fixed effects and CCW (Table 6). A total of 340 RF models were built using only the 3D measurements, and the accuracy for these models ranged between 48 and 52%. The best model (ConfRF1) was

Table 4
Goodness of fit and prediction accuracies resulting from the multiple linear regression (MLR) models built for the prediction of EUROP conformation class (Conf) of live beef animals.

		Train			Validation		
Model	Predictors	Adjusted R^2	RMSE	AIC	R^2	RMSE	MAE
ConfMLR1: Fixed effects only							
	Breed + sex + camera number	0.189	1.529	485	0.252	1.356	1.060
ConfMLR2: 3D measurements only							
	WidS + widM + widR + lenS_MS + lenMS_M + lenM_RM + lenTOT + heightS + heightMS + heightM + heightR + areaMS2 + areaRM1 + areaRM2 + areaTR + areaB + volMS2 + volTR + diagMS2 + diagRM1 + diagRM2	0.274	1.432	435	0.129	1.514	1.185
ConfMLR3: 3D measurements and fixed effects							
	WidS + widM + widR + lenS_MS + lenRM_R + lenTR + lenTOT + heightS + heightMS + heightM + areaMS2 + areaRM1 + areaTR + areaB + volMS2 + diagRM1 + diagRM2 + breed + sex + camera number	0.347	1.351	383	0.252	1.393	1.111
ConfMLR4: 3D measurements, fixed effects and CCW							
	WidtS + lenS_MS + lenMS_M + lenTOT + heightMS + heightRM + heightR + areaMS2 + areaTR + volRM2 + volTR + breed + sex + camera number + month + CCW	0.555	1.109	179	0.379	1.272	0.999

Abbreviations: MAE = mean absolute error, AIC = Akaike information criterion, CCW = cold carcass weight. See Table 1 for the description of 3D measurements used as predictors.

Table 5
Confusion matrix for the actual EUROP conformation class (Table 2), and predicted EUROP conformation class of live beef animals in the validation dataset, when converted back to the corresponding class on the traditional grid used in the UK, predicted using the best multiple linear regression model (ConfMLR4) and the best random forest model (ConfRF2)[1].

	Multiple Linear regression (ConfMLR4)									Random Forest (ConfRF2)								
	Actual									Actual								
Predicted	E	U+	U-	R	O+	O-	P+	P-	Total	E	U+	U-	R	O+	O-	P+	P-	Total
E	0*	0#	0	0	0	0	0	0	0	0*	0#	0	0	0	0	0	0	0
U+	0#	3*	1#	0	0	0	0	0	4	0#	0*	0#	0	0	0	0	0	0
U-	0	5#	26*	12#	0	0	0	0	43	0	6#	28*	21#	2	0	0	0	57
R	0	1	45#	94*	17#	1	0	0	158	0	3	45#	83*	16#	1	0	0	148
O+	0	0	2	1#	3*	4#	0	0	10	0	0	1	3#	2*	4#	0	0	10
O-	0	0	0	0	0#	0*	0#	0	0	0	0	0	0	0#	0*	0#	0	0
P+	0	0	0	0	0	0#	0*	0#	0	0	0	0	0	0	0#	0*	0#	0
P-	0	0	0	0	0	0	0#	0*	0	0	0	0	0	0	0	0#	0*	0
Total	0	9	74	107	20	5	0	0	215	0	9	74	107	20	5	0	0	215

[1] Correctly classified conformation classes are denoted with * (black shading) and classes estimated as a neighbouring class are denoted by # (grey shading).

Table 6
Results from the random forest (RF) models built for the prediction of EUROP conformation class (Conf) and fat class (Fat) of live beef animals.

Model	ntree	mtry	Train		Validation		
			Accuracy	Kappa	% correctly classified	% classified as neighbouring grade	AUC
3D measurements only							
ConfRF1	200	7	0.522	0.173	53	40	0.67
FatRF1	700	1	0.432	0.064	43	49	0.65
3D measurements and fixed effects							
ConfRF2	1 000	2	0.547	0.193	58	39	0.74
FatRF2	900	32	0.473	0.148	45	49	0.71
3D measurements, fixed effects and CCW							
ConfRF3	200	24	0.563	0.249	52	45	0.74
FatRF3	300	5	0.485	0.161	48	46	0.72

Abbreviations: ntree = number of trees in the final random forest, mtry = number of variables tried at each split, AUC = area under curve, CCW = cold carcass weight.

Table 7
Goodness of fit and prediction accuracies resulting from the multiple linear regression (MLR) models built for the prediction of EUROP fat class (Fat) of live beef animals.

Model	Predictors	Train			Validation		
		Adjusted R^2	RMSE	AIC	R^2	RMSE	MAE
FatMLR1: Fixed effects only							
	Breed + sex + camera number + month	0.151	2.108	858	0.152	2.077	1.694
FatMLR2: 3D measurements only							
	widRM + widR + lenTOT + heightS + heightM + heightRM + heightR + areaB + diagMS2 + diagRM2	0.117	2.170	869	0.143	2.083	1.783
FatMLR3: 3D measurements and fixed effects							
	widM + widRM + lenTOT + heightS + heightM + heightR + areaB + breed + sex + month	0.197	2.050	827	0.238	1.964	1.608
FatMLR4: 3D measurements, fixed effects and CCW							
	lenM_RM + lenTR + lenTOT + heightS + heightM + heightR + areaRM1 + areaB + diagMS2 + diagRM1 + breed + sex + CCW	0.187	2.076	827	0.208	2.001	1.661

Abbreviations: MAE = mean absolute error, AIC = Akaike information criterion, CCW = cold carcass weight. See Table 1 for the description of 3D measurements used as predictors.

built with 200 trees and a mtry of 7 (accuracy = 52%, kappa = 0.17). When testing this model using the unseen data of the validation dataset, 53% of classes were predicted correctly and 40% were predicted as one of the neighbouring classes. The AUC for this model was 0.67.

A total of 390 random forest models were built using the 3D measurements and the fixed effects. The accuracies for these models ranged between 50 and 55%. The best model (ConfRF2, Table 6) resulted from a parameter combination of mtry = 2 and 1 000 trees in the forest (Accuracy = 55%, kappa = 0.19). When testing the model on the validation dataset, the confusion matrix showed that 58% of classes were correctly predicted and 39% were classified as the adjacent grade. The AUC was 0.74.

When including CCW as a predictor in the models, the accuracy for the resulting 400 RF models ranged between 52 and 56%, with the best model (ConfRF3) resulting from a parameter combination of 200 trees and a mtry of 24 (accuracy = 56%, kappa = 0.25). When using this model to predict the conformation classes of the animals in the validation dataset, 52% of classes were classified correctly and an additional 45% were classified as the neighbouring class (Table 5). The AUC was 0.75. Importance of variables in the best RF model (ConfRF3) are listed in Supplementary Table S5. The CCW was again the most important predictor in the model. The months and camera numbers were generally of the lowest importance in the model.

Fat class results

Multiple linear regression models

For the MLR models predicting numeric fat class, the goodness of fit for all models were low (Table 7). The model built with only the 3D measurements (FatMLR2) explained the lowest amount of variance seen across all models (adjusted R^2 = 0.12, RMSE = 2.17, AIC = 869.42). The MLR models built with only fixed effects (FatMLR1) (adjusted R^2 = 0.15, RMSE = 2.11, AIC = 857.68), or combining fixed effects and 3D measurements (FatMLR3; adjusted R^2 = 0.20, RMSE = 2.05, AIC = 827.47), or including CCW in the model (FatMLR4; adjusted R^2 = 0.19, RMSE = 2.08, AIC = 826.96), resulted in slight increases in goodness of fit. Trends in the prediction accuracies resulting from model validation were similar to those of the goodness of fit, with FatMLR2 resulting in the lowest prediction accuracy (R^2 = 0.14, RMSE = 2.08, MAE = 1.78). Only slightly higher accuracies were seen from the model built using only the fixed effects (FatMLR1; R^2 = 0.15, RMSE = 2.07, MAE = 1.69). The model built combining the fixed effects and 3D measurements resulted in higher accuracies (FatMLR3; R^2 = 0.24, RMSE = 1.96, MAE = 1.61). When including CCW as a predictor, it was retained during the stepwise feature selection process, indicating this variable is significant for the prediction of EUROP fat class. The model, however, resulted in lower prediction accuracy (FatMLR4; R^2 = 0.21, RMSE = 2.00, MAE = 1.66) compared to the model excluding CCW (FatMLR3; R^2 = 0.24, RMSE = 1.96). The numeric fat classes predicted using the best MLR model (FatMLR3) were converted back to the corresponding 7-point scale fat class (traditional EUROP grid), and the confusion matrix (Table 8) shows 44% of classes were estimated correctly, and a further 47% were over/under-scored by one neighbouring class. Importance of variables in the best MLR model (FatMLR3) are listed in Supplementary Table S6. The sex was identified as the most important predictor in the model. The differences in importance for the remaining variables were limited; however, the months tended to be the least influential in the model.

Random forest models

Results from the best RF models are displayed in Table 6. The random forest models built using the 3D measurements alone to predict fat class had accuracies ranging between 38 and 43%. The best performing model resulting for these inputs (FatRF1; accuracy = 43%, kappa = 0.06) was built with a mtry of 1 and 700 trees in the forest. When using this model to predict the fat classes of animals in the validation dataset, 43% of classes were correctly classified and a further 49% were estimated as the neighbouring grade. The AUC for this model was 0.65.

When combining the 3D measurements and the fixed effects, the RF models predicted the fat class again with moderate accuracy (44–47%). The best model (FatRF2) had an mtry of 32, and 900 trees (accuracy = 47%, kappa – 0.15). This model predicted 45% of the fat classes in the validation dataset correctly, and a further 49% as the neighbouring class. The AUC for this model was 0.71.

When including CCW in the RFs, the accuracy ranged between 44 and 49%. The best model (FatRF3) was built with 300 trees and an mtry of 5 (accuracy = 49%, kappa = 0.16). When testing this model using the validation dataset, 48% of fat classes were predicted correctly and 46% as the neighbouring class (Table 8). The AUC for this model was 0.72. Importance of variables in the best RF model (FatRF3) are listed in Supplementary Table S7. The CCW was not identified as the most important model, unlike the

Table 8
Confusion matrix indicating the actual EUROP fat class (Table 2), and the predicted EUROP fat class of live beef animals in the validation dataset, when converted back to the corresponding class on the traditional grid used in the UK, predicted using the best multiple linear regression model (FatMLR3) and the best random forest model (FatRF3)[1].

	Multiple Linear Regression (FatMLR3)								Random Forest (FatRF3)							
	Actual								Actual							
Predicted	1	2	3	4L	4H	5L	5H	Total	1	2	3	4L	4H	5L	5H	Total
1	0*	0#	0	0	0	0	0	0	0*	0#	0	0	0	0	0	0
2	0#	0*	0#	0	0	0	0	0	0#	0*	0#	0	0	0	0	0
3	1	4#	24*	7#	3	0	0	39	1	4#	24*	14#	6	0	0	49
4L	0	5	34#	53*	21#	0	0	113	0	5	41#	73*	32#	1	0	152
4H	0	0	8	31#	17*	0#	0	56	0	0	1	7#	6*	0#	0	14
5L	0	0	0	3	3#	1*	0#	7	0	0	0	0	0#	0*	0#	0
5H	0	0	0	0	0	0#	0*	0	0	0	0	0	0	0#	0*	0
Total	1	9	66	94	44	1	0	215	1	9	66	94	44	1	0	215

[1] Correctly classified conformation classes are denoted with * (black shading) and classes estimated as a neighbouring class are denoted by # (grey shading)

Table 9
Goodness of fit and prediction accuracies resulting from the multiple linear regression (MLR) models built for the prediction of cold carcass weight (CCW) of live beef animals.

Model	Predictors	Train			Validation		
		Adjusted R^2	RMSE	AIC	R^2	RMSE	MAE
CCWMLR1: Fixed effects only							
	Breed + sex + camera number + month + days before slaughter	0.286	27.098	3653.606	0.282	27.487	21.722
CCWMLR2: 3D measurements only							
	widS + widM + lenS_MS + lenM_RM + lenRM_R + heightMS + heightR + areaMS1 + areaMS2 + areaRM1 + areaTR + areaB + volMS2 + volRM2 + diagMS1 + diagMS2	0.347	26.039	3600.004	0.231	29.097	22.503
CCWMLR3: 3D measurements and fixed effects							
	widS + widM + widR + lenS_MS + lenMS_M + lenRM_R + lenTR + lenTOT + heightS + heightMS + heightR + areaMS1 + areaMS2 + areaRM1 + areaTR + areaB + volMS2 + volRM2 + diagMS1 + diagMS2 + diagRM1 + breed + sex + camera number + month + days before slaughter	0.478	22.699	3501.825	0.380	26.075	19.910

Abbreviations: MAE = mean absolute error, AIC = Akaike information criterion, CCW = cold carcass weight. See Table 1 for the description of 3D measurements used as predictors.

other models containing this variable. Despite this, the relative importance of all the variables were similar, once more indicating that no clear variable or sets of variables (i.e. widths, lengths, heights, volumes, areas or fixed effects) were more important. Again, the months and camera numbers tended to be of the lowest importance.

Cold carcass weight results

Multiple linear regression models

The MLR models built for the prediction of CCW resulted in low-moderate goodness of fit (Table 9). The lowest adjusted R^2 and highest RMSE and AIC resulted from the model built using only the fixed effects (CCWMLR1; adjusted R^2 = 0.27, RMSE = 27.10, AIC = 3 654). The 3D measurements alone explained more of the variation seen compared to that of the model built using only fixed effects (CCWMLR2; adjusted R^2 = 0.35, RMSE = 26.04, AIC = 3 600). When combining both the fixed effects and the 3D measurements, the goodness of fit further increased (CCWMLR3; adjusted R^2 = 0.48, RMSE = 22.70, AIC = 3 502). The prediction accuracies resulting from the MLR using the validation data set were slightly lower than the goodness of fit resulting from the training data set, with the R^2 ranging between 0.23 and 0.38.

Testing on the validation data set, the model built with only the 3D measurements resulted in the lowest accuracy (CCWMLR2; R^2 = 0.23, RMSE = 29.10, MAE = 22.50). The MLR built using only the fixed effects resulted in higher prediction accuracy (CCWMLR1; R^2 = 0.28, RMSE = 27.49, MAE = 21.72). When combining both the fixed effects and 3D measurements, prediction accuracies were highest (CCWMLR3; R^2 = 0.38, RMSE = 26.08, MAE = 19.91). Importance of variables in the best MLR model (CCWMLR3) are listed in Supplementary Table S8. The AreaTR was the most important variable in the model; however, its importance was not substantially higher than the other variables which had similar relative importance.

Random forest models

The RF models built for the prediction of CCW (Table 10) using the 3D measurements only resulted in low accuracy (R^2 = 0.27–0.31). The best RF model had a mtry of 7 and 100 trees (CCWRF1: R^2 = 0.31, RMSE = 27.52 kg). When using this model to predict the CCW of animals in the validation dataset, the prediction accuracy was low (R^2 = 0.34, RMSE = 26.54 kg, MAE = 20.83).

The RF models built including the fixed effects resulted in slightly higher accuracies (CCWRF2: R^2 = 0.34–0.39). The best model (mtry = 10, ntree = 700) was used to predict the CCW for the animals in the validation dataset, and this resulted in moderate prediction accuracy (R^2 = 0.41, RMSE = 25.46 kg, MAE = 20.68). Importance of variables in the best RF model (CCWRF2) are listed in Supplementary Table S9. HeightTR was the most important variable in the model but again, the differences in importance across the variables were limited. In this model, however, the "tail to rear" measurements (HeightTR, LenTR, AreaTR and VolTR) were all ranked with high importance, all being within the top 5 most influential variables.

Discussion

Three-dimensional measurements, extracted from images of live animals, were coupled with additional details (breed, sex, camera number, month, and number of days before slaughter as fixed effects, and CCW) to predict EUROP conformation and fat classes, and CCW. Random forest models and MLR models were built, with the best models resulting in moderate accuracy for the prediction of conformation class and CCW, and low accuracy for the prediction of fat class. The RF models resulted in higher accuracy than the MLR models.

Prediction of conformation class

Conformation class was predicted with moderate accuracy when using the 3D measurements extracted from images of the

Table 10
Results from the random forest (RF) models built for the prediction of cold carcass weight (CCW) of live beef animals.

Model	ntree	mtry	Train		Validation		
			R^2	RMSE	R^2	RMSE	MAE
CCWRF1: 3D measurements only							
	100	7	0.307	27.516	0.338	26.539	20.832
CCWRF2: 3D measurements and fixed effects							
	700	10	0.366	26.538	0.406	25.463	20.675

Abbreviations: ntree = number of trees in the final random forest, mtry = number of variables tried at each split, MAE = mean absolute error.

live animal. The RF models resulted in higher accuracy when tested on the validation dataset compared to the MLR models.

In a study by Miller et al. (2019), alternative ML techniques, i.e. artificial neural networks (**ANN**) were used to predict the EUROP conformation class using the same set of 3D measurements extracted from live animals, and there the ANN models yielded higher accuracies than the MLR models. The results from the ANN models (55.1% classes predicted correctly) were similar to the RF model results from the best–performing RF model in the current study (58% of classes classified correctly). The ML results from both studies outperformed the resulting accuracies from the MLR model in the current study (R^2 = 0.37). This is similar to results predicting the conformation class using 3D measurements extracted from images of beef carcasses, where both RF and ANN models (Nisbet et al., 2024b) resulted in higher accuracies (71%) than MLR models (R^2 = 0.48, implying prediction accuracy of 48%) (Nisbet et al., 2024a), further indicating the superiority of machine learning methods over traditional statistics for the prediction of categorical traits such as conformation. In the current study, however, when mapping the predicted numeric classes resulting from the best MLR model onto the traditional EUROP grid used within the UK, 59% of classes were estimated as the correct class, resulting in slightly higher accuracy than the RF model.

Prediction of fat class

The 3D measurements predicted the EUROP fat class with moderate accuracy, with the best RF model resulting in a prediction accuracy of 48% when the 3D measurements were paired with the fixed effects and CCW. Similar to the models built for the prediction of EUROP conformation class, the RF models built for the prediction of EUROP fat class resulted in higher accuracies than the MLR models. Despite this, the fat classes predicted for the validation data set on the 15-point scale using the best MLR model resulted in similar accuracies to the RF models when mapped onto the traditional grid used in the UK (44% classified correctly). The MLR model with the highest R^2 was the model excluding fixed effects. The RF model with the highest accuracy, however, resulted from the model including CCW. Previous studies have indicated that the CCW is an important predictor of EUROP fat class, with this variable being ranked as the most important predictor in RF models built using 3D measurements of beef carcasses and other carcass details as fixed effects, or the fixed effects on their own (Nisbet et al., 2024b). Despite this, higher accuracies have resulted from models excluding CCW, with Miller et al. (2019) predicting both the EUROP fat class and conformation class with moderate accuracy (55.1 and 55.2%, respectively) when using ANN models. Not only were these accuracies higher than the current study, but the differences in accuracy between the two traits were negligible. In the current study, however, greater differences were noted between the two traits for both techniques tested, with EUROP fat class resulting in lower accuracies. As the EUROP fat class is determined by the coverage of fat on a carcass rather than the physical shape of the carcass (as is the case with conformation), it can be expected that the morphological measurements of the live animal have a limited relationship with EUROP fat class. It could therefore be assumed that alternative technologies that relate directly to fat content in the live animal could result in higher accuracies; however, this has not always been the case previously. For example, lower accuracies than the current study were seen for the prediction of EUROP fat class when using ultrasound measurements of live beef animals, with regression models built by Beriain et al. (2021) resulting in moderate accuracy (R^2 = 0.46). Higher values, however, were noted for the prediction of EUROP fat class by Lambe et al. (2010), using ultrasound measurements of beef cattle at the end of the finishing period. Although these results were higher than those of the current study, they were still of moderate accuracy (R^2 = 0.60). Other imaging technologies, such as computed tomography (CT) scanning, resulted in higher accuracy when predicting alternative fat traits (i.e. carcass fat %) using scans of live calves (R^2 = 0.66, Font-i-Furnols et al., 2021). Although these scanning methods produced higher accuracies, the practicality of scanning live cattle on commercial farms is limited. The limited infrastructure required to capture the images in this study suggests more suitability and practicality for commercial use.

Prediction of cold carcass weight

Cold carcass weight was predicted with low-moderate accuracy using the live animal data. The RF models resulted in superior accuracies compared to the MLR models. This is similar to results found previously when predicting the CCW using 3D measurements of beef carcasses, where RF models resulted in slightly higher accuracies (R^2 = 0.72) than MLR techniques (R^2 = 0.70) (Nisbet et al., 2024a, 2024b). Despite this, for prediction of alternative carcass weight traits (saleable meat yield and primal cut weights), MLR models outperformed RF methods when using similar input data (Nisbet et al., 2025). Alternative ML techniques (ANN models) have also been used and compared to MLR when predicting the CCW of beef animals using on-farm 3D measurements (Miller et al., 2019). The ANN models resulted in superior accuracies to the MLR models (R^2 = 0.88 and 0.83, respectively). The results were also substantially higher than the best MLR and best RF method in the current study (R^2 = 0.38 and 0.41, respectively). Despite this, the models built by Miller et al. (2019) included liveweight as a predictor, and this variable has previously been identified as having a strong linear relationship with CCW. This, along with the liveweight being the most important predictor in the models, explains the higher accuracies. Unfortunately, liveweight was not included as a predictor in the current study as there were too few carcasses with suitable liveweight recordings.

Future outlook and limitations

The results suggest there is potential for the on-farm imaging system and the models created for the prediction of EUROP conformation class, fat class and CCW. Additional work, however, is needed before this can be considered as a viable option commercially. For the MLR models, the increase in accuracy resulting from models built including the 3D measurements as predictors compared to models built using only fixed effects was minimal. Despite this, it is likely that this is due to the limitations of the dataset rather than the measurements being unsuitable for predictions. Due to the majority of the grades being centred around the middle of the grid, there was a tendency or models to overscore the lower classes and underscore the higher classes. A larger dataset, with a higher representation of carcasses with less common fat and conformation grades, would allow for more robust models for the prediction of these outlying classes. A larger dataset also holds the potential for breed and sex–specific models, something that has previously been noted as important (Miller et al., 2019). Miller et al. (2019) also noted the liveweight to be an important predictor for the estimation of the traits assessed. Unfortunately, this could not be included in the current study due to low numbers of cattle with suitable liveweight data. The study would therefore benefit from the inclusion of liveweight recordings which are likely to improve prediction accuracies, rather than the use of CCW as a proxy for liveweight. The limited number of extreme grades means the models are less robust for the prediction of these grades, as for conformation classes such as P+, there was only one observation for training the models. P- conformation classes and 5H fat classes were not present in the dataset at all.

The dataset suggests that the producers in this study are selecting the optimum slaughter date of their cattle effectively, as 78 and 88% of the animals in the dataset were awarded with target EUROP fat classes (classes 1, 2, 3, and 4L) and conformation classes (classes E, U+, U-, and R), respectively. This, however, is much higher than the average seen across the UK, with AHDB (2024) data indicating that 50.67% of cattle (steers, heifers, cows and young bulls) sent to slaughter in 2023 did not reach the target classification grades. Similarly, there are limitations of the traits assessed, such as the categorical nature of the EUROP fat and conformation classes. The 3D measurements extracted from the images have the potential to perform better for the estimation of alternative, yield–based metrics. This has been seen in the abattoir, where 3D measurements of carcasses predicted saleable meat yield and primal cut traits with higher accuracy (Nisbet et al., 2025) than EUROP classes (Nisbet et al., 2024a, 2024b). The disadvantages associated with over/under-finish cattle are clear, both in terms of economics and environmental emissions. Data–driven solutions provide a suitable opportunity for accurately estimating these traits, thus indicating their suitability within the industry and the need for further exploration of systems such as that tested in the current study. Despite this, the 3D measurements may be more suited to predicting quantifiable traits, rather than the categorical EUROP classes, which generally rely on subjective visual grading for assessment. Additional carcass traits could therefore be explored, such as saleable meat yield (SMY) traits or the weight of individual primal cuts. In-abattoir imaging technologies have previously been used to successfully predict these traits (Allen and Finnerty, 2000; Alves et al., 2019; Shahinfar et al., 2019, Nisbet et al., 2025, indicating the potential for on-farm imaging to predict these traits also. Miller et al. (2019) explored the use of on-farm measurements of beef cattle to predict SMY, with artificial neural network models resulting in high prediction accuracy (R^2 = 0.72), suggesting there is the potential for the estimation of this trait and other similar meat yield traits, and benefits would result from further exploring this with the current system.

Conclusion

The best performing models built with 3D measurements extracted from images of live beef animals were capable of predicting the EUROP fat class, conformation class, and CCW with moderate accuracy when coupled with the additional animal/carcass details as fixed effects. This indicates the potential for the imaging system and the measurements to be used for predicting these traits. Limitations, however, have been acknowledged, and further work is required before this system can be suitable for commercial use.

Supplementary material

Supplementary Material for this article (https://doi.org/10.1016/j.animal.2025.101529) can be found at the foot of the online page, in the Appendix section.

Ethics approval

The animal trials described were approved by the Animal Experiment Committee of Scotland's Rural College (SRUC) and conducted in accordance with the requirements of the UK Animals (Scientific Procedures) Act 1986.

Data and model availability statement

The data analysed in this study and the models created are private. Requests to access these datasets/models should be directed to Holly Nisbet.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) did not use any AI and AI-assisted technologies.

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Declaration of interest

Authors DB and AW were employed by the company Innovent Technology Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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