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Using 3D Imaging and Machine Learning to Predict Liveweight and Carcass Characteristics of Live Finishing Beef Cattle

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Selection of finishing beef cattle for slaughter and evaluation of performance is currently achieved through visual assessment and/or by weighing through a crush. Consequently, large numbers of cattle are not meeting target specification at the abattoir. Video imaging analysis (VIA) is increasingly used in abattoirs to grade carcasses with high accuracy. There is potential for three-dimensional (3D) imaging to be used on farm to predict carcass characteristics of live animals and to optimise slaughter selections. The objectives of this study were to predict liveweight (LW) and carcass characteristics of live animals using 3D imaging technology and machine learning algorithms (artificial neural networks). Three dimensional images and LW's were passively collected from finishing steer and heifer beef cattle of a variety of breeds pre-slaughter (either on farm or after entry to the abattoir lairage) using an automated camera system. Sixty potential predictor variables were automatically extracted from the live animal 3D images using bespoke algorithms; these variables included lengths, heights, widths, areas, volumes, and ratios and were used to develop predictive models for liveweight and carcass characteristics. Cold carcass weights (CCW) for each animal were provided by the abattoir. Saleable meat yield (SMY) and EUROP fat and conformation grades were also determined for each individual by VIA of half of the carcass. Performance of prediction models was assessed using R^2 and RMSE parameters following regression of predicted and actual variables for LW ($R^2 = 0.7$, RMSE $= 42$), CCW ($R^2 = 0.88$, RMSE $= 14$) and SMY ($R^2 = 0.72$, RMSE $= 14$). The models predicted EUROP fat and conformation grades with 54 and 55% accuracy (R^2), respectively. This study demonstrated that 3D imaging coupled with machine learning analytics can be used to predict LW, SMY and traditional carcass characteristics of live animals. This system presents an opportunity to reduce a considerable inefficiency in beef production enterprises through autonomous monitoring of finishing cattle on the farm and marketing of animals at the optimal time.

Keywords: finishing beef cattle, 3D imaging, carcass characteristics, machine learning, precision livestock farming

INTRODUCTION

In 2017, 51% of prime beef carcasses in the UK did not meet target fat and conformation grades: 40% had poor conformation and 15% were too fat (AHDB, 2018a). The cost to UK producers of sending over-finished cattle to slaughter has been estimated at £8.8 million per year (AHDB, 2018b). For example Roehe et al. (2013) estimated that for an increase in EUROP grade from R4L to R4H for an intensively fed steer of a medium sized breed, a loss of £11.37 would be made in feeding costs alone. Furthermore, processors set weight limits on carcasses and penalise producers for sending overweight cattle, despite them being otherwise to specification. Sending cattle to slaughter too lean equally results in a loss due to the lower price paid for the carcass. Identifying the optimum slaughter point to meet market specifications for beef cattle has economic benefits (Roehe et al., 2013), and reduces the environmental impact of cattle production (de Vries and de Boer, 2010). Therefore, to improve sustainability in the beef production sector it is important for farmers to be able to predict carcass value in the live animal.

Some equations exist for the prediction of carcass characteristics in live animals (Realini et al., 2001; Greiner et al., 2003; Afolayan et al., 2006; Lambe et al., 2008; Minchin et al., 2009; Pogorzelska-Przybylek et al., 2014) but they generally rely on obtaining manual measurements of body dimensions, body condition or tissue depth using ultrasound scanners. Obtaining these measurements is time consuming, may require a level of training and skill, and they can be stressful and potentially dangerous for both animals and handlers.

As imaging technologies become more advanced and affordable it is now economically feasible to implement them on commercial farms. Ozkaya et al. (2016) demonstrated that body measurements of cattle (body length, wither height, chest depth. and hip height) can be accurately determined from 2-dimensional (2D) digital image analysis (90–98% accuracy). Applications for 2D imaging have included estimating liveweight (LW) of broiler chickens (Mollah et al., 2010), pigs (Kashiha et al., 2014; Wongsriworaphon et al., 2015; Shi et al., 2016) and beef cattle (Ozkaya et al., 2016), and LW (Tasdemir et al., 2011), body condition score (Bewley et al., 2008), and lameness (Viazzi et al., 2014) in dairy cows.

Using both Limousin or Aberdeen Angus crossbred steers managed under typical UK conditions Hyslop et al. (2008, 2009) used 2D digital imaging to estimate LW and carcass characteristics. Successful prediction of slaughter parameters included LW ($R^2 = 0.81$, RMSE = 15.7); cold carcass weight (CCW) ($R^2 = 0.81$, RMSE = 10.4); killing out proportion ($R^2 = 0.91$, RMSE = 5.3), sirloin weight ($R^2 = 0.58$, RMSE = 2.1) and proportions ($R^2 = 0.61$, RMSE = 5.1) along with fat ($R^2 = 0.81$) and conformation ($R^2 = 0.81$) gradings.

Advances in imaging technology have allowed for the use of three-dimensional (3D) imaging in the livestock sector with applications in estimating LW (Mortensen et al., 2016) and lying behaviour (Aydin, 2017) in broiler chickens and body condition scoring (Weber et al., 2014; Fischer et al., 2015; Kuzuhara et al., 2015), LW (Kuzuhara et al., 2015), milking traits (Kuzuhara et al., 2015), and lameness (Van Hartem et al., 2014; Viazzi et al., 2014) in dairy cows. 3D imaging is also successfully used in estimating LW in pigs (Wang et al., 2008). There are no known reports where 3D imaging has been applied in estimating both LW and carcass characteristics of beef cattle.

Whilst multiple 2D cameras have been investigated (Hyslop et al., 2009), it was concluded that a "top down" camera view rather than the addition of side and rear view 2D cameras was sufficient for accurate prediction. Application of a 3D camera suspended above the animal would extend the range of potential "top down" predictor variables and refine prediction models further, with the continued advantage of equipment being kept away from animals and potential damage as well as being accessible for both installation and maintenance.

Increasingly, video image analysis (VIA) is being used to grade carcasses in the abattoir, improving the consistency of grading by removing subjective differences in visual assessment by trained graders (Craigie et al., 2012). However, many producers still subjectively select animals for slaughter by visual assessment of fat and condition score and by weighing manually through a crush. This is a clear inefficiency in the beef market. 3D imaging technology has the potential to provide predictions of carcass characteristics from live animals on farm, allowing farmers to send cattle to slaughter as soon as they are within the parameters specified by the abattoir. Having more animals slaughtered within specification increases the profit to the producer, improves the uniformity of the products produced for down-stream customers and reduces the environmental impact per kg of product produced (i.e., lower greenhouse gas emissions and reduced water use).

The objectives of this study were to use live animal body measurements automatically extracted from 3D images to build machine learning algorithms to predict LW and carcass characteristics of finishing beef cattle.

METHODS

Ethics Statement

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

Measurements—Live Animals

The 3D cameras used were Basler Time-of-Flight near infrared cameras (Basler Inc., Exton, PA). The camera specifications are as follows: 640 × 480 pixels, 20 frames *per second*, 57° horizontal × 43° vertical angular field of view, accuracy of +/− 1 cm. Eighteen measurements (5 widths, 6 lengths, 5 heights, and 2 diagonals, **Figure 1**) were extracted from each 3D image and 20 ratios, 11 areas, and 11 volumes were calculated, giving a total of 60 potential predictor variables available for evaluation. Measurements were extracted in real time from 3D images using algorithms developed by Innovent Technology Ltd. using Halcon software (MVTec Software GmbH, München, Germany).

Live animal data was gathered from a range of sources: including both commercial and research farms and from an abattoir lairage.

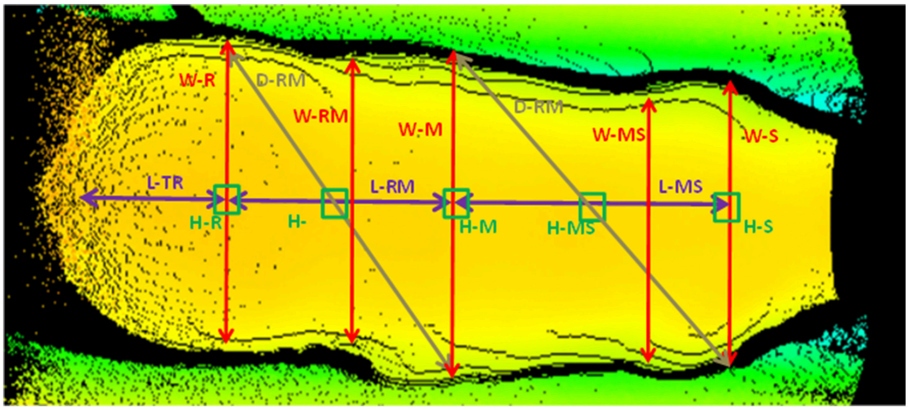

FIGURE 1 | Measurements acquired from 3D images. W, width; L, length; D, diagonal; H, height; S, shoulder; M, middle; R, rump, T, tail.

Farm Trials

Five automatic Beef Monitor weigh crates (Ritchie Ltd, Turriff, UK) fitted with Tru-test weigh heads and electronic ID (EID) readers (Tru-Test Corporation Ltd., Auckland, New Zealand) were installed on four commercial finishing units throughout Scotland and two were installed at SRUC's Beef Research Centre near Edinburgh. The crates were the sole water source for up to 50 steers or heifers in group pens. All animals behind the system were allocated low frequency EID ear tags to allow individual identification and automated weight recording. Three dimensional cameras were suspended from custom made frames 3 m above each crate. Liveweight and 3D images were recorded at every visit to the water trough. Variables were automatically linked to the EID and LW recorded by the Beef Monitor crate and immediately uploaded to a database. Data extracted from images which had poor animal outlines (determined visually) or where the automatically calculated variables were 0 (i.e., a height, width etc. cannot be 0) were removed from the analysis. Poor outlines were generally caused by strong direct sunlight below the camera, a second animal's head against the rear of the animal being measured or the animal leaning against the side of the crate or race. Across the five farms, 17127 LWs were collected from 674 animals (see **Table 1** for a breakdown of sexes and breeds).

Abattoir Trial

A ten day data collection trial was undertaken in a commercial abattoir in Scotland. This allowed a large number of individual animal data points from a variety of breeds, sexes, and animal types with a range of conformation and fat grades to be obtained rapidly. A weigh platform was placed between two sliding gates in the race leading up to the stun box and a 3D camera was secured 3 m above the platform. This allowed individual animals to be held for a short time immediately pre-slaughter to record UKID and LW and to capture a 3D image. Liveweights and clear images were recorded for 1,484 beef animals. A summary of animal numbers by breed and sex are shown in **Table 1**.

TABLE 1 | Summary of cattle used in the development of liveweight prediction algorithms.

	AA (x)	LIM (x)	SIM (x)	CH (x)	Other	Total
Total	909	556	300	225	168	2158
FARM TRIALS						
Total	88	253	139	118	76	674
Steers	5	203	99	91	34	432
Heifers	83	50	40	27	42	242
ABATTOIR TRIAL						
Total	821	303	161	107	92	1484
Steers	436	190	93	52	59	830
Heifers	385	113	68	55	33	654

AA, Aberdeen Angus; LIM, Limousin, SIM, Simmental; CH, Charolais.

Measurements—Slaughter Data

Cattle were stunned by captive bolt, exsanguinated and their hides were removed. Carcasses were split down the midline and dressed as per normal abattoir practice. Conformation class and fatness class were visually assessed for each carcass by trained abattoir staff (according to the abbreviated EUROP grid commonly used in UK abattoirs). VIA technology (VBS 2000, E+V GmbH, Germany) was operated on-line to predict fat and conformation grades on both the 15 point scale and the EUROP grid (7 fat and 8 conformation grades). Cold carcass weight, saleable meat yield (SMY) estimated by VIA along with visually assessed EUROP fat and conformation grades were provided by the abattoir. Carcass characteristics data for a total of 1649 carcases from both the abattoir and on-farm trial datasets were matched to clear pre-slaughter 3D images, see **Table 2** for a breakdown of breeds and sexes.

Statistical Analysis and Development of Predictive Models

Data from all abattoir and on-farm sources were combined into one dataset. For the LW predictions the abattoir data consisted of a single LW per animal taken immediately pre-slaughter. The commercial and SRUC on-farm trial data consisted of multiple

TABLE 2 | Summary of cattle used in the development of carcass characteristics prediction algorithms.

	AA(x)	LIM(x)	SIM(x)	CH(x)	Other	Total
Total	842	395	175	131	106	1649
Farm Trials	22	92	15	24	14	167
Steers	0	77	3	11	2	93
Heifers	22	15	12	13	12	74
FAT GRADE						
1	28	31	13	12	10	94
2	373	194	103	69	38	777
3	339	112	43	35	38	567
4L	85	50	15	15	14	179
4H	17	8	1	0	6	32
5L	0	0	0	0	0	0
CONFORMATION GRADE						
–P	0	0	0	0	1	1
P+	24	2	1	0	6	33
–O	286	41	25	7	46	405
O+	395	118	95	51	38	697
R	127	146	47	59	14	393
–U	10	83	7	14	1	115
U+	0	5	0	0	0	5
E	0	0	0	0	0	0

*See **Table 1** for breakdown of animal breeds and sexes from the abattoir trial. Fat and conformation grades as predicted by VIA. AA, Aberdeen Angus; LIM, Limousin; SIM, Simmental; CH, Charolais.*

weights per animal across the finishing period. For the fat grade, conformation grade, CCW and SMY predictions, only the final LW recorded in the beef monitor crates on farms was used alongside the LWs collected in the abattoir trial. No 5L or 5H fat grades and no E and insufficient U+ conformation grades ($n = 5$) were recorded and so these grades could not be included in the prediction model. A summary of the breeds, sexes, fat grades and conformation grades are shown in **Table 2**.

Sex was included as a factor in the model. Cattle were categorised as either native type (smaller, quick finishing breeds such as Aberdeen Angus) or continental type (larger breeds such as Charolais) (see **Supplementary Table 1** for categorisation of breeds), and this was also included as a factor in the model. From the commercial farm trials, the final measured LW from the weigh crate was included as a predictor variable for carcass characteristics.

Artificial neural networks (ANNs) were selected for this study as they can be used for both regression and classification problems and are capable of handling complex non-linear relationships between large numbers of variables. ANNs comprise a framework of "neurons" which are connected by weighted links (Agatonovic-Kustrin and Beresford, 2000). ANNs can be used for regression and classification problems and have many applications in financial forecasting, machine vision, game theory, medicine and ecology to name only a few. ANNs were developed using the caret package in R (version 3.4.1, R Core Team, 2017). To optimise neural network training, continuous input variables were standardised using a Gaussian transformation (subtracting the mean and dividing by one standard deviation) and min-max scaling between −0.9 and 0.9. The data was then randomly split into training (70%) and validation (30%) subsets.

In this study ANNs were developed through supervised training by backward propagation. The model was presented with the training set and known target values. Weights and biases were automatically randomly initialised to non-zero values (between 1 and −1) by the ANN software and during the training phase the model adjusted the weighted connections by feeding back the error and optimising the weights to decrease the difference between target and output values. Repeated training iterations (three repeats of 10-fold repeated cross validation) further reduced the model error. Models were regularised to prevent overfitting to the training data subset by applying a penalty (a weight decay value) to weights which became relatively much larger than others in the model. Parameter estimation (model size and weight decay values) were optimised after testing 100 potential models (10 possible values per parameter). Several topographies (number of hidden layers and nodes in each layer) were tested for each ANN. The topography which produced the best performance results without overfitting to the training data sub-sets was selected for each ANN. All of the ANNs had one hidden layer with five nodes, except the fat grade classification ANN which only had one node in the hidden layer. The model was then tested on the validation data subset. Model performance was assessed by R^2 and RMSE for regression (LW, CCW, and SMY). Classification accuracy for fat and conformation grades were assessed by way of confusion matrices. A confusion matrix is a table summarising the number of validation sub-set data points in each class and the predicted classes, and the sensitivity (Equation 1) and specificity (Equation 2) for each class.

$$\text{sensitivity} = \text{true positive}/\text{true positive} + \text{false negative} \quad (1)$$

$$\text{specificity} = \text{true negative}/\text{true negative} + \text{false positive} \quad (2)$$

Where for any class (x), a true positive is a data point that is correctly predicted to be within class x, a false negative is a data point incorrectly predicted to not be in class x, a true negative is a data point which is correctly predicted to not be in class x and a false positive is a data point which is incorrectly predicted to be in class x.

Stepwise linear regression models were also created for the continuous variables (LW, CCW, and SMY) using the same training and validation data subsets as were used to create the ANNs and were cross validated using the same method. Summary results (R^2 and RMSE) are reported alongside the ANN results.

Finally, the importance of each predictor variable to the overall ANN was assessed using the VarImp function in R. This function calculates the influence each input variable has on the output by using the connection weight between the input and each hidden neuron and apportioning the connection weights between each hidden neuron and the output between each input variable (based on the method described in Gevrey et al., 2003). Connection weights are analogous to coefficients in a linear model (although the number of connection weights in an ANN is excessive compared to coefficients in a linear model) and so dictate the influence any variable has on the hidden nodes and ultimately on the output e.g., variables with low weights are suppressed and so have little importance and those with large weights are influential and have high importance. Variable importance was scaled from 100 to 0 with 100 being the predictor variable with the highest calculated influence and 0 being redundant. The following calculations below are quoted from Gevrey et al. (2003).

1. For each hidden neuron, divide the absolute value of the input-hidden layer connection weight by the sum of the absolute value of the input-hidden layer connection weight of all input neurons, i.e.,

For h = 1 to *n*h, and for i = 1 to *n*i

$$Q_{ih} = \frac{|W_{ih}|}{\sum_{i=1}^{ni} |W_{ih}|}$$

2) For each input neuron i, divide the sum of the Q_{ih} for each hidden neuron by the sum for each hidden neuron of the sum for each input neuron of Q_{ih}, multiply by 100. The relative importance of all output weights attributable to the given input variable is then obtained.

For i = 1 to *n*i

$$RI\,(\%) = \frac{\sum_{h=i}^{nh} Q_{ih}}{\sum_{h=i}^{nh} \sum_{i=1}^{ni} Q_{ih}}\ x\ 100$$

Where Q is the proportional influence an input neuron has on a hidden neuron, h is a hidden neuron, i is an input neuron, W is a weight and RI is the relative influence of an input neuron (%).

RESULTS AND DISCUSSION

3D Image Collection

A total of 18,134 3D images were collected during this trial. Of the 16,100 3D images collected on commercial and research farms 1,292 (8%) of images were removed due to a poor outline being obtained. From the abattoir trial 550 of 2,034 3D images (27%) were removed from the analysis. The more stressful environment in the abattoir lairage led to a higher proportion of 3D images being removed from the analysis. Animals were more likely to be agitated and so a good quality 3D image was difficult to obtain. Removal of images from the on-farm data sets is not deemed to be a concern for commercial implementation as multiple images are collected per animal per day; therefore not all images of each individual animal are required to provide a prediction to the end user.

Prediction of Liveweight, Cold Carcass Weight, and Saleable Meat Yield

Pre-slaughter LW's ranged from 341 to 774 kg and the mean weight at slaughter was 608 ± 57 kg. The mean CCW was 339 ± 39 kg and mean SMY was 223 ± 32 kg.

In this study LW was predicted for a wide variety of breeds, both steers and heifers, with an R^2 of 0.70 (RMSE = 42, *n* = 4443, **Figure 2**). The performance of the stepwise linear regression for LW was much poorer than the ANN (R^2 = 0.54, RMSE = 51). Ozkaya et al. (2016) used multiple linear regression of measurements extracted from lateral 2D digital images of Limousin cattle to predict LW with an R^2 of 0.89. Although sex and breed type had low importance (3 and 0, respectively, **Table 3**), to investigate the performance of sex and breed specific models the ANN was trained only using the Aberdeen Angus steers data subset (*n* = 441, **Table 1**). The model performance increased to R^2 = 0.77 (RMSE = 37), suggesting that the further development of this system may benefit from breed and sex specific models. As LW had the highest importance (100) for the prediction of CCW, SMY and fat grade, and the importance of sex (CCW: 51, SMY: 29, conformation grade: 1, fat grade: 11) and breed type (CCW: 32, SMY: 15, conformation grade: 18, fat grade: 32) are generally of higher importance for prediction of carcass characteristics (**Table 3**), breed and sex specific LW models should also improve prediction of these carcass characteristics.

Carcasses which are over a defined weight face a penalty at the abattoir. Being able to predict CCW in the live animal would allow producers to ensure that animals are sent to slaughter before they grow beyond the weight limit. The ANN predicted CCW with R^2 = 0.88 (RMSE = 14, *n* = 449, **Figure 3**) and SMY with R^2 = 72 (RMSE = 14, *n* = 448, **Figure 4**). The stepwise linear regression models predicted CCW with R^2 = 0.83 (RMSE = 16) and SMY with R^2 of 0.63 (RMSE = 16). LW was of most importance in the ANNs for CCW and SMY in this study (**Table 3**). LW has previously been shown to have a strong linear relationship with CCW (Minchin et al., 2009), hot carcass weight (Pogorzelska-Przybylek et al., 2014), and SMY (Realini et al., 2001; Greiner et al., 2003). However, predictor variables extracted from the 3D images still had significant influence over the ANN model outputs (**Table 3**), and the ANNs had improved performance over the stepwise linear regression

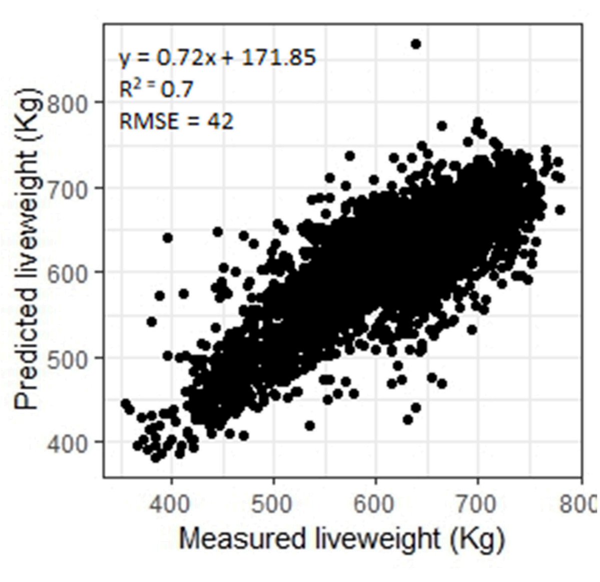

FIGURE 2 | Measured liveweights plotted against liveweights predicted using an artificial neural network.

TABLE 3 | Relative importance (scaled from 100 to 0 where 100 is most influential in the model and 0 is redundant) of the 5 predictor variables with highest influence [and liveweight (LW), sex and breed type if not already included], for each ANN.

ANN	Predictor variable	Scaled relative importance
LW		
	Height (S)	100
	Height (R)	80
	Diagonal (RM)	79
	Length ratio (RM/MS)	75
	Width ratio (R/RM)	71
	Sex	3
	Breed "type"	0
CCW		
	LW	100
	Sex	51
	Breed "type"	32
	Volume (MS)	24
	Height (M)	18
SMY		
	LW	100
	Diagonal (MS)	30
	Sex	29
	Width (RM)	27
	Length ratio (RM/MS)	26
	Breed "type"	15
CONFORMATION GRADE		
	Height (M)	100
	Width (M-S)	79
	Width Ratio (R/M)	78
	Diagonal (MS)	78
	Length (TM)	78
	LW	30
	Breed "type"	18
	Sex	1
FAT GRADE		
	LW	100
	Height (M)	68
	RateA_TR_RM	49
	Height (R)	36
	VolumeTR	35
	Breed "type"	32
	Sex	11

*See **Figure 1** for definition of predictor variables.*

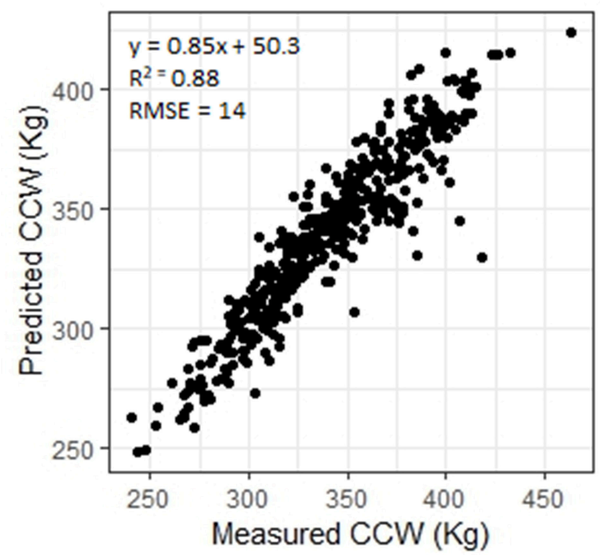

FIGURE 3 | Measured cold carcass weight (CCW) plotted against CCW predicted using an artificial neural network.

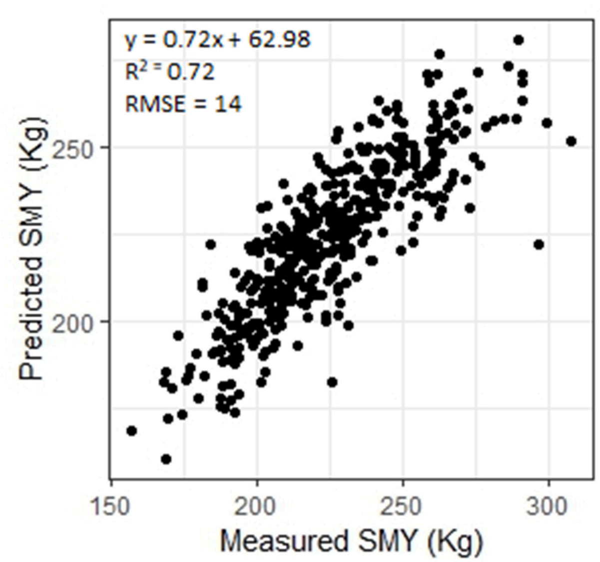

FIGURE 4 | Measured saleable meat yield (SMY) plotted against SMY predicted using an artificial neural network.

models. Greiner et al. (2003) found that when LW was used as a single predictor for SMY their regression model had an R^2 of 0.66 for a more limited range of animals (534 crossbred steers) than used in the present study, demonstrating the potential of 3D imaging to provide more accurate predictions of carcass characteristics.

Prediction of Fat and Conformation Grades

Farmers in the UK are currently paid for their animals on both carcass weight and fat and conformation grades. ANNs were developed for fat and conformation grade using the abbreviated EUROP scale in operation at the abattoir. The accuracy of the classification ANNs for the validation data subset were 54.2% for fat grade and 55.1% for conformation grade. The confusion matrices are shown for the fat (**Table 4**) and conformation grades (**Table 5**), along with the sensitivity (ability of the model to correctly classify a data point to that particular grade) and specificity (ability of the model to correctly identify a data

TABLE 4 | Confusion matrix for the fat grade classification artificial neural network and the sensitivity and specificity of the model to each grade.

	VIA predicted fat class				
ANN predicted fat class	**1**	**2**	**3**	**4L**	**4H**
1	0	0	0	0	0
2	24	191	98	16	1
3	3	40	62	25	1
4L	0	0	9	12	7
4H	0	0	0	0	0
Sensitivity	0	0.83	0.37	0.23	0
Specificity	1	0.46	0.78	0.96	1
Observations in validation dataset	27	231	169	53	9

TABLE 5 | Confusion matrix for the conformation grade classification artificial neural network and the sensitivity and specificity of the model to each grade.

	VIA predicted conformation class					
ANN predicted conformation class	**P+**	**–O**	**O+**	**R**	**–U**	**U+**
P+	0	0	0	0	0	0
–O	5	58	37	2	0	0
O+	4	61	146	50	10	0
R	0	2	23	55	13	0
–U	0	0	1	11	11	1
U+	0	0	0	0	0	0
Sensitivity	0.00	0.48	0.71	0.47	0.32	0.00
Specificity	1.00	0.88	0.56	0.90	0.97	1.00
Observations in validation dataset	9	121	207	118	34	1

point as not belonging to that particular grade) of the model to each grade.

The majority of carcasses were classed as fat grade 2 (47%) or 3 (34%) (**Table 2**). The fat grade model had a sensitivity of 0.83 for grade 2, but a specificity of 0.46 (**Table 4**). This low specificity was due to the tendency of the algorithm to classify the grade 3 carcasses as grade 2. The model classified all of the grade 1 carcasses in the validation subset as grade 2 and most of the 4H carcasses as 4L. It did not correctly classify to either grade 1 or 4H (sensitivity equal to 0, **Table 4**), this was likely due to there being insufficient data points in the training set for these two grades. The specificity of the conformation grade classification ANN model to both P+ and U+ was 1 (**Table 5**). There were also only a small number of data points collected for carcases of these grades. There was a tendency for the model to classify the O- and R carcases as O+ (O+ had a specificity of 0.56), likely due to the relatively large number of data points in the training data set which were grade O+. It is anticipated that increasing the number of data points in the less desirable grades would improve the predictive performance of these models.

Lambe et al. (2010) used ultrasound measurements of tissue depth in live finishing beef steers and heifers to predict conformation and fat grades using linear regression. The predictions in their study were slightly more accurate (R^2 = 0.60) for fat grade and similar (R^2 = 0.56) for conformation class than in the present study, however their models performed poorly on validation data sets (fat class: R^2 = 0.39–0.46, conformation class: R^2 = 0.07–0.24). SMY has also been successfully (R^2 = 0.80) predicted using similar ultrasound measurements (Realini et al., 2001). No literature could be found where a classification model had been used to predict fat and conformation grade of beef carcases. The advantage of a 3D imaging system over manual measurements such as ultrasound are the reduction in stress caused by handling of animals and the automated system can passively provide multiple estimates per animal per day at minimal cost.

In this study LW was found to be the most important predictor of fat grade (weighted importance of 100, **Table 3**), and was less important, but not redundant (weighted importance of 30) for conformation grade. Minchin et al. (2009) found that LW was not a significant predictor of fat or conformation grade for cull cows from either dairy or beef sired lines. This is likely due to the generally lower body condition and fat cover of cull cows compared to finished beef heifers and steers.

CONCLUSIONS

This study has shown that there is potential to use 3D imaging technology to automate the process of selecting cattle for slaughter at the correct specification, so improving the efficiency and profitability of beef enterprises through marketing of animals at the optimal time. Further work to improve the prediction of fat and conformation grades in the live animal is required. Particularly more data needs to be collected from animals with carcass grades out with the desirable target grades. Addressing this imbalance of carcass grades in the dataset will allow the model to better distinguish between grades. Further development of this technology also requires the development of breed and sex specific algorithms for LW and carcass characteristics.

ETHICS STATEMENT

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

AUTHOR CONTRIBUTIONS

C-AD, JJH, WT, DB, and AE conceived and designed the project. GAM, DB, WT, and AE collected the data. GAM and JJH processed the data. GAM analysed the data. GAM and C-AD prepared the manuscript which was reviewed by all authors.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2019.00030/full#supplementary-material

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Conflict of Interest Statement: DB was an employee of Innovent Technology Ltd., AE was an employee of Ritchie Ltd., and WT was an employee of Harbro 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.