# Estimating body weight of individual beef heifers using point-cloud reconstruction and machine learning

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## Abstract

Body trait measurements (e.g., body weight) are routinely performed and provide critical information for producers to assess growth, reproductive performance, and marketing window for individual beef cattle in extensive ranches. However, most of the body trait information is obtained via visual assessment conducted by experienced workers, which has a high rate of inaccuracy. This study aimed to estimate the live body weight of individual beef heifers via three-dimensional (3D) sensing, point-cloud reconstruction, and machine learning regression. 67 beef yearling heifers weighing between 282.13 and 439.98 kg were used for data collection. Top-view RGB-depth videos were recorded when individual heifer walked through by using a 3D sensing camera. Selected RGB-depth images were used to reconstruct point clouds, in which backgrounds were removed. Cattle point clouds were preprocessed to extract 2D and 3D features. Eight machine learning regression models were developed and assessed to determine the optimal model for estimating body weights. Results show that middle slices along *x*- and *y*-axis provide good cattle's back features and support estimation purposes. Using the Adaptive Bosting model, the best $R^2$ and mean absolute errors for liveweight regression were 0.934 and 5.632 kg, respectively. The developed pipeline, including preprocessing of point clouds, point clouds feature extraction, and machine learning model prediction, took 3.670±0.013 seconds per heifer point cloud for weight regression. The developed techniques provide supportive tools for precision beef cattle management.

**Keywords**: artificial intelligence, body weight, computer vision, high-throughput phenotyping

## Introduction

Timely acquisition of body trait measurements of beef cattle is of primary importance to improve management, productivity, health, and economic profits. Particularly if body weight could be routinely measured, this data could provide critical decision-making information for producers to assess growth, reproductive performance, and marketing window for individual beef cattle in forage-based livestock operations. Commercially available walk-over scales, in combination with individual identification methods (e.g., radio frequency identification systems, electronic identification), can identify and record the body weight of individual cows as walk over a platform scale (Dickinson et al., 2013). Although the systems can achieve accurate weights, they may lead to considerable investment, development, and customization in existing cattle infrastructure.

As noninvasive imaging technologies become more advanced and affordable, they have been progressively researched for animal applications. The set of technologies consists of sensing devices for data collection and embedded models for predicting or estimating traits of interest. Both two- and three-dimensional (2D and 3D) sensing techniques have been applied for acquiring cattle body trait information. With 2D sensing techniques, spatial information of interest is projected onto an *XY*-plane with each pixel representing an intensity formed with various channels of signals (e.g., Red-Green-Blue, RGB; Hue-Saturation-Value, HSV). Weber et al. (2020) captured RGB images of individual beef cows drinking around a water trough in a feedlot and segmented cattle dorsal areas for body weight estimation. Alternatively, signals collected by 3D sensing technologies form depth images (Alvarez et al., 2018) or reconstruct point clouds (Kojima et al., 2022). Depth images containing distances between cattle and sensors or RGB-depth images containing both the spatial information and distances were used to predict body weight (Na et al., 2022) and body condition scores (Alvarez et al., 2018) of cows. To date, few research has explored the possibility of the application of reconstructed 3D point clouds for cattle body trait prediction. Researchers developed a multi-view real-time acquisition and 3D reconstruction of point clouds, then extracted key regions and measured body dimensions based on reconstructed point clouds for beef cattle (Li et al., 2022a; 2022b; 2022c). They demonstrated that the accuracy of calculated body dimensions, such as length, height, width, and trunk circumference was over 89%.

Machine learning techniques have been developed for big data analytics in animal industry. Based on the types of predicted variables, machine learning was categorized as regression for continuous variables and classification for discrete variables. Supervised machine learning classification algorithms, such as convolutional neural network (Alvarez et al., 2018), were used to classify discrete outputs of body condition scores. Unsupervised machine learning algorithms (without manual labels for model development), were utilized to remove invalid files and retain informative image data from large video datasets. Both supervised and unsupervised machine learning models may be helpful for the body trait prediction and valid data selection from 3D point clouds, but these ideas should be rigorously verified.

The objective of this research was to predict body weight of yearling beef heifers based on 3D data using point cloud reconstruction and machine learning techniques.

## Materials and methods

### Animals and data acquisition

Data collection was conducted at the Gudmundsen Sandhills Laboratory of University of Nebraska-Lincoln, near Whitman, NE, USA. Seventy yearling heifers (body weights ranged from 282.1 to 440.0 kg with a mean ± standard deviation of 308.4 ± 28.03 kg) were used for data collection. Heifers were limit-fed 24 hours prior to the data collection. All animals in the study were under approval of the University of Nebraska-Lincoln Institution of Animal Care and Use Committee (protocol number: 2345).

An RGB-depth camera (Azure Kinect DK, Microsoft, Redmond, Washington, USA) was installed at nearly 3.6 m above the floor with its lens pointing downward to capture heifer top views. Through an USB 3.0 cable, the camera was connected to a desktop with an Intel® Core™ i7-8700K CPU @ 3.70 GHz processor, 16.0 GB RAM, and Windows 10® 64-bit operation system. Heifers walked through a walking chute for regular health check and weighing before depth-video collection. Each heifer was individually recorded into a video episode at a sampling rate of 30 frames per second. Each video episode contained spatially aligned RGB and depth frames for 3D reconstruction and point cloud processing.

### Feature extraction development schemes

Figure 1 demonstrates the overall development scheme consisted of five major components. The first component was to select key frames from collected videos. Including all frames into the analytics may be computationally inefficient, and meanwhile frames at the beginning or the end of a video may not contain all body parts of a cow entering or exiting field of views of the camera. The second component was to crop point clouds of individual beef cattle reconstructed by selected RGB and depth frames (Figure 2). Unnecessary objects (e.g., chute, fence, and wall) within each selected frames may interfere the feature extraction of a cow, thus being removed. The third component was to automatically remove noisy points around the edges of a cropped point cloud, and those points were small and sparse and cannot remove by operators. The fourth component was to extract 2D or 3D features from the valid point clouds of individual beef cattle, and the fifth component was to develop machine learning models for estimating body weight with extracted features. The computer used for implementing the four parts was with a processor of Intel(R) Core (TM) i7-8850H CPU @ 2.60GHz 2.59 GHz, an installed RAM of 32.0 GB. All computing environments were built with Python (version 3.8.13), and the major pythonic libraries are Joblib 1.1.0, Matplotlib 3.2.2, NumPy 1.22.4, Open3D 0.15.1, OpenCV 4.6.0.66, Pandas 1.4.3, Pyk4a 1.4.0, PyntCloud 0.3.1, PyVista 0.36.1, Scikit-learn 1.1.2, and SciPy 1.9.0.

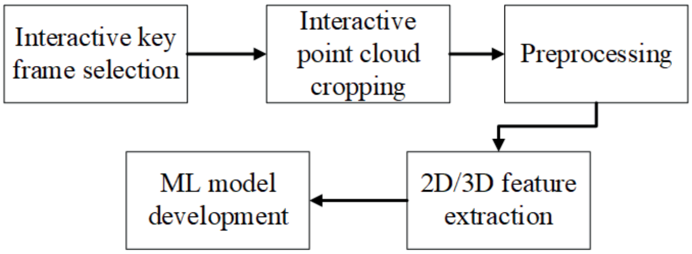


Figure 2: Illustration of the overall development scheme. ML is machine learning, and 2D/3D indicates two-dimensional or three-dimensional.

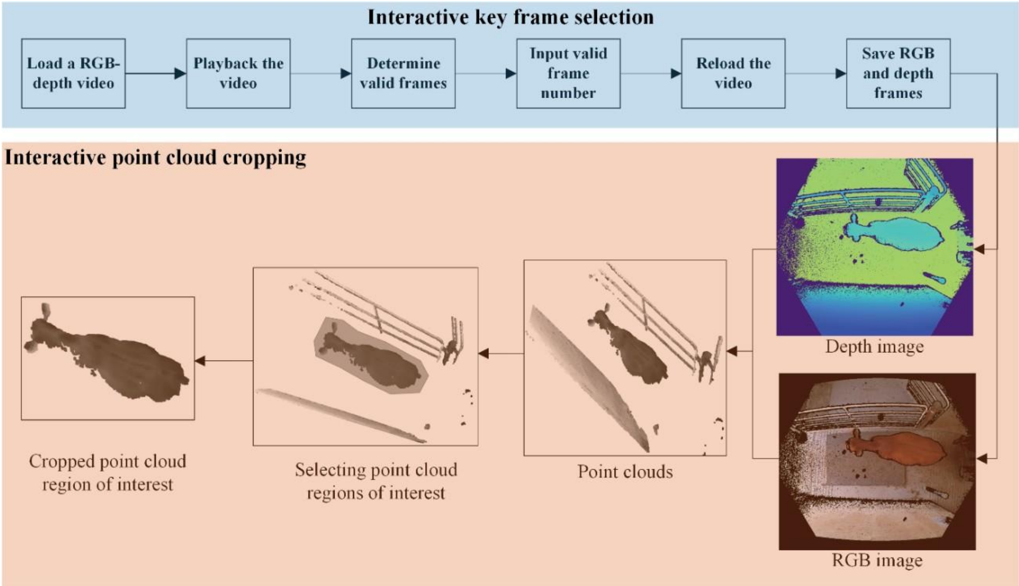


Figure 3: Illustration of the procedures of cropping a cow from a reconstructed point cloud via a developed interactive tool.

Two sets of features were extracted from the preprocessed point clouds of individual cows, namely overall body features and back shape features. The overall body features described the general characteristics of beef cattle from top-view captured point clouds. The total counts of a point cloud for each cow were summarized. Every convex point set in a point cloud was detected (Figure 3), and every three nearest neighbor convex lines were connected to form triangles. The total counts of convex points and triangles were summarized for each cattle point cloud. An aligned 3D bounding box was detected and fitted to the dimensions and orientation of each cattle's point cloud. Length, width, and height of each aligned 3D bounding box or cuboid were calculated from vertex coordinates, and volume, area, and perimeter of the box or cuboid were calculated in Equations 1-3.

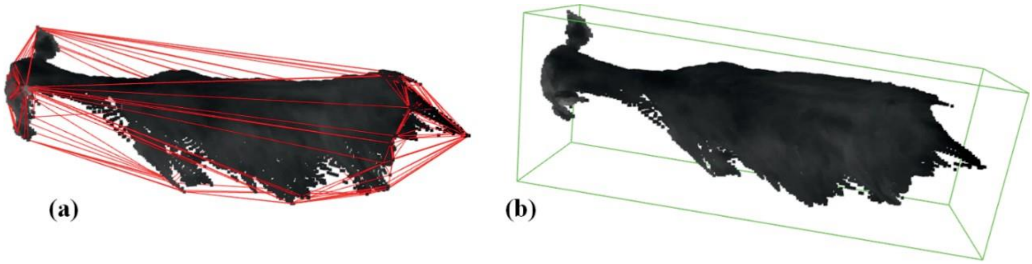

Figure 4: Overall features of a cattle point cloud: (a) convex detection with red lines highlighting sides of triangles connected with three nearest convex lines; and (b) aligned three-dimensional bounding box detection with green lines highlighting sides of a cuboid.

$$Volume = length \times width \times height \tag{1}$$

$$Area = 2 \times (length \times width + length \times height + width \times height) \tag{2}$$

$$Perimeter = 2 \times (length + width + height) \tag{3}$$

### Machine learning model development

A set of regression machine learning models were developed for liveweight prediction. A total of eight models that had a regressor were selected and compared, namely Adaptive Boosting (Adaboost) (Freund and Schapire, 1997), Bagging (Breiman, 1996), Decision Tree (DT) (Quinlan, 1986), K-Nearest Neighbors (KNN) (Altman, 1992), Random Forest (RF) (Liu et al., 2012), Ridge (Saunders et al., 1998), Stochastic Gradient Descent (SGD) (Kiefer and Wolfowitz, 1952), and Support Vector Machine (SVM) (Hearst et al., 1998). The dataset contains 1163-point cloud information (1163 rows × 15 columns + body weight) and was split into 80% for training and 20% for testing with a cross-validation strategy. The 15 features included total counts of points, convex point sets and triangles in a cloud; length, width, height, volume, area, and perimeter of each aligned 3D bounding box; values of a, b, and c for fitted parabola functions of heifer back curves along *x*- and *y*- axes. Common evaluation metrics, including $R^2$ and Mean Absolute Error (MAE) were used to evaluate the regression models. All models were trained with default configurations.

## Results and discussion

For feature extraction from point-clouds, Li et al. (2022c) extracted features of slices from point clouds of beef cattle and found the most reliable feature extraction appeared in the middle slices, which agree with this study. Slices on both sides along each axis had low counts of points, high variance, and high standard deviations. Due to heifers presenting different body postures and positions such as shaking, head nodding, and head turning while walking through the camera's field of view, these different behaviors can result in distortion or irregularities of cattle body shapes (Li et al., 2022a), and slices on both sides were affected more than the middle slices. These findings supported our feature extraction strategy that retaining the slice with minimal variance along each axis for further analysis, as the slice had rich and reliable points for the parabola fitting purposes and good parabola fitting performance.

Performance of the eight models for regressing liveweight based on extracted 2D and 3D features of the cattle point clouds is presented in Table 1. Both the ensemble machine learning models (Adaboost for liveweight regression) and SVM had similar performance in predicting body weight and they slightly outperformed tree models (DT), K-nearest neighbor's model (KNN), and a linear model (Ridge). Between the AdaBoost and SVM models, the AdaBoost achieved a smaller mean absolute error of 5.632 kg, compared to that of the SVM (5.688 kg). Na et al. (2022) compared Linear Regression, SVM, Ridge, LASSO, Bayesian Ridge, Multi-Layer Perceptron, DT, and RF for automatic body weight prediction of beef cattle and reported the Linear Regression, Bayesian Ridge, and RF performed better than other models. Regardless of variations caused by animals or the data collected (e.g., cattle breed, extracted 2D/3D features), various machine/deep learning models could perform differently in estimating body weight and thus, further tuning of model parameters becomes critical to achieve desired model performance.

Table 1: Machine learning model performance for body weight regression of yearling beef heifers

| Model | Body weight regression | |
|---|---|---|
| | $R^2$ | Mean absolute error (kg) |
| AdaBoost | **0.934** | **5.632** |
| Bagging | 0.933 | 5.754 |
| Decision Tree | 0.932 | 5.750 |
| *k*-Nearest Neighbors | 0.933 | 5.759 |
| Random Forest | 0.931 | 5.725 |
| Ridge | 0.931 | 5.761 |
| Stochastic Gradient Descent | 0.931 | 5.775 |
| Support Vector Machine | **0.934** | **5.688** |

Note: The bold fonts highlight the best performance among the models.

## Conclusions

This study illustrates the ability to predict body weight of individual yearling beef heifers via depth sensing and machine learning models. Three-dimensional point cloud data was reconstructed for 70 heifers. Two- and three-dimensional features from the point clouds were extracted and used for body weight regression. Eight machine learning models were fine-tuned and evaluated to determine the optimal model. The developed techniques can predict body weight with $R^2$ of 0.934, with a mean absolute error of 5.632 kg (1.8% of the mean heifer weight, 308.44 kg). The techniques will support precision ranch management.

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