# Deep learning models to estimate finishing pig weight using point clouds

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## Abstract

The selection of animals to be marketed is largely completed by visual assessment of the animals. The ability to monitor the weight of farm animals in real time would provide important information for better and more profitable livestock farming. In addition, continuous and automatic monitoring of individual animal weight could help identify health and well-being issues. The objective of this study is to develop and evaluate a method based on 3D Convolutional Neural Network to predict weight from point clouds. Intel Real Sense D435 camera placed at 2.7 m height was used to capture the videos of a finishing pig between 20-120 kg freely walking in a holding pen. Point clouds were manually extracted from the recorded 3D video. 3D deep learning architecture is implemented using PointNet method that directly takes 3D points of animal body as input to extract the features and regress those features to estimate the weight of the animal. A total of 1186 images from a total of 249 pigs were used for model training and validating with a 9:1 split. Pearson's correlation coefficient (r=0.97) was achieved on randomly selected 112 test points clouds. The validation RMSE of the model was 6.79 kg with a test RMSE of 6.88 kg. The results clearly showed that 3D deep learning on point sets has a good potential for accurate weight prediction even with a limited training dataset. Therefore, this study confirms the usability of 3D deep learning on point sets for farm animals' weight prediction, while a larger data set needs to be used to ensure the most accurate predictions.

**Keywords**: 3D deep learning, PointNet, weight estimation

## Introduction

Live weight measurement is an important factor for management of farm pigs (Halachmi et al., 2019). The body weight provides important information regarding the animal's health and wellbeing (Dickinson et al., 2013). Animal weights are typically not captured in commercial settings. The ability to capture individual weights would help with the marketing decisions. In addition, tracking of weights could add the potential of identifying animals with chronic health conditions. Machine vision based automatic weight prediction is noninvasive and cost efficient, which makes them ideal for livestock management.

Digital image processing is the most used vision-based weight prediction method. In digital image processing, images of pigs' body are analyzed, and animal dimensions such as area, body length, width, chest depth were calculated and correlated to animals' weight (Arulmozhi et al., 2021). Brandl et al. in mid-nineties analyzed pig's body area from digital image to estimate the weight and were able to predict with less than 6% deviation (Brandl and Jørgensen 1996). Although digital image processing has shown great results, it comes with challenges such as pigs needing to be in under the camera at somewhat predetermined position and lighting conditions needing to be consistent.

To overcome the challenge faced by digital image analysis, depth images have been used to extract features of pigs' body (Condotta et al., 2018; Okayama et al., 2021). Depth images extract three dimensional (3D) features of animal's body such as height, volume, curvature, and height. Pezzulo et. al, used Microsoft Kinect to measure heart grith, length and height and used linear and nonlinear mode to get coefficient of determination ($r^2$>0.95). Manual feature extraction is insufficient for a precise prediction as limited numbers of parameters can be extracted and a small change in posture alters all the parameters (Okayama et al., 2021). Okayama et al. (2021) tried extracting information about spinal cord bend to make their model stable even with the change in posture. Although their work has shown an improvement in prediction, this approach is strictly restricted to implementation in the predefined close space. Deep learning approaches are presented as solution to make vision-based weight estimation reliable even with the slight changes in postures of animals.

Largely Artificial Neural Network (ANN)/deep learning have been implemented on digital RGB image of animal to estimate the weight (Bhoj et al., 2022; Cang, He, and Qiao 2019). Hidden fully connected or 2D convolution layers have been used to extract the features from the image with additional regression layer at the end to estimate weight. Jun et al. (2018) tried to address the problem of posture and lighting by introducing curvature and deviation, but they could only achieve coefficient of determination of ($r^2 < 0.79$). In some approaches depth images were colorized based on height of the animal before presenting it to ANN (Meckbach, Tiesmeyer, and Traulsen 2021). The benefit from the colorization is very minimal and becomes almost like that of using RGB images.

Furthermore, all these approaches are common in using predefined lab setup to collect pigs' RGB or depth images. Even though studies have shown correlation up to ($r = 0.99$) with RSME below 1kg, their constrained experimental design makes it impossible to implement them in natural farms (Condotta et al., 2018; Meckbach et al., 2021). There is a strong need for a method which can effectively predict animal weight in natural farm settings/conditions. In recent days 3D deep learning methods are being studied for weight prediction (He et al., 2021) as they are robust in predicting weights even with changes in posture and lighting conditions but have never been tested in commercial Farms.

The objectives of this study were to 1) develop and evaluate a 3D deep learning method to predict pig weight from the point cloud collected with free movement as a typical pen environment and 2) compare the use of deep learning modelling with the linear regression model between pig weight and volume.

## Materials and methods

The animal care and handling techniques were approved by the Animal Use Ethics Committee of the Faculty of Animal Science and Food Engineering at the University of São Paulo (FZEA-USP), under protocol 6526160720.

### Data collection

The collection of images and weighing of pigs was carried out in experimental farms at FZEA-USP (Faculdade de Zootecnia e Engenharia de Alimentos, University de Sao Paulo). Two hundred forty-nine grow-finish pigs (7 to 20 weeks old) were housed in ten pens with 25 animals per pen. The animals always had *ad libitum* access to food and water. 3D videos and weight of pigs were collected between August and November in five different dates. The data acquisition was done using a portable station composed of 3D camera (Intel RealSense D435) and a computer. The weight of individual animals was recorded while in the scale and top-down videos were recorded when pigs were freely moving in holding pen after the weight was taken. A total of 249 videos of individual pigs each with duration 3-5 second were collected, with the intention of extracting seven point clouds of each animal.

### Image extraction and preprocessing

The first step of data processing consisted of extracting 3D images (point clouds) from the collected 3D videos. For this, the Intel Realsense Viewer application was used, the same application that was used to collect the 3D videos. At this stage, during the capture of videos in a period of 3 to 5 seconds, it was intended to extract about seven 3D images, this condition being linked to the quality of the videos.

The entire set of filters and functions developed allowed the 3D images to be read, aligned, filtered, converted, and stored (Figure 1). Points whose values on the z-axis were below or above pre-defined limits were removed according to the minimum and maximum average depth found in the 3D images of the pigs. In this way, the points referring to the floor and the side walls were removed. Points referring to structures that are outside the area of interest, that is, any point that is not referring to the swine, were also extracted through "xy" points that were outside a pre-defined polygon. Further extraction is performed by removing points whose color was different and does not belong to the swine. The color threshold was found automatically by the Otsu method. However, the pigs must have a good contrast with the floor. Finally, the point clouds were subsampled to 1500 points and removal of outliers took place to obtain the final extracted image of the pig. The processed data is composed of a total of 1298 point clouds out of which 645 were of weight below 55 kg, 323 between 55 and 90 kg, and 333 above 90 kg.

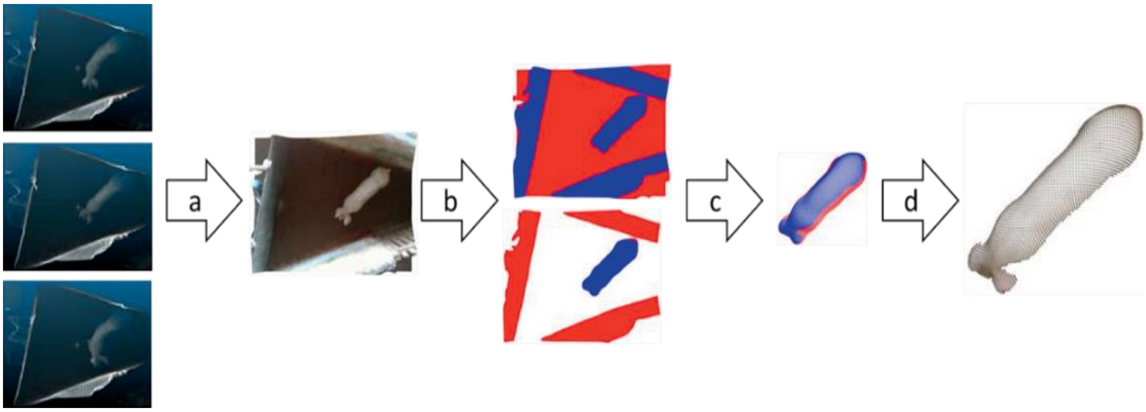


Figure 1: Basic steps for RGB-D image processing to identify and select the animal in the scene (swine): (a) image selection; (b) thresholding and empty points removal; (c) color threshold filtering; (d) final statistical filtering.

## Volume calculation

Literature has shown that volume of the pig's body directly correlates to the mass (Condotta et al., 2018). Space within pig's body surface area (Figure 1(d)) and constant plane 'L' at 2.5m from camera was considered as volume. The volume was calculated using CloudCompare software's 2.5D volume function. The grid with step size 0.01 was projected in 'Z' direction. The maximum height on body from constant plane 'L' was considered as height of the point when multiple points fall inside a cell.

## PointNet

PointNet is a recently proposed algorithm that directly takes points for training (Cherabier et al., 2016; Qi et al., 2017). PointNet has shown a great potential in 3D classification and segmentation, but it has never been explored for livestock weight prediction. A big advantage is it directly takes set of points as input and extracts features of the point clouds. The PointNet architecture takes point cloud with N points as input and utilizes input transformation to extract features (Figure 2).

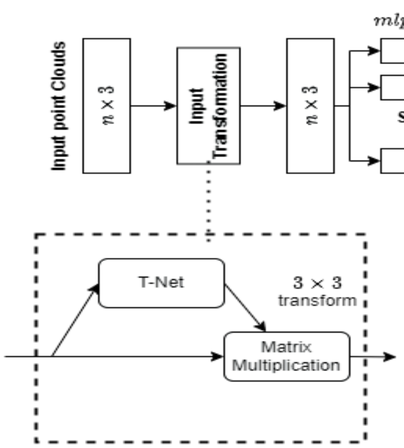


Figure 2: PointNet architecture implemented for weight prediction from a point cloud.

The max pooling layer was used to aggregate the point features and finally K score classes for classification. The input transformation layer is a mini-PointNet network which transforms point clouds to another coordinate system with the same dimension. Successive MLP (multilayered perceptron) layers were shared by each point on cloud. The max pooling layer was used to aggregate the global point features vectors. Finally, the global point features were then passed through another MLP with regression layer on top to output regress weight. The feature transformation layer in between successive shared MLP was removed for computational simplicity.

After preprocessing and selection of the point clouds, the PointNet architecture was trained. The PointNet algorithm was implemented on Google Colab GPU Python version 3.7.15 platform with Keras package (Version 2.9.0) using TensorFlow (version 2.9.2) as backend. Open3d (version 0.16.0) package was used to visualize and read point cloud corresponding to weight levels. PointNet implementation on TensorFlow Keras by David Griffiths was taken as reference for algorithm implementation. Adam with a learning rate of 0.01 was used as optimizer. Root Mean Square Error (RMSE) was used as accuracy metrics and Mean Square Error (MSE) was used as loss function. The model was trained for 1000 epoch with early stopping callback with a patience of 10. The points were jittered between [-0.005, +0.005] to create variability in training data. The dataset was split into 9:1 for the training and validation. A testing dataset containing 112 different images of the same 246 pigs was created.

## Results and discussion

### Volume to weight correlation

Out of 246 pigs, 112 best point clouds were selected for volume correlation. The selected pigs had uniform weight distribution through the 20-120 kg weight range. Initially the correlation between volume and weight was investigated. It was found that the coefficient of determination of 0.7392 (r=0.86) obtained when complete volume of pig including head was correlated to the weight (Figure 3). The correlation did not come close to correlation reported by Condotta et al. (2018) ($r^2$= 0.9907) and Brandl and Jørgensen (1996) ($r^2$=0.98) in their experiment. It is evident the point cloud under investigation were taken at different pigs' position in holding barn which led to variation in volume of pigs compared to the stationary experiment approach followed in most of the literature. Even though the weight seemed to be varying with volume the changes in volume itself with the movement of pigs withing the barn led to less efficient prediction compared to mentioned studies.

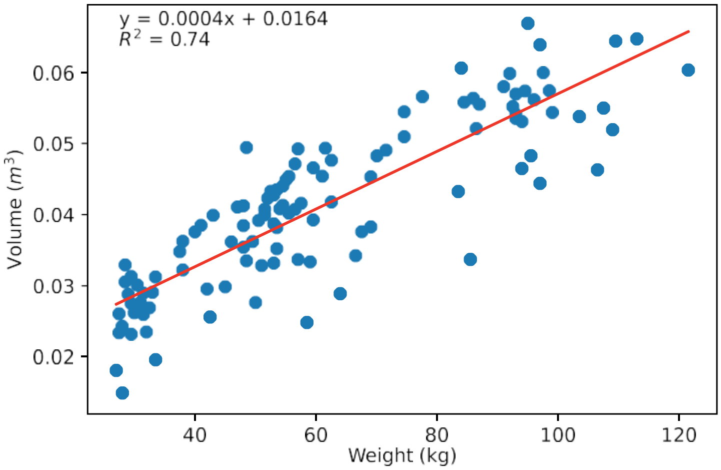


Figure 3: Correlation between the weight of the pig and calculated volume using CloudCompare software's 2.5D function.

## PointNet for weight estimation

One hundred and thirteen point clouds were set aside for testing, the remaining were split into 9:1 for training and validation. Change in Root Mean Squared Error (RMSE) was recorded throughout the training period, Figure 4 shows the learning curve of the change in RSME. The minimum root mean square error of 6.03 kg was obtained at 28th the epoch of the training. Figure 5 shows point cloud along with true labels and predicted labels. Some of the point clouds as shown in Figure 5 were missing big chunks of points from the body area because of some unknown problem in the experimental setup. Those point clouds were considered good and included in training and testing. For the volume correlation, this missing chunk of points might have led to poor correlation, but the deep learning model is good enough to predict the weight even with such points.

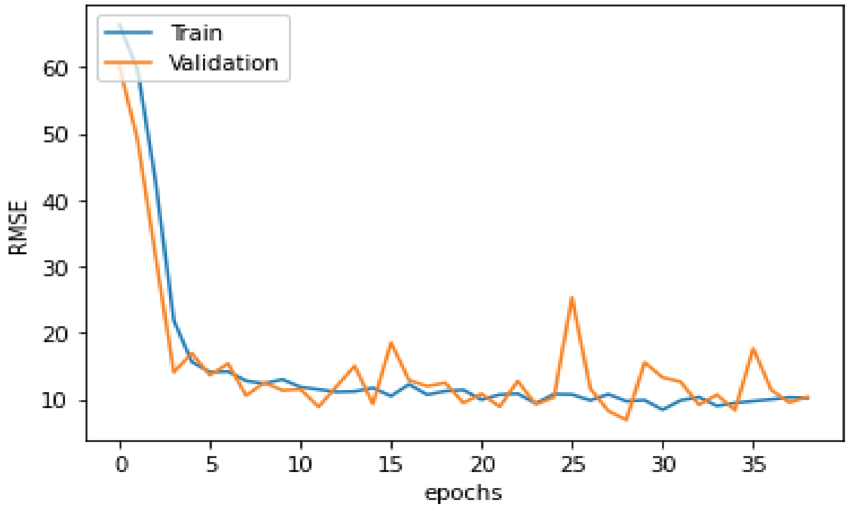


Figure 4: Training history of PointNet architecture over the complete training period

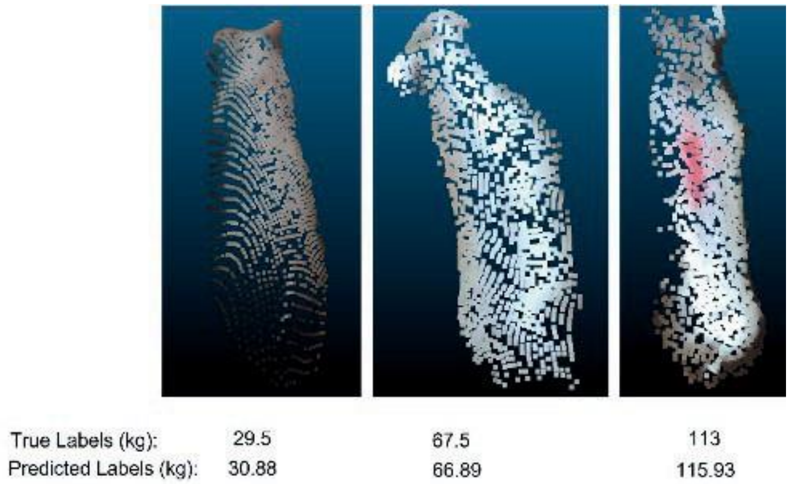


Figure 5: Point clouds, actual and predicted weight values from three different pigs

114 random different points cloud were used for the testing. The trained model was presented with a new set of data for prediction. Figure 6 shows correlation between true weight and the predicted weight. It achieved overall determination coefficient of 0.9421 (r=0.9731) with root mean square error of 6.87 kg. However, the prediction was efficient compared to the volume correlation, the performance could have been better with bigger datasets.

In addition, the experimental setup for further studies should be designed such that the images are taken only when pigs are some what stationary and in a similar position. This can be achieved by placing a camera over the drinker or feeder of pens. First, this will reduce the stress in animals; second, points clouds of the stationary pigs would be homogeneous resulting in better quality of training data. The performance of deep learning algorithm ultimately comes to the database which should be big enough and balanced, therefore we would also like to point out that for further study, design should also consider for collection of higher number of data points.

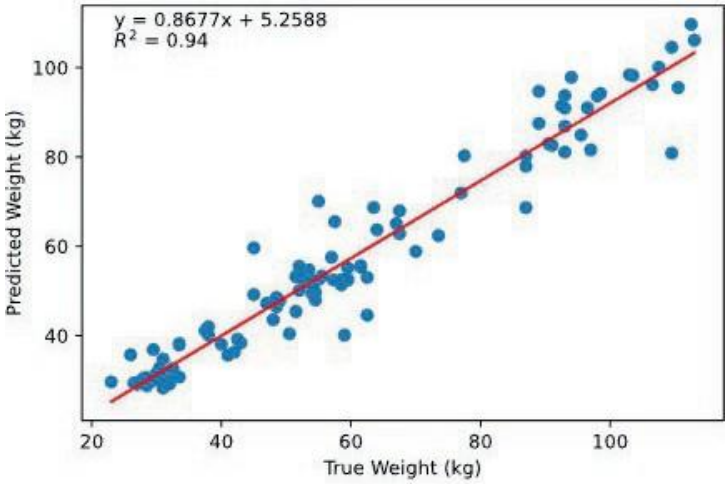


Figure 6: Overall correlation between predicted weight and true weight using PointNet model. The dotted line indicates the optimal fitting

## Conclusions

A 3D deep learning weight prediction model was developed for pigs housed in holding pens using PointNet approach. The deep learning model achieved an overall root mean square error of 6.03 kg on validation dataset. Tested on 112 different point clouds, the model achieved a root mean square error of 6.87 kg with determination coefficient of 0.9421. The volume of the same animals was calculated and correlated with weight, the best determination coefficient between volume and weight of pigs was found to be 0.7392. The results show that 3D deep learning can extract features from the point cloud of pigs in general housing conditions to predict weight despite adverse conditions with the animal in free movement evidenced by the median correlation between animal weight and volume.

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