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# Estimation of Muscle Scores of Live Pigs Using a Kinect Camera

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**ABSTRACT** The muscle grading of livestock is a primary component of valuation in the meat industry. In pigs, the muscularity of a live animal is traditionally estimated by visual and tactile inspection from an experienced assessor. In addition to being a time-consuming process, scoring of this kind suffers from inconsistencies inherent to the subjectivity of human assessment. On the other hand, accurate, computer-driven methods for carcass composition estimation, such as magnetic resonance imaging (MRI) and computed tomography scans (CT-scans), are expensive and cumbersome to both the animals and their handlers. In this paper, we propose a method that is fast, inexpensive, and non-invasive for estimating the muscularity of live pigs, using RGB-D computer vision and machine learning. We used morphological features extracted from the depth images of pigs to train a classifier that estimates the muscle scores that are likely to be given by a human assessor. The depth images were obtained from a Kinect v1 camera which was placed over an aisle through which the pigs passed freely. The data came from 3246 pigs, each having 20 depth images, and a muscle score from 1 to 7 (reduced later to 5 scores) assigned by an experienced assessor. The classification based on morphological features of the pig’s body shape—using a gradient boosted classifier—resulted in a mean absolute error of 0.65 in tenfold cross-validation. Notably, the majority of the errors corresponded to pigs being classified as having muscle scores adjacent to the groundtruth labels given by the assessor. According to the end users of this application, the proposed approach could be used to replace expert assessors at the farm.

**INDEX TERMS** Computer vision, RGB-D imaging, precision farming, machine learning.

## I. INTRODUCTION

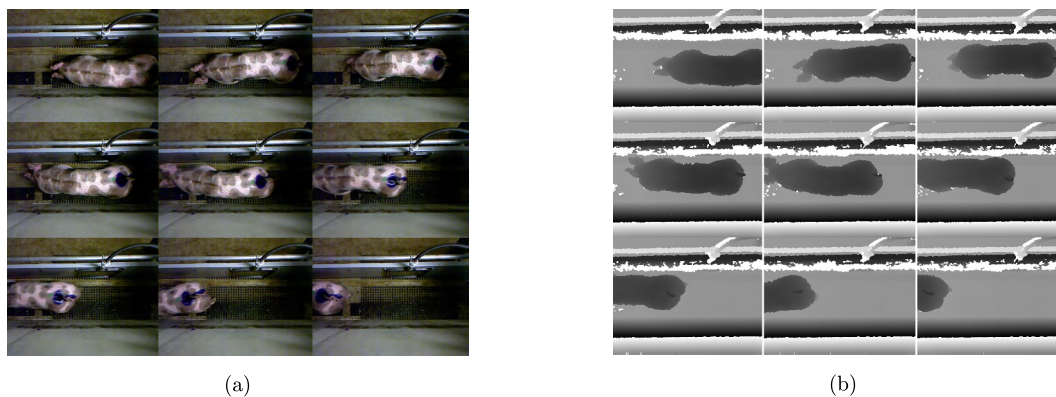
### A. BACKGROUND

The value of a commercial pig largely depends on the composition of its carcass. Heavier pigs yield more meat in general, though at the same weight, some pigs are observed to yield more meat than others. This difference is explained by muscularity. In order to estimate a pig’s potential economic value, it is useful to estimate its body composition, and muscularity, in vivo. This can be done using advanced imaging techniques, such as magnetic resonance imaging (MRI), computed tomography scans (CT-scans), ultrasound, and dual-energy X-ray absorptiometry (DXA) [1], [2].

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Despite the accuracy of those methods in estimating carcass related phenotypes, their high cost and complexity prevent them from being deployed on large industrial scales. Moreover, while these methods are non-invasive, they still require extensive handling of the animals, and often require sedation [2]; thus, making them cumbersome to both the pigs and their handlers.

Alternatively, pigs can be classified into different grades of muscularity at a lower cost, based on visual and tactile inspections by experienced human assessors. Contrary to carcass grading of pigs, these assessments are done while the pig is still alive to estimate the future value of its carcass. Naturally, such assessments are subject to human error and variability from one assessor to another. Additionally, the heuristics based on which the assessors make their



**FIGURE 1.** (a) 9 RGB images of a pig as it passed through the aisle and (b) the corresponding depth images.

decisions are not fully known. However, they are still considered a valuable tool in the meat industry, due to being affordable and accessible.

In this study, we propose an automated alternative to these assessments that can have the same utility of approximating future carcass value, while being faster, cheaper, and more reliable. We design such an automated system by using features extracted from Kinect images of the pigs, and training a classifier on the muscle scores given by an expert assessor. The assessor had used an ad-hoc scoring system of muscularity, where each pig was given a score from 1 to 7. The most extremely muscled pigs were given a score of 7, whereas those without any visible muscling were given a score of 1.

## B. RGB-D COMPUTER VISION

The Microsoft Kinect is a low-cost, consumer RGB-D sensor that provides synchronized color and depth images. Originally introduced as an input device for gaming purposes, it has since been widely used in computer vision research [3]. Owing to the combination of RGB and depth cameras in a single low cost device, the Kinect has had an advantage in some computer vision applications over RGB-only cameras or traditional 3D sensors (e.g. stereo cameras and time-of-flight cameras) [4].

In this study, we exploit one particular advantage, which is the ease of isolating the object of interest - a pig's body, in this case - from the background. The process is also known as background subtraction, or foreground detection. In RGB-based imaging, background subtraction is commonly achieved with methods that assume a static background and a moving object in a temporal sequence of images or video frames [5]. This condition holds in the application of this study, since multiple images were taken of each pig as it passed through a static aisle. However, the presence of a depth sensor makes background subtraction a simpler and more reliable task [6]. Specifically, the object can be extracted from a single image if it is known to be at a distance from the depth sensor that is sufficiently different from the background and other foreground objects. And unlike color-based methods, this approach does not suffer from

difficulties due to illumination changes or color camouflage between the background and the foreground objects.

The rest of paper is structured as follows. In section II-A, we give a description of the utilized data and how it was collected. Then, sections II-B and II-C describe the image pre-processing and feature extraction procedures, respectively. Section III contains the classification results. Finally, in section IV we discuss both the implications and limitations of applying the proposed method in practice, followed by conclusions in section V.

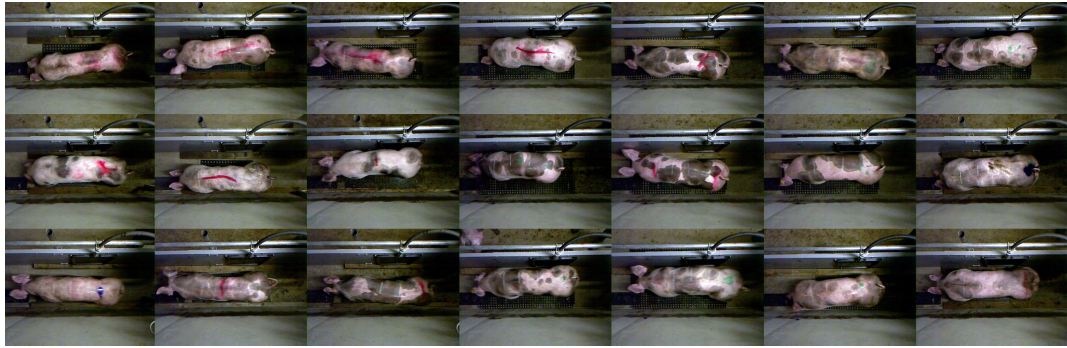
## II. DATA, METHODS, AND EXPERIMENTAL SETTINGS

### A. DATA DESCRIPTION

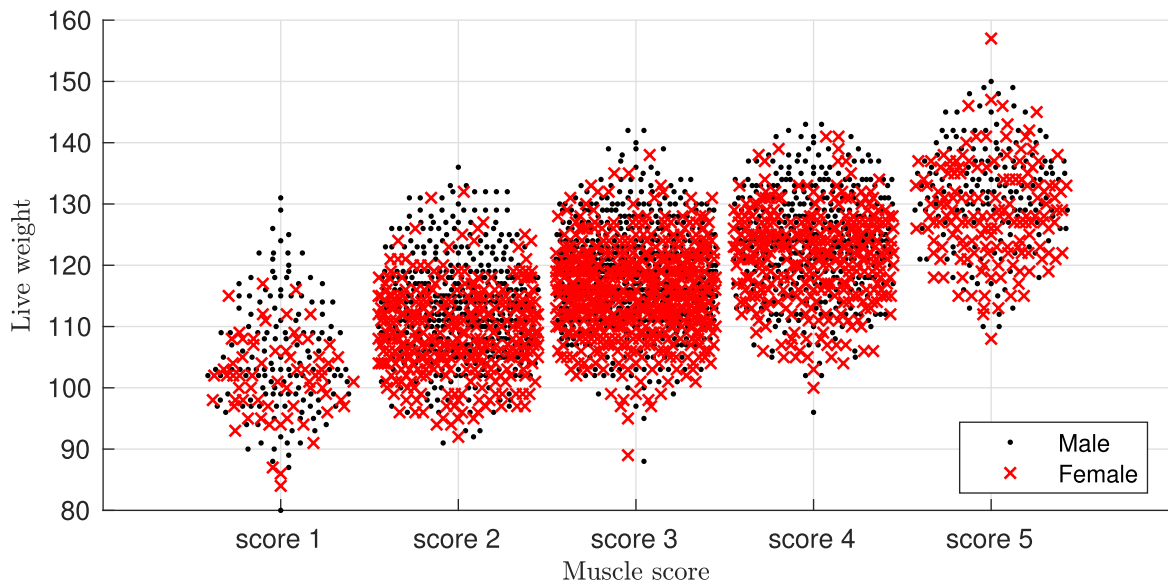
The images were captured using a Kinect v1 camera placed over an aisle through which the pigs passed individually. For each pig, 20 images (of size  $480 \times 640$  pixels) were captured to increase the likelihood of obtaining usable images; defined here as those containing the pig in its entirety, in an appropriate posture, and without occlusion. Fig. 1 shows the RGB and depth images of a pig as it passed through the aisle (9 images out of 20 are shown). In total, we analyzed data from 3246 pigs, 1487 females, and 1759 males. The average age of the pigs at the time of capturing the images and assessing the muscle scores was  $(169 \pm 5.8)$  days, while the average weight was  $(116.9 \pm 10.9)$  kg.

An expert assessor used an ad-hoc discrete muscularity scale to judge each individual pig's muscularity. The scale had been designed to roughly forecast the pig's value. In particular, the score is meant to reflect the carcass quality, and the yield of its primal cuts. Each pig had been given a score from 1 to 7. Besides looking for overall muscularity, the inspector was instructed to judge muscularity independently from size (or weight). In other words, both small and large pigs could be judged as being muscular, and would thus be given a high score. Fig. 2 shows RGB images of three pigs from each muscle score.

Very few pigs were given a score of 1 and 2 (15 and 56 animals, respectively). Therefore, we chose to group the first 3 scores into a single class, leading to a 5-label classification problem instead of 7. According to the end users, this change does not undermine the applicability of the proposed



**FIGURE 2.** Each column of RGB images shows three pigs from one of the muscle score classes, with the least muscular pigs (score 1) on the leftmost column.



**FIGURE 3.** A beeswarm plot [7], showing the distribution of the live weight of pigs across the 5 muscle scores.

approach. Fig. 3 shows the distribution of live weights across the resulting 5 muscularity scores. The plot shows that despite there being a correlation with weight, muscularity is indeed a different attribute, as pigs of varying weights were judged to have the same muscularity score.

**B. IMAGE PRE-PROCESSING AND SELECTION**

For each pig, we applied a series of filters to the 20 depth images that separate the pig’s body form the background. We did this in a similar manner to [8]. First, we converted the gray scale depth image to black and white. Then, we removed all but the largest connected object in the image. As was mentioned in section I-B, the fact that the pig’s body and background are at different distances from the depth sensor makes the separation simple. Finally, we removed the head and tail using erosion and dilation with a 40 pixel radius disk element [9]. Fig. 4 shows these stages for a sample image.

The next step was to automatically select the best out of 20 images for each pig, and remove from the dataset those without any usable images. Some of the causes that made images unusable included occlusion by a farmer, the pig not

being fully within frame, more than one pig being in the frame, or the pig’s body being contorted. To know if the pig’s body was contorted, we measured the symmetry of the pig’s body shape along its longitudinal axis, defined by a symmetry index (*SI*). We computed the index by mirroring one half of the body along its longitudinal axis, then counting the pixel overlap with the other half, and normalizing by one half of the total pixel count of the body’s shape (1).

$$SI = \frac{2A_{ol}}{A_t} \tag{1}$$

Above, *SI* is the symmetry index, *A<sub>ol</sub>* is the area of the overlapping pixels when the top half of the pig’s body shape is mirrored and superimposed on the bottom half,<sup>1</sup> and *A<sub>t</sub>* is the total area of the pig’s body shape.

Fig. 5 shows a visual description of the the symmetry evaluation procedure. This is shown with two images of the same pig; one in which its body is straight (high *SI*), and another where the body is contorted (low *SI*). The latter

<sup>1</sup>If, conversely, the bottom half was mirrored and superimposed on the top half, the value of *SI* would not change.



**FIGURE 4.** The image processing procedure: (a) the grayscale Kinect depth image before processing, (b) the image after conversion to binary with an appropriate threshold, (c) the binary image after removing all but the largest connected object, and (d) the binary image after erosion and dilation.

is rejected based on this criterion. We set a value of 0.92 for the symmetry index, below which images were rejected. We determined the threshold by visual inspection of the images and their corresponding  $SI$ 's. We did this to guarantee that all pigs were compared based on images in which they stood in a uniform posture. Overall, images were rejected if one or more of the following conditions held:

- The processing procedure resulted in more than a single object.
- The contour of the pig's body was in contact with the image's boundaries.
- A symmetry index lower than 0.92.

In cases where multiple images of the same pig were found acceptable, the image where the pig's body had its centroid closest to the center of the image was selected.<sup>2</sup>

### C. FEATURE EXTRACTION

From the pig's connected body object - the result of processing procedure in section II-B - we extracted 10 morphological features detailed in Table 1.<sup>3</sup>

We also added as a feature the volume of the object derived from the depth values. We computed the volume using a procedure described in [8], which was used in that study to regress the live weight of the pigs at the time the images were captured. The procedure works by applying the binary mask that results from the pre-processing steps to the original gray scale depth image. Then, the gray scale pixel values are inverted such that the pixels closest to the sensor have the highest value. The sum of the inverted pixel values are defined as the volume.

Finally, we included two additional features to the feature set that were not derived from the depth images; namely, the sex of the pig, and its weight and age at the time of the test. Table 1 shows a list of the features and their definitions.

### D. CLASSIFICATION

We treated the prediction of the muscle scores as a classification problem with 5 unbalanced class labels. The features described in section II-C form a feature matrix that we denote as  $\mathbf{X} \in \mathbb{R}^{n \times m}$ , with  $m = 13$ , and we denote the muscle score labels as  $Y \in \mathbb{R}^{n \times 1}$ . We performed the classification

<sup>2</sup>The contour and centroid of the objects were computed using the MATLAB function `regionprops`. MATLAB 2018a was used.

<sup>3</sup>We obtained the features by applying MATLAB's `regionprops`. MATLAB 2018a was used.

**TABLE 1.** List of input variables used for classification and their definitions. Inputs obtained from MATLAB's `regionprops` are in single quotation marks.

Feature name	Definition
$X_1$ : 'Sex'	Sex of the pig.
$X_2$ : 'Age'	Age of the pig in days.
$X_3$ : 'Area'	Number of pixels in the object.
$X_4$ : 'MajorAxisLength'	Number of pixels in the major axis of the ellipse that has the same normalized second central moments as the region.
$X_5$ : 'MinorAxisLength'	Number of pixels in the minor axis of the ellipse that has the same normalized second central moments as the region.
$X_6$ : 'Eccentricity'	Eccentricity of the ellipse that has the same normalized second central moments as the region.
$X_7$ : 'Orientation'	Angle between the $x$ -axis and the ellipse that has the same normalized second central moments as the region.
$X_8$ : 'Solidity'	Proportion of the pixels in the convex hull that are also in the object.
$X_9$ : 'Perimeter'	Number of pixels in the boundary of the object.
$X_{10}$ : 'ConvexArea'	Number of pixels in the convex hull of the object.
$X_{11}$ : 'FilledArea'	Number of pixels in the smallest rectangle that bounds the object.
$X_{12}$ : 'Extent'	Ratio of the numbers of pixels in the object to the number of pixels in the bounding rectangle.
$X_{13}$ : 'Volume'	Depth image derived volume [8].

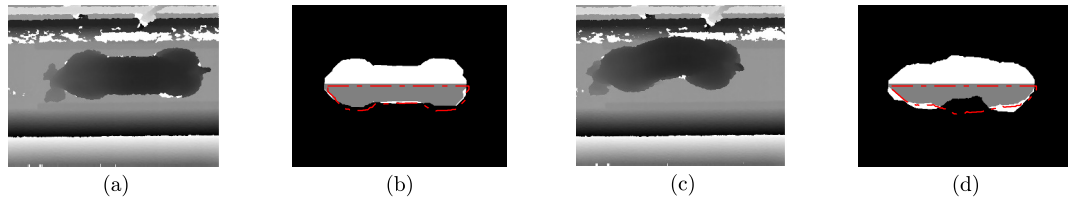
using XGBoost, a fast gradient tree boosting classifier [10]. We made this choice to ensure that any possible non-linear relations between the shape characteristics and the muscle scores could be modeled. Moreover, the speed of the model could compensate for the time taken to process the images and extract their features. This speed advantage becomes relevant in large-scale implementations of the proposed method, e.g. if the method is periodically used to assort pigs into groups based on muscularity at a large farm.

The model parameters we set were the number of trees (1000), and the learning rate of (0.01). We evaluated the performance of the classification using stratified 10-fold cross-validation.

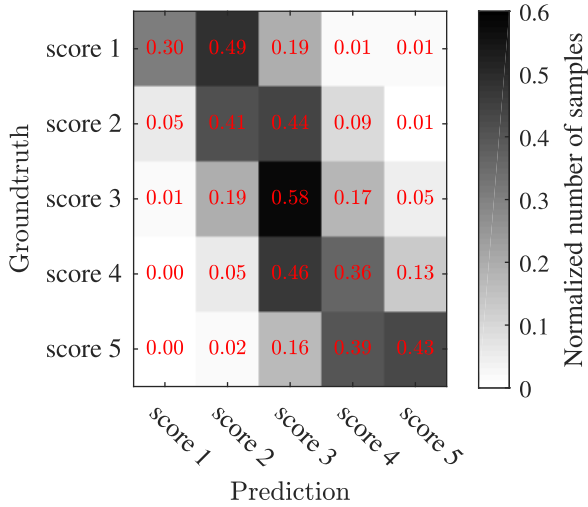
### III. RESULTS

Out of the 3246 pigs, we found 414 (12.75%) to have no usable images after the image processing procedure. The distribution of muscle scores, from score 1 to 5 of the remaining 2832 pigs was as follows: [206, 686, 983, 650, 307].

We constructed the input feature matrix  $\mathbf{X}$  by extracting the features described in section II-C from the best image of each pig. The classification task, performed using



**FIGURE 5.** Two images of the same pig with different postures, (a) a straight body posture, (c) a contorted body posture, and the corresponding processed images for computing the symmetry index in (b) and (d) respectively.



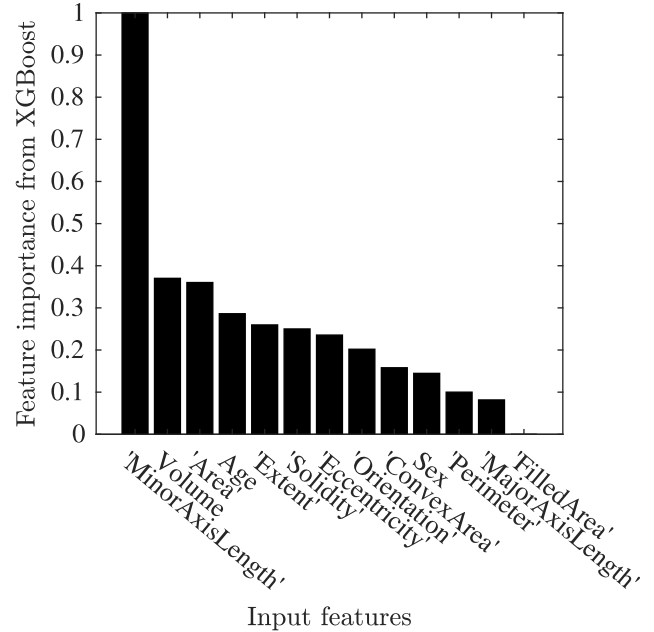
**FIGURE 6.** An accumulated confusion matrix computed by summing the confusion matrices of the test folds of 10-fold cross-validation, then normalizing for each label.

XGBoost in 10-fold cross-validation, yielded a mean absolute error (MAE) equal to 0.65. We computed the MAE because the classes in this problem are ordered, making it a suitable evaluation metric [11]. Fig. 6 shows the accumulated, normalized confusion matrix from the test sets of the cross-validation procedure.

We computed the normalized feature importance scores and show them in Fig. 7. We derived these scores from the training of the XGBoost model with the entire sample set. Feature importance in XGBoost is defined as the total number of times a feature was used to split the data in the tree ensemble. The input variable 'MinorAxisLength' is shown to be the most relevant feature for classifying the target variable. This feature could have acted as a proxy for the pig's abdomen width; a measurement that was computed using a Kinect camera in [12], and used to regress live weight therein.

**IV. DISCUSSION**

The confusion matrix in Fig. 6 shows that most classification errors result from classifying samples in adjacent labels to the true ones, whereas there were significantly less errors between distant labels, e.g., muscle scores 1 and 5. This shows that the model choice of XGBoost classifiers implicitly handles the ordinal nature of the output labels without any customization. This is further shown by the cross-validated average MAE of 0.65.



**FIGURE 7.** Relative feature importance scores derived from the XGBoost model, normalized by the score of the most important feature.

Computer vision technology has been used in several pig farming applications [13]. Most pertinent to our problem are attempts to analyze or estimate carcass composition in-vivo using image-based solutions [1], [2]. In that context, the authors of [2] highlight the differences between MRI, CT-scans, Ultrasound, DXA, and visual image analysis by monitoring (VIA), the latter being a blanket term for methods of estimating carcass characteristics based on 2D images or video, using one or more cameras [14]. The main advantage of MRI, CT-scans, Ultrasound, and DXA is their ability to take internal images of the animal, potentially enabling them to estimate the ratios of body's composing tissues. On the other hand, VIA methods rely on extracting a set of external measurements of the animal that could correlate to its lean mass or muscularity [15], [16].

The solution we propose in this paper is based on a single Kinect sensor. Kinect sensors have been used in the past for pig farming applications, namely, for monitoring and detecting pig behaviors in a pen [17], in automated weight estimation [8], [12], and in the assessment of walking patterns [18]. As we have shown, the sensor is capable of extracting the external shape of the pig, similarly to VIA methods. Unlike VIA methods, however, the depth sensor of a Kinect is not

sensitive to illumination conditions. Therefore, special light installations are not needed [15].

In terms of cost, a Kinect-based approach compares favorably with the other methods. The authors of [2] notably report the high prices of CT-scanners and MRI machines, with new units costing upward of €100,000. Following those in cost are Ultrasound and XDA machines, which are approximately an order of magnitude cheaper. For VIA, the cost depends on the number and type of cameras used, the type of computer, and the mounting installations. In [19], a portable example of a VIA system was constructed for €8,000. By comparison, a ceiling mounted Kinect camera is a relatively inexpensive solution.<sup>4</sup>

A thorough discussion of the time requirements of the preceding methods is given in [2]. In addition to lengthy scanning times, methods like DXA, MRI, and CT-scans require additional time for sedation or anesthesia (which incur additional costs as well). Ultrasound and VIA, while not requiring sedation, are more effective when the animal is stationary, and thus restrained by a human or by a structural confinement. Our proposed approach requires only that the animals pass through an aisle in succession, thus making it the least disruptive solution.

Another important difference between approaches to carcass composition analysis is the target variables that they try to predict. In some studies, the target variables are the true percentages of different tissues in the carcass (fat, lean muscle, bones), obtained after the animal is slaughtered, dissected, and its tissues carefully separated and weighed [22]. In other cases, the weights of primal cuts and their composition are substituted for the true percentages [23].

Conversely, the target variable in this study is a subjectively determined quantity. The scores given by the inspector are not guaranteed to directly correspond to any objective measurements, and the groundtruth values are likely to suffer from human error. Moreover, the inspector gave their assessment based on a comprehensive view of the pigs, and possibly tactile inspection, whereas the input features to the classification model consisted only of objective measurements obtained from a top-view depth image. This dichotomy between how the groundtruth and the predictions are obtained presents a challenge in applied machine learning.

Similar scenarios occur, for example, when computer vision or machine learning are used to replicate the diagnoses - given by doctors - of various medical conditions [24], [25]. Or when a machine learning model is trained on objective measurements to learn the subjective assessments of quality in audio [26], video broadcast [27], or vehicle handling [28]. In the latter cases, the subjective assessments are considered the true benchmarks. Objective alternatives are developed to approximate the subjective assessments, and are preferred for their convenience,

<sup>4</sup>Though the Kinect v1 and v2 have been discontinued, alternative sensors exist in the market which have been used in RGB-D research, like the VicoVR [20] and Orbbec devices [21], priced at \$239.99 and \$149.99 respectively, as of February 2018.

consistency, and low cost. Nevertheless, the subjective assessments are given primacy. On the other hand, in our application, and similarly in the case of the aforementioned medical applications, the subjective quantity is merely a proxy for a more relevant objective one. In other words, the true condition of a patient is the relevant quantity, rather than a doctor's assessment of it. Similarly, the true muscle mass of a pig and its carcass tissue composition are the quantities of interest, rather than a subjective assessment thereof.

In the absence of an objective groundtruth measurement for validation, it is difficult to fully evaluate the performance of the classification. In particular, it is impossible - under such limitations - to determine how accurate the groundtruth is. This is not to be conflated with the kind of overfitting error that can be remedied with cross-validation or regularization. In this case, even when the model generalizes well to the available data, the data itself is not general enough and may contain errors. The author of [29] proposed a framework for evaluating different classifiers relative to each other given the presence of groundtruth errors. However, no guarantees can be given for the absolute accuracy of a single classifier under those conditions.

To compensate for this in our application, the performance of the classifier could be compared to one in which the same input variables are fit to objective measurements that correspond to muscularity. Examples of such measurements are post mortem scan data, or carcass prices. However, even without the use of those measurements, improvements could be made. One way to do that is by training a similar classifier on a larger dataset of pigs, particularly one which includes the muscle score assessments of multiple independent human experts. Such a classifier would be more robust and reliable, as it would model the average expertise of multiple people, instead of being biased by a single human's decisions. Similar measures are typically taken when models are trained to replace subjective audio and video broadcast quality assessments, where Mean Opinion Scores (MOS) are used as the prediction target. With these amendments, the proposed classification system could substitute human assessors at the farm, with similar or improved outcomes.

## V. CONCLUSION

In this paper, we presented a procedure for automatic scoring of pig muscularity using a Kinect camera. The mean absolute error we achieved was judged by end users and field experts to be adequate for replacing the human assessors. Ultimately, an automatic system for muscularity scoring that reduces human-animal interaction at the farm could lead to higher welfare for the animals.

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